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NOVEL RISKS AND SOURCES OF VOLATILITY:
Identification and Measurement Challenges for Portfolio Management

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Editors' Introduction to the Special Issue on Novel Risks and Sources of Volatility: Identification and Measurement Challenges for Portfolio Management

Frank J. Fabozzi and Ahmet K. Karagozoglu

INTRODUCTION

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In a broad sense, novel risks arise from environmental-, governance-, healthcare-, social responsibility–, sustainability-, and technology-related shortcomings of or challenges faced by firms, as well as the uncertainty caused by potential domestic and global regulatory policy responses. The recent announcements made by the Securities and Exchange Commission during the first quarter of 2021 highlight the importance of environmental, social, and governance (ESG) risk and climate change risk, as well as how rapidly the regulatory and policy framework is evolving for these risks. The most recent ransomware attacks in May 2021 targeting a major US energy distributor and a major US food processor underscore the proliferation of potential vulnerabilities from cybersecurity risk. These developments have been taking place as the financial markets process the impact of COVID-19 pandemic, which has been affecting the world since February 2020 (as of writing in August 2021), bringing pandemic risk to the forefront of risk taxonomy and heightening sensitivity to geopolitical risk as the perfect storm of novel risks seems to converge on economies across the globe.

In the lead article, "Novel Risks: A Research and Policy Overview," Ahmet K. Karagozoglu presents a review of the recent academic literature, identifying common themes for data and measurement and discussing future directions for research and regulatory policy development. According to the author, recent academic literature suggests that there are parallels among ESG risk, climate change risk, cybersecurity risk, and geopolitical risk in terms of measurement challenges, including but not limited to emerging data and measurement methods; similarities in terms of their insufficient, noncomparable, less-specific, and non–decision-useful disclosures; and the potential interaction between these risks. Karagozoglu concludes that the establishment of consistent disclosure policy and reporting requirements and improvement in measuring the impact of these novel risks on asset prices, volatility, and global financial stability are at the forefront of contemporary financial economics and portfolio management.

Many corporations will have to adjust their operations and/or their products and services to meet their countries' nationally determined contributions and future climate policies, which vary significantly across countries, to reduce greenhouse gas emissions in line with the 2015 Paris Agreement's goal of keeping the increase in global average temperatures to well below 2°C. In their article, "Foundations of Climate Investing: How Equity Markets Have Priced Climate-Transition Risks," Guido Giese, Zoltán Nagy, and Bruno Rauis examine the extent to which climate risk has been priced into equity markets by developing fundamental economic transmission channels to explain the potential impact of climate change on equity prices. They find that carbon-intensive companies have seen a relative downward trend in their price-to-book ratio valuation, which means markets started to effectively discount book values that can be linked to carbon-intensive activities. In contrast, their results show that companies with high exposure to green revenue have seen their price-to-earnings ratio rise, which means investors are willing to pay an increasing premium to gain exposure to technology that has the potential to replace the existing carbon-intensive infrastructure. They conclude with a discussion of how to measure and categorize companies' climate-risk exposures and how to integrate climate-transition risks into risk models.

Climate risk has become another important dimension, especially because minimum-variance strategies are massively implemented by ESG institutional investors. Therefore, the question of carbon metrics is important for portfolio construction. In "The Market Measure of Carbon Risk and Its Impact on the Minimum Variance Portfolio," Theo Roncalli, Theo Le Guenedal, Frederic Lepetit, Thierry Roncalli, and Takaya Sekine decompose carbon financial risk into a common (or systematic) risk factor and a specific (or idiosyncratic) risk factor. Focusing on the common risk factor that drives carbon risk, the authors assert that the carbon betas they introduce in their article are market-based measures that are complementary to carbon intensities or fundamental-based measures when managing investment portfolios. They show that this market measure is very different from a traditional fundamental measure of carbon risk because, according to their findings, carbon intensity is not the only dimension that is priced by the market. Their results show that investors that are sensitive to relative carbon risk prefer stocks with a negative carbon beta over stocks with a positive carbon beta, whereas investors that are sensitive to absolute carbon risk prefer stocks with a carbon beta close to zero. The authors conclude that managing relative carbon risk implies having a negative exposure to the carbon risk factor, whereas managing absolute carbon risk implies having zero exposure to the carbon risk factor.

Climate change is a source of considerable uncertainty, especially for long-term investors. The transition to a sustainable economy in various climate change scenarios poses significant risks and opportunities for investors' portfolios. In "Top-Down Portfolio Implications of Climate Change," Yesim Tokat-Acikel, Marco Aiolfi, Lorne Johnson, John Hall, and Jessica (Yiwen) Jin present a quantitative assessment of the impact of climate change on expected returns and strategic portfolio allocation across major public assets from a top-down macroeconomic perspective. They use estimates in well-accepted risk scenarios to assess the potential impact of alternative climate scenarios on economic growth, inflation, and asset returns for major asset classes. Their top-down cross-asset analysis suggests that the most direct impact will be on growth-oriented assets, such as equities and corporate credit. They find that the impact on developed sovereign bonds, real-estate investment trusts, and commodities is likely to be more localized at the micro level of individual securities than at the asset-class level. Using hypothetical portfolios designed based on top-down assumptions, the authors explore portfolio allocation implications and show that a climate risk–aware portfolio would tilt away from regions and assets that are expected to be adversely affected to obtain better risk-adjusted returns.

Among nonfinancial drivers of financial risk, perhaps none is at the forefront of investors' minds more than geopolitical risk. Financial markets are governed by institutions that are part of the connective tissue of nation-states, which in turn are the primary actors in international affairs. Therefore, the interactions of states with one another and important non-state actors can have significant impacts on market performance. Joseph Simonian, in “Geopolitical Risk in Investment Research: Allies, Adversaries, and Algorithms,” defines and explains the basic dimensions of geopolitical risk as it pertains to portfolio management, in particular considering the challenges of uncovering and analyzing the sources, dimensions, and potential impacts of geopolitical risk on investment outcomes. Simonian’s article provides an overview of the rational choice paradigm and its applicability to the analysis of geopolitical risk, especially discussing how game-theoretic methods can be combined with machine learning to build detailed simulations of strategic interactions. The author also demonstrates how a well-known matching algorithm can be used to analyze international alliances and how the incorporation of geopolitical views in portfolio construction can be achieved by presenting a concise and simple optimization approach.

The recent prevalence of ransomware attacks shows that cybersecurity exposure has a direct impact on targeted firms’ operating cash flows and how it affects the financial situation of targeted firms more directly than reputational damage. Such incidents highlight the vulnerability of the overall economy and the necessity of managing and controlling cybersecurity risk at the firm level. Nazli Sila Alan, Ahmet K. Karagozoglu, and Tianpeng Zhou, in their article “Firm-Level Cybersecurity Risk and Idiosyncratic Volatility,” develop a measure of firm-level cybersecurity risk by employing a pattern-based sequence-classification method from computational linguistics to determine the proportion of time devoted to issues related to cybersecurity risk during earnings conference calls. They use this new firm-specific cybersecurity risk measure to investigate the relationship between cybersecurity risk and firm-level return volatility, which in turn is a novel intraday return-based measure of idiosyncratic volatility. The authors find that firm-level cybersecurity risk is positively correlated with idiosyncratic volatility on the days that earnings calls are held, suggesting that the discussion of issues related to cybersecurity risk during earnings calls is related to an increase in the component of volatility that responds only to firm-specific news. Their results indicate that this positive relationship is robust to alternative measurements of the language in the earnings call discussions and to industry classifications.

Environmental issues, including mitigating climate change, reducing pollution, and halting exhaustion of natural resources, are no longer marginal cultural issues but have become parts of serious government plans, with substantial funding in both the United States and Europe. Government plans explicitly call for sustainable growth with no (or minimal) use of resources. In “Investment Management Post Pandemic, Post Global Warming, Post Resource Depletion,” Frank J. Fabozzi, Sergio Focardi, and Zenu Sharma argue that moving from the current notion of quantitative growth to a new notion of growth that is both quantitative and qualitative requires changes in economic activity and theoretical changes in economics that should allow policymakers to gain a proper understanding of qualitative growth. They assert that the green transition has two aspects. The first is that a progressive reduction of emission of greenhouse gases is a major change of technology that will offer several profit opportunities; the second is that sustainable growth without the use of natural resources will require profound social changes. The authors suggest that in aggregate the green transition might not reduce the amount of profit available to investors; however, the redistribution of profit opportunities from conventional to more complex and environmentally friendly goods and services would result in a substantial overhaul to investment management.

Early in 2020, the world was severely disrupted by COVID-19 as the pandemic triggered extensive health, environmental, and social devastation. As the scale of the effects quickly escalated, investors—probably for the first time—witnessed how a medical phenomenon can have an enormous financial impact on businesses and investors worldwide. Dominique Outlaw, Aimee Hoffmann Smith, and Na Wang, in their article "The Implications of Contemporary Research on COVID-19 for Volatility and Portfolio Management," synthesize recent and ongoing research in finance and economics on pandemic and disaster risk related to the COVID-19 pandemic, which is characterized by pronounced market movements and extreme volatility. They indicate that the uniqueness of the COVID-19 pandemic's shock to market returns and volatility has shed light on several puzzles in finance and motivated the updating of asset-pricing models by incorporating novel risk factors. According to the authors, financial economists now have fresh perspectives on the transmission of pandemic-induced uncertainty to the financial markets via channels pertaining to investor beliefs and behaviors and corporate strategies and outcomes. Although some effects of the pandemic on market volatility are transitory in nature, there is evidence suggesting long-lasting impacts resulting from investors' updated risk perceptions and corporate management's evolving approaches to investing and financing decisions.

It is certainly too early to claim that the COVID-19 pandemic will mark a turning point in favor of a better integration of environmental, social, and governance issues—the so-called ESG factors—into firms' valuation. In "Socially Responsible Investing Strategies under Pressure: Evidence from the COVID-19 Crisis," Gunther Capelle-Blancard, Adrien Desroziers, and Olivier David Zerbib investigate the resilience of socially responsible (SR) strategies during the COVID-19 crisis using SR indexes from a worldwide sample and comparing them to conventional benchmarks to control for sectoral and geographic biases. The financial performance of SR strategies is shown to have substantial heterogeneity, whereas SR impact strategies slightly outperform corresponding benchmarks. The authors find that the resilience of SR strategies is a little stronger in countries and during periods in which the number of COVID-19 cases was increasing. They control for public attention to the COVID-19 pandemic, as well as the economic effects of new policies implemented during the crisis, including lockdowns and fiscal and monetary policy changes. The authors conclude by recommending a careful review of SR investment selection because not all such investments have provided equal returns in the face of the pandemic.

Over the past decade, sustainable and responsible investing have gained momentum and continue to grow in popularity among investors, and it is increasingly recognized that the financial system has a particularly important role to play in the transition toward a low-carbon and climate-resilient economy. In "Measuring and Managing ESG Risks in Sovereign Bond Portfolios and Implications for Sovereign Debt Investing," Lionel Martellini and Lou-Salomé Vallée examine the impact of ESG factors on the risk and return of sovereign bonds. In particular, they investigate how to measure and manage ESG risks in sovereign bond portfolios and the implications for sovereign bond portfolio strategies. They show that implementation choices matter with respect to how ESG constraints are incorporated into sovereign bond portfolio construction and present evidence that negative screening leads to more diversified portfolios and lower levels of tracking error, whereas positive screening leads to higher levels of improvement of ESG scores at the cost of an increase in absolute and relative risk budgets. Martellini and Vallée conclude that sound risk management practices are critically important in allowing investors to incorporate ESG considerations into investment decisions at an acceptable cost in terms of dollar or risk budgets.

TOPICS: ***Risk management, tail risks, ESG investing, legal/regulatory/public policy****

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INTRODUCTION

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TOPICS: ***Risk management, tail risks, ESG investing, legal/regulatory/public policy****

Countries have set varying targets to reduce greenhouse gas emissions in line with the Paris Agreement's goal of keeping the increase in global average temperatures to well below 2°C. In this article, the authors examine to what extent climate risk has been priced into equity markets and whether climate change can be modeled using a typical risk model structure. They develop the fundamental economic transmission channels to explain the potential impact of climate change on equity prices, including empirical evidence for climate policies and green technology as financial risk drivers. They also study the impact of climate-transition risk on valuation levels

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Novel Risks: A Research and Policy Overview

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KEY FINDINGS

- A broad characterization of novel risks is presented, and environmental, social, and governance (ESG) risk, climate change risk, cybersecurity risk, and geopolitical risk specifically are defined.
- An overview of the recent academic literature suggests that there are parallels among these novel risks in terms of measurement challenges and disclosure regulations.
- Measures based on novel applications of text and news analytics are identified as proxies for novel risks as investigated in the recent academic literature.

ABSTRACT

In a broad sense, novel risks arise from environmental-, governance-, healthcare-, social responsibility–, sustainability-, and technology-related shortcomings of or challenges faced by firms, as well as the uncertainty caused by potential domestic and global regulatory policy responses. Recent academic literature suggests that there are parallels among environmental, social, and governance (ESG) risk, climate change risk, cybersecurity risk, and geopolitical risk in terms of measurement challenges, including but not limited to emerging data and measurement methods; the similarities in terms of their insufficient, noncomparable, less-specific, and non–decision-useful disclosures; and the potential interaction between these risks. Establishment of consistent disclosure policy and reporting requirements as well as improvement in measuring the impact of these novel risks on asset prices, volatility, and global financial stability is at the forefront of contemporary financial economics and portfolio management.

TOPICS

Risk management, tail risks, ESG investing, legal/regulatory/public policy*

Numerous terms entered the risk taxonomy during the last decade. Within the context of the financial services industry, these new or emerging risks have been referred to as *nonfinancial risks*. According to a global advisory firm, this "is a broad term that is usually defined by exclusion, that is, any risks other than the traditional financial risks of market, credit, and liquidity." For example, in a declaration of the nonfinancial performance section of its recent regulatory filing, a major global bank lists, among others, the following nonfinancial factors: climate risk, cybersecurity risk, and geopolitical risk. Although some novel risks may be labeled as nonfinancial, their impact needs to be measured financially. The recent global pandemic highlights the challenges in identifying emerging risks and measuring their impact on asset prices and volatility.

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Referring to these novel risks simply as nonfinancial may hinder efforts to create a unified regulatory framework for their measurement and disclosure policymaking. Furthermore, novel risks affect a broad range of industries differently; as such, it is worthwhile to address whether corporations might be less equipped to measure novel risks than financial institutions because this would have important policy implications.

What makes focusing on these novel risks of interest to financial market participants is the parallels among these risks in terms of measurement challenges, including but not limited to emerging data and measurement methods; the similarities in terms of their insufficient, noncomparable, less-specific, and non–decision-useful disclosures; and the potential interaction between these risks (e.g., climate change risk and pandemic risk; cybersecurity risk and geopolitical risk). Establishment of consistent disclosure policy and reporting requirements as well as improvement in measuring the impact of these seemingly nonfinancial and nontraditional risks on asset prices, volatility, and global financial stability is at the forefront of contemporary financial economics and portfolio management.

NOVEL RISK TAXONOMY

In a broad sense, novel risks arise from environmental-, governance-, healthcare-, social responsibility–, sustainability-, and technology-related shortcomings of or challenges faced by firms, as well as the uncertainty caused by potential domestic and global regulatory policy responses. Novel risk may be considered an evolving concept—that is, a risk factor that used to be novel becomes traditional as its measurement and management enter into established practices. Therefore, environmental, social, and governance (ESG) risk, climate change risk, cybersecurity risk, and geopolitical risk (presented in alphabetical order in the rest of this article) should not be considered an exhaustive list of current or future novel risks in financial markets.

ESG Risk

ESG risk considers exposure to the environmental, social, and governance factors. Historically, environmental factors in this risk category included firms' actions that had negative impact on their surroundings (e.g., polluting rivers, violating Environment Protection Agency regulations). According to the CFA Institute, *environmental* refers to "conservation of the natural world," including firms' carbon emissions, air and water pollution, biodiversity, energy efficiency, and waste management; *social* refers to "consideration of people and relationships," including firms' practices in diversity, community relations, and labor standards; and *governance* refers to "standards for running a company," including firms' board composition, audit committee structure, and executive compensation.[1]

Dyck et al. (2019) stated that investors want to assess, and easily track, measures of a firm's financial performance as well as metrics covering a firm's environmental and social (E&S) performance, which, according to the authors, are the two components of corporate social responsibility (CSR). Chen, Dong, and Lin (2020) indicated that sustainable and responsible investments (SRI) have become part of mainstream investing strategies, and more institutional investors are committing to integrate ESG into their capital allocation process to meet clients' demand for sustainable investments. Dyck et al. (2019) provided an excellent example by referring to a statement by Norges Bank, which manages Norway's government pension fund: "as

[1] https://www.cfainstitute.org/en/research/esg-investing.

a large, long-term investor, we [Norges Bank] engage directly with companies' board and management. … Our investment management takes account of environmental, social and governance issues that could have a significant impact on the fund's performance over time. We seek to further the long-term economic performance of our investments and reduce financial risks associated with the environmental, social and governance practices of companies we have invested in." Therefore, ESG risk can be viewed as financial losses that are caused by firms' lack of adherence to ESG standards.

Climate Change Risk

Climate change risk considers the impact of climate change on firms' operations, the availability of resources, and firms' inability or inaction to identify and mitigate this impact. According to Condon et al (2021), measuring and disclosing firms' climate risk requires consideration of both *physical risk*, which "encompasses the harmful effects of climate change on a corporation's physical assets or operations," and *transition risk*, which reflects "the actions that society takes in response to those physical effects." Schlenker and Taylor (2021) stated that "scientists overwhelmingly agree that the climate is changing because of human activity," but "views on climate change vary greatly across geography, political affiliation, educational status, and economic sector." The authors indicated that how and to what extent financial markets price climate change risks have implications for financial stability. Although it is possible to consider climate (change) risk within the ESG risk category, recent academic research and policy initiatives indicate that climate risk is a standalone factor that should not be subsumed into ESG risk. Although components of ESG risk and climate change risk are interconnected, climate change risk exhibits systemic characteristics owing to its magnitude and potential effect on global financial stability; therefore, it should be treated as a distinct risk.

Cybersecurity Risk

Cybersecurity risk considers the risks associated with cybersecurity incidents, in which such an incident is defined as "an occurrence that actually or potentially results in adverse consequences to an information system or the information that the system processes, stores, or transmits and that may require a response action to mitigate the consequences."[2] Jiang, Khanna, and Yang (2020), referring to an insurer's definition, indicated that "cyber risk commonly refers to any risk of financial loss, disruption or damage to the reputation of an organization resulting from the failure of its information technology systems."[3] Historically, information technology–related risks, especially for financial institutions, were considered within the operational risk category. Aligned with this view, Risk.net's 2020 annual ranking of the top operational risks, based on a survey of operational risk practitioners across the globe, lists cyber incidents, especially "threat from hostile hacking groups and even nation states," as the highest concern.[4] However, recent cybersecurity-related incidents show that cybersecurity risk exposure, resources needed for its mitigation, and its impact on asset prices require cybersecurity risk to be considered as a standalone factor that should not be subsumed into a broader operational risk category.

[2] US Computer Emergency Readiness Team, available at https://niccs.us-cert.gov/glossary#I.
[3] Northbridge Insurance, available at https://www.nbins.com/blog/cyber-risk/what-is-cyber-risk-2/.
[4] https://www.risk.net/risk-management/7450731/top-10-operational-risks-for-2020.

Geopolitical Risk

Geopolitical risk is defined by Caldara and Iacoviello (2019) as "the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations and it captures both the risk that these events materialize, and the new risks associated." The 2020 World Economic Forum Global Risks Perception Survey identifies "interstate relations fracture" and "interstate conflict" to be among the top medium-term global risks.[5] Recently, trade policy uncertainty (TPU) has become a predominant factor in geopolitical risk. Engle and Campos-Martins (2021) indicated that geopolitical risk has become an increasingly important component of risk analysis and can be broadly defined as the exposure of one or more countries to political actions in other countries. According to the authors, although the Brexit referendum in 2016 is clearly a geopolitical event, central bank or regulatory actions can also be interpreted as geopolitical events when they simultaneously affect numerous firms across regions and countries. Even local financial events, cyberattacks, trade wars, and climate change can have global financial impacts.

BACKGROUND

Investors and asset managers have a particular interest in the risks that arise from firms' shortcomings in ESG, sustainability, and cybersecurity- and technology-related practices, as well as the uncertainty caused by potential domestic and global policy and regulatory responses. However, measurement of novel risks is more challenging than measurement of risks historically managed by portfolio managers, such as market risk, credit risk, and, to a certain extent, operational risks. A unified framework for regulatory disclosure policymaking for novel risks would lead to an increase in the effectiveness of their measurement and management, especially in light of the recent pandemic having highlighted the interaction between novel risks, which amplifies their effect on asset prices, volatility, and the stability of domestic and global financial systems.

A modeling framework developed by Pástor, Stambaugh, and Taylor (2020) illustrates that the strength of ESG concerns can change over time, both for investors in firms' shares and for the customers who buy firms' goods and services. Although the authors initially modeled investing that considers ESG criteria, they extended their model to include climate risk while emphasizing their narrow interpretation of climate (E in ESG). According to the authors, sustainable investing (SI) is motivated in part by concerns about climate change, and they suggested that many experts expect climate change to impair quality of life, lowering the utility of the typical individual beyond what is captured by the climate's effect on wealth. Pástor, Stambaugh, and Taylor asserted that unanticipated climate changes present investors with an additional source of risk, which is nontraded and only partially insurable, and they suggested that SI has a positive social impact by making firms greener and by shifting real investment toward green firms because SI considers not only financial objectives but also ESG criteria. Although the research by Pástor, Stambaugh, and Taylor highlights the overlapping nature of the ESG risk and climate change risk, the authors' emphasis on their narrow interpretation of *environmental risk* supports the approach of treating climate change risk separately from broader factors included in environment as part of ESG risk.

On February 10, 2021, the Institute of Policy Integrity at the New York University (NYU) Law School and Environmental Defense Fund published a policy report (Condon et al. 2021) that states that "unlike other financial risks, climate risk is not routinely

[5] http://wef.ch/risks2021.

disclosed to the public" and "urge[d] the Securities and Exchange Commission (SEC) to issue new, mandatory disclosure rules focused on climate risk." Specific recommendations in this report included "drawing best practices from existing frameworks and standards; soliciting input from financial and climate experts, corporations, and investors through concept releases and/or a climate risk advisory committee; coordinating with other financial regulators and drawing on climate-related expertise at other federal agencies through interagency working groups; and developing greater SEC expertise in this area by having the Division of Economic and Risk Analysis conduct economic research on climate risk," with the conclusion that "these actions will facilitate informed investing, sustainable growth, and a more resilient economy" (Condon et al. 2021).

Although in 2010 the SEC issued interpretive guidance that "did not create new legal requirements nor modify existing ones" but provided "guidance on certain existing disclosure rules that may require a company to disclose the impact that business or legal developments related to climate change may have on its business,"[6] on February 24, 2021, the Commission announced that the Division of Corporation Finance has been directed to enhance its focus on climate-related disclosure in public company filings.[7] On March 4, 2021, the SEC announced the creation of a Climate and ESG Task Force in the Division of Enforcement.[8] On March 15, 2021, the SEC opened its 90-day public comment window in an announcement that, in part, stated that "in light of demand for climate change information and questions about whether current disclosures adequately inform investors, public input is requested from investors, registrants, and other market participants on climate change disclosure."[9] These recent developments highlight the importance of ESG risk and climate change risk, as well as how rapidly the regulatory and policy framework is evolving for these risks.

Cybersecurity is among the significant risk factors that are of concern to financial market participants, including regulators, investors, and managers of public firms. In October 2011, the SEC's Division of Corporation Finance issued guidance "regarding disclosure obligations relating to cybersecurity risks and incidents." At the time of that guidance, "although no existing disclosure requirement explicitly refers to cybersecurity risks and cyber incidents, companies nonetheless may be obligated to disclose such risks and incidents."[10] In February 2018, the SEC issued its "Statement and Guidance on Public Company Cybersecurity Disclosures," which suggested that "after the issuance of the [2011] guidance, many companies included additional cybersecurity disclosure, typically in the form of risk factors."[11]

Historically, cyberattacks on businesses mainly compromised customer records and other operational data of the target, and the decrease in a targeted firm's (equity) value following such incidents usually was due to reputation damage for failing to protect those data. However, daily operations of targeted firms usually were not significantly interrupted. In contrast, ransomware cyberattacks are now noticeably more frequent and directly affect the targeted firm's daily operations by blocking access to their computer systems and/or shutting down their facilities until a ransom is paid by a deadline. Such cybersecurity incidents highlight the vulnerability of cybersecurity systems, the necessity of managing and controlling cybersecurity risk at the firm level, and possible systemic effects of one or more cyberattacks on individual firms.

[6] https://www.sec.gov/news/press/2010/2010-15.htm.
[7] https://www.sec.gov/news/public-statement/lee-statement-review-climate-related-disclosure.
[8] https://www.sec.gov/news/press-release/2021-42.
[9] https://www.sec.gov/news/public-statement/lee-climate-change-disclosures.
[10] https://www.sec.gov/divisions/corpfin/guidance/cfguidance-topic2.htm.
[11] https://www.sec.gov/rules/interp/2018/33-10459.pdf.

Academic research articles, review papers, policy guidance reports, and task force findings suggest that disclosure of ESG risk, climate change risk, and cybersecurity risk factors will benefit investors and markets, as well as regulators, because more and better information regarding exposure to these novel risks eventually leads to more financial stability. Furthermore, these "disclosures [should be] more comparable, specific, and decision-useful."[12]

The next section presents an overview of the recent academic literature, and the following section discusses the common themes that emerge for measurement and data sources related to the novel risks. The remaining two sections synthesize future directions for research as well as regulatory and policy developments. The last section concludes the article.

RECENT ACADEMIC LITERATURE

This section presents an overview of a select group of academic research articles from 2019 to 2021 for each of the four novel risk categories.

Literature on ESG Risk

Bansal, Wu, and Yaron (2021) examined the time variability of abnormal returns from SRI using three distinct sources of CSR data: MSCI/KLD, RepRisk, and CSRWire. Using portfolio regressions and event studies on multiple data sources, including analyst ratings, firm announcements, and realized incidents, the authors found that highly rated SRI stocks outperform low-rated SRI stocks during good economic times (e.g., periods with high market valuations or aggregate consumption) but underperform during bad times (e.g., recessions). They suggested that the observed variation in abnormal returns of highly socially responsible (SR) stocks versus low-SR stocks is consistent with a wealth-dependent investor preference for SR stocks that leads to an increased (decreased) demand for SRI during good (bad) times. Bansal, Wu, and Yaron stated that SRI reflects the common asset market factor risks and interpreted their results by suggesting that, during good economic times, households have greater financial wealth and can afford to be more SR conscious, either because of their wealth-dependent preference for SRI or possibly because of relaxed constraints in their SR-focused investment process. According to the authors, this drives up demand for high-SR stocks, resulting in higher realized alphas. Bansal, Wu, and Yaron also suggested that, during bad times, households have lower wealth and face more binding wealth constraints and might have to pull back on their concerns for SRI, thus reducing the demand for high-SR stocks and decreasing the alpha spread between high-SR and low-SR stocks.

Flammer (2021) examined corporate green bonds whose proceeds are committed to financing environmental and climate-friendly projects, such as renewable energy, green buildings, or resource conservation. The author asserted that green bonds have become more prevalent over time, especially in industries in which the environment is financially material to firm operations, and showed that investors respond positively to the issuance announcement of green bonds, with a stronger response for first-time issuers and for bonds that are certified by third parties. The author found that issuers improve their environmental performance post-issuance (i.e., higher environmental ratings and lower CO_2 emissions) and experience an increase in ownership by

[12] See the introduction written by Richard Berner and Robert F. Engle, co-directors of NYU's Volatility and Risk Institute, for the policy report "Mandating Disclosure of Climate-Related Financial Risk" by Condon et al. (2021).

long-term and green investors. According to Flammer, these findings are consistent with a signaling argument; that is, by issuing green bonds, companies credibly signal their commitment to the environment.

Barber, Morse, and Yasuda (2021), focusing on impact investing, investigated whether the theoretical assumption that investors are willing to pay for impact holds true and asserted that two primary instrument types that receive the largest capital allocation among impact investors are private debt and private equity.[13] According to the authors, although private debt is the largest category, because they were not aware of any data sources for private debt impact investments, their research focused on impact funds, which are predominantly venture capital (VC) and growth equity funds that are structured as traditional private equity funds but with the intention of impact investing. Barber, Morse, and Yasuda suggested that investors derive nonpecuniary utility from investing in dual-objective VC funds, thus sacrificing returns. They found that impact funds earn, ex post, 470 bps lower internal rates of return (IRRs) than traditional VC funds, whereas in random utility/willingness-to-pay (WTP) models, investors accept IRRs that are 2.5–3.7 percentage points lower ex ante for impact funds. Barber, Morse, and Yasuda suggested that development organizations, foundations, financial institutions, public pensions, European investors, and the signatories of United Nations Principles of Responsible Investment have high WTP, whereas the investors who have mission objectives and/or face political pressure exhibit high WTP; those subject to legal restrictions (e.g., Employee Retirement Income Security Act) exhibit low WTP.

Cerqueti et al. (2021), focusing on a network of equity mutual funds characterized by different levels of compliance with ESG aspects, measured the impact of portfolio liquidation in a stress scenario on funds with different ESG ratings. They found evidence that the relative market value loss of high ESG-ranked funds is lower than the loss experienced by their low ESG-ranked counterparts during low volatility periods, whereas no clear dominance of one class over another is observed during higher volatility periods. The authors asserted that their findings offer new insights to both asset managers and policymakers to exploit the aggregate effect of portfolio diversification related to the system as a whole (i.e., whether the ESG compliance of assets held in a portfolio by equity mutual funds mitigates the negative effects of financial distress that propagates from a fund to another).

Pástor, Stambaugh, and Taylor (2020) developed a theoretical model in which firms differ in the sustainability of their activities: Green firms generate positive externalities for society and brown firms impose negative externalities, and firms have different shades of green and brown. In the model, agents differ in their preferences for sustainability, or ESG preferences, which have two dimensions: First, agents derive utility from holdings of green firms and disutility from holdings of brown firms, and second, agents care about firms' aggregate social impact. According to their model, in equilibrium, green assets have low expected returns because investors enjoy holding them, but these assets nevertheless outperform when positive shocks hit the ESG factor; this captures shifts in customers' tastes for green products and investors' tastes for green holdings.

Pedersen, Fitzgibbons, and Pomorski (2020) developed a theory in which each stock's ESG score plays two roles—providing information about firm fundamentals and affecting investor preferences—and in which the solution to the investor's portfolio problem is characterized by an ESG-efficient frontier, showing the highest attainable Sharpe ratio for each ESG level. The authors referred to this theoretical foundation

[13] The Global Impact Investing Network defines impact investing as "investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return." See https://thegiin.org/impact-investing/need-to-know/#what-is-impact-investing.

as *ESG integration*, meaning that ESG characteristics are used directly in portfolio construction as opposed to just as screens, in which the equilibrium asset prices are determined by an ESG-adjusted capital asset pricing model. Pedersen, Fitzgibbons, and Pomorski tested their theory's predictions using each company's carbon intensity as a proxy for E, a non-sin stock indicator as a measure of S, how (un)aggressive a company is in its accounting choices based on the accruals in the financial statements as a proxy for G, and overall ESG ratings.[14] They showed that different ESG screens can have surprising effects and provided a rationale for why certain ESG measures predict returns positively (some aspects of governance) and others negatively (non-sin stocks, a measure of S) or close to zero (low carbon emissions, an example of E, and commercial ESG ratings). The authors asserted that high-ESG firms are more profitable if they benefit from being less wasteful, having more motivated employees, being better governed, or having customers who are willing to pay a higher price for their products. Pedersen, Fitzgibbons, and Pomorski concluded that their results highlight nuances in optimally incorporating ESG into portfolio construction and suggested improvements to traditional approaches based on simple screening.

Chen, Dong, and Lin (2020) showed that an exogenous increase in institutional holdings caused by Russell Index reconstitutions improves portfolio firms' CSR performance and also found that firms have lower CSR ratings when shareholders are distracted owing to exogenous shocks. They reported that this observed effect of institutional ownership is stronger in CSR categories that are financially material. The authors concluded that institutional shareholders can generate real social impact through the CSR-related proposals and showed that institutional investors mainly drive improvements in CSR issues that are financially material to firm values. In addition, they found that higher institutional ownership specifically reduces certain negative CSR issues that might lead to lawsuits or regulatory penalties due to gender discrimination, unsafe workplaces, noncompliance with environmental regulations, or improper marketing.

Berg, Koelbel, and Rigobon (2020) investigated the divergence of ESG ratings. Using data from six ESG rating providers—KLD (MSCI Stats), Sustainalytics, Vigeo Eiris (Moody's), RobecoSAM (S&P Global), Asset4 (Refinitiv), and MSCI—the authors decomposed the divergence into three sources: scope, measurement, and weights. They found that scope and measurement are the main drivers of the observed divergence in ESG ratings, whereas weights remain less important. Berg, Koelbel, and Rigobon also detected a "rater effect," in which a rater's overall view of a firm influences the assessment of specific categories, and asserted that the methodology proposed improves investors' and firms' decision-making by detecting where the divergence comes from and offering avenues to resolve it.

Dyck et al. (2019) indicated that institutional investors are motivated by financial returns, social returns, or a combination of both in their push for firms' E&S performance. They suggested that E&S investment could be value-enhancing by providing a form of insurance against event risk, product market differentiation, or both and reported that many investors use such motivations to explain their E&S activism. According to the authors, these investors often note that their E&S spending is aimed at a long-term, instead of short-term, payoff. They investigated whether institutional shareholders drive E&S performance, across 41 countries, by testing test whether lagged total institutional ownership is associated with E&S performance, controlling for observable factors that can affect E&S performance directly, and showed that greater institutional ownership is associated with higher firm-level E&S scores. Dyck et al. found that a one-standard-deviation change in institutional ownership is associated with an increase of 4.5% in the authors' overall score for environmental performance

[14] The authors used the Hong and Kacperczyk (2009) classification of sin industries.

and an increase of 2.1% for social performance. They reported that the corresponding increases are stronger when ASSET4 z-scores from Thomson Reuters ASSET4 ESG database are used: 6.8% and 8.2%, respectively.

Literature on Climate Change Risk

Ilhan, Sautner, and Vilkov (2021) showed that uncertainty of future climate regulation is priced in the options market and that the cost of option protection against downside tail risks is larger for firms with more carbon-intense business models. They used the term "priced" to indicate that option prices reflect certain stocks as being riskier than others, rather than that the market compensates investors for taking a certain risk by offering an expected return. They found that a one-standard-deviation increase in a firm's log industry carbon intensity increased the implied volatility slope by 0.014, or by 10% of the variable's standard deviation. Ilhan, Sautner, and Vilkov also confirmed their finding for sector exchange-traded fund options that the cost of option protection against downside tail risks is higher for the more carbon-intense sectors of the S&P 500. According to the authors, their findings suggest that options written on carbon-intense firms are relatively more expensive, especially for the far-left tail region, because they provide protection against downside tail risks associated with climate policy uncertainty. Ilhan, Sautner, and Vilkov also showed that, for carbon-intense firms, the cost of protection against downside tail risk is magnified when the public's attention to climate change spikes, using two proxies for attention to climate change: the negative climate change news index (CCNI) developed by Engle et al. (2020) and the Google search volume data for the topic "climate change." Ilhan, Sautner, and Vilkov found that the effect of carbon intensities on downside tail risk intensifies with more negative climate change news when attention to climate change is measured by the CCNI but not when it is measured by Google search data. They attributed this result to the CCNI being a more appropriate measure because it captures downside aspects associated with climate change more directly, as it focuses on negative news.

Giglio et al. (2021), using private housing sale price data and a new climate attention index, showed that housing markets provide information about the appropriate discount rates for valuing investments in climate change abatement. They indicated that real estate is exposed to both consumption and climate risk, with the term structure of discount rates being downward sloping, reaching 2.6% for payoffs beyond 100 years.

Huynh and Xia (2021), using the CCNI developed by Engle et al. (2020), investigated whether climate change news risk is priced in corporate bonds by estimating the climate change news beta from the monthly rolling regression of bond excess returns on innovations in the monthly CCNI over a 60-month window. They found that bonds with a higher climate change news beta earn lower future returns, which is consistent with the asset pricing implications of demand for bonds with high potential to hedge against climate risk. Moreover, they indicated that when investors are concerned about climate risk, they are willing to pay higher prices for bonds issued by firms with better environmental performance. Huynh and Xia suggested that corporate policies aimed at improving environmental performance pay off when the market is concerned about climate change risk.

Using the weather futures contracts traded at the Chicago Mercantile Exchange (CME), Schlenker and Taylor (2021) compared prices of financial derivatives whose payouts are based on future weather outcomes to CMIP5 climate model predictions and observed weather station data across eight cities in the United States from 2001 through 2020.[15,16] They found that the futures prices respond both to short-term weather forecasts for the next two weeks and longer-term warming trends. Schlenker and Taylor also found that, in examining the spatial and temporal heterogeneity in trends, futures prices are more aligned with climate model outputs than observed weather station trends, suggesting that market participants form their expectations based on scientific projections rather than recent observations.

Flammer, Toffel, and Viswanathan (2021) examined whether—in the absence of mandated disclosure requirements—shareholder activism can elicit greater disclosure of firms' exposure to climate change risks and found that environmental shareholder activism increases voluntary disclosure of climate change risks, especially if initiated by institutional investors and even more so if initiated by long-term institutional investors. They showed that companies that voluntarily disclose climate change risks following environmental shareholder activism achieve a higher valuation after disclosure, suggesting that investors value transparency with respect to firms' exposure to climate change risks.

Blasberg, Kiesel, and Taschini (2021) constructed a novel market-based measure of exposure to transition risk, which they referred to as a *transition risk factor*, and examined how this risk affects firms' creditworthiness by using credit default swap (CDS) spreads to capture differential exposure to transition risk across economic sectors. They showed that the transition risk factor is a relevant determinant of CDS spreads, but this relation varies substantially across industries, reflecting the fact that transition risk affects firms' valuation differently depending on their sector. Blasberg, Kiesel, and Taschini suggested that investors seek greater protection against transition risks in the short to medium term, indicating an expectation of a swift transformation of the entire economic structure.

Engle et al. (2020) implemented a procedure to dynamically hedge climate change risk by extracting innovations from climate news series via textual analysis of newspapers. They used a portfolio-mimicking approach to build climate change hedge portfolios and, using third-party ESG scores to model firm-specific climate risk exposures, showed that these parsimonious and industry-balanced portfolios perform well in hedging innovations in climate news both in sample and out of sample.

Painter (2020), using data on municipal bond offerings, found that counties more likely to be affected by climate change pay more in underwriting fees and higher initial yields to issue long-term municipal bonds compared to counties unlikely to be affected by climate change. The author indicated that observed difference disappears when comparing short-term municipal bonds, implying the market only prices climate change risks for long-term securities. Painter also found that the higher issuance costs for climate-risk counties are driven by bonds with lower credit ratings and asserted that investor attention is a driving factor; the difference in issuance costs on bonds issued by climate-affected and non–climate-affected counties increased after the release of the 2006 Stern Review on climate change (Stern 2006). The author showed that, on average, a 1% increase in climate risk for a county is associated with a statistically

[15] The CME offers futures contracts for eight cities on two main weather products: cooling degree days, which measure how much cooling is necessary during high temperatures in summer, and heating degree days, which measure how much heating is required during low temperatures in winter. https://www.cmegroup.com/trading/weather/.

[16] In 2008, the World Climate Research Programme Working Group on Coupled Modelling (WGCM), at its 12th session, endorsed the CMIP5 protocol, which defined a set of 35 climate model experiments designed to be useful in (1) assessing the mechanisms responsible for model differences in poorly understood feedback associated with the carbon cycle and clouds, (2) examining climate "predictability" and exploring the ability of models to predict climate on decadal time scales, and, more generally, (3) determining why similarly forced models produce a range of responses. See https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip5.

significant increase 23.4-bps in annualized issuance costs for long-term bonds; the additional issuance cost is economically significant because a 1% increase in climate risk is associated with an average rise in total annualized issuance costs of $1.7 million for the average county.

Krueger, Sautner, and Starks (2020) indicated that, based on their survey of 439 institutional investors about climate risk perceptions, institutional investors believe that climate risks have financial implications for their portfolio firms and that these risks, particularly regulatory risks, already have begun to materialize.[17] Their survey results revealed that long-term, larger, and ESG-oriented institutional investors consider risk management and engagement, rather than divestment, to be the better approach for addressing climate risks.

Choi, Gao, and Jiang (2020) tested how investors react to abnormal local temperatures by examining their attention to climate change and stock prices using data from 74 cities around the world with major stock exchanges. They found that during abnormally warm months in a particular city, the volume of Google searches for the topic of "global warming" increases in that city and that the effect is most prominent when the local abnormal temperature is in the city's top quintile because this weather experience is more salient. They also showed that carbon-intensive firms earn lower stock returns than other firms when the local exchange city is abnormally warmer in that month. They used proxies for different investors' trading behavior focusing on local block holders, local institutional investors, and retail investors, of which the majority are local, to investigate the mechanism through which temperature affects stock prices. Choi, Gao, and Jiang found that retail investors sell high-emission firms and buy low-emission firms, whereas institutional investors (local and foreign) do not respond systematically to abnormal temperatures, and local block holders trade in the opposite direction of retail investors.

Pástor, Stambaugh, and Taylor (2020), in extending their model for investing that considers overall ESG criteria, showed that, in equilibrium, green assets have low expected returns because investors enjoy holding them and because green assets hedge climate risk. Emphasizing their narrow interpretation of climate (E in ESG), the authors showed how unanticipated climate changes present investors with an additional source of risk (i.e., shocks to climate affecting asset prices as these shocks enter the average agent's utility). According to Pástor, Stambaugh, and Taylor, in considering the customer channel, unexpected worsening of the climate can heighten consumers' climate concerns, prompting a greater demand for goods and services of greener providers that can arise not only from consumers' preferences but also from government regulation. They suggested that negative climate shocks can prompt government regulations that favor green providers or penalize brown ones (e.g., new regulations that subsidize green products and tax, or even prohibit, brown ones). According to the authors, in considering the investor channel, unexpected worsening of the climate can strengthen investors' preference for green holdings, possibly as a result of stronger public pressure on institutional investors to divest from brown assets. They concluded that climate shocks are likely to correlate negatively with both components of the ESG factor in their equilibrium model.

Using a hedonic model for house prices that they augmented with measures of climate risks and households' beliefs about climate change, Baldauf, Garlappi, and Yannelis (2020) investigated whether residential real estate prices are affected by differences in beliefs about the occurrence and effects of climate change. They analyzed the link between differences in expectations about future risks and real estate

[17] The survey designed by Krueger, Sautner, and Starks addressed four key areas: "the role of climate risks in investment decisions; climate risk management; shareholder engagement related to climate risks; and the implications of climate risks for asset pricing."

prices by focusing on changes in flood risk associated with rising sea levels due to climate change. They found that differences in beliefs about climate change significantly affect house prices, specifically, "a one standard deviation increase above the national mean in the percentage of climate change 'believers' is associated with an approximate 7% decrease in house prices for homes projected to be underwater." They attributed this observed effect to the overreaction by "believers," underreaction by "deniers," or a combination of both.

Addoum, Ng, and Ortiz-Bobea (2020) found that high temperature shocks can negatively affect companies' earnings in certain industries, in particular electric utilities, leisure products, construction and engineering, capital markets, gas utilities, and machinery, and reported that four of these six industries (electric utilities, construction and engineering, gas utilities, and machinery) are classified as high-emission industries according to Intergovernmental Panel on Climate Change classifications.

Alok, Kumar, and Wermers (2020) found that managers within a major disaster region underweight disaster zone stocks to a much greater degree than distant managers. This aversion to disaster zone stocks is related to a salience bias that decreases over time and distance from the disaster, rather than to superior information possessed by managers located closer to the disaster region. They indicated that this overreaction can be costly to fund investors for some especially salient disasters, such as hurricanes and tornadoes. They showed that a long–short strategy that exploits the overreaction generates a significant DGTW-adjusted return over a two-year horizon following a disaster.

Hong, Li, and Xu (2019) documented an underreaction of food companies' stock prices to trends in droughts that are exacerbated by global warming. Focusing on climate change–induced droughts, they showed that markets underreact to this risk and that production risk from prolonged droughts forecasts a negative effect on the stock returns of firms in the food industry.

Bernstein, Gustafson, and Lewis (2019) found that homes exposed to sea level rise sell at a discount relative to otherwise similar unexposed homes. They showed that the physical risk of sea level rise negatively affects the price of exposed homes. However, they found little evidence that prices are affected by sea level rise when the housing market is particularly liquid.

Literature on Cybersecurity Risk

Kamiya et al. (2021) developed a model in which a firm has an optimal exposure to cybersecurity risk and found that, with rational, fully informed agents and no hysteresis, a successful cyberattack should have no impact on a financially unconstrained target's reputation and post-attack policies. However, they found that, on average, a successful cyberattack (i.e., an external attack that breaches the firm's defenses) with loss of personal financial information decreases shareholder wealth by 1.09% in the three-day window around the cyberattack. Contrary to the prediction of a simple, full-information, rational expectations model, the authors found that successful cyberattacks have the potential to cause economically large reputation costs in that shareholder wealth loss far exceeds the out-of-pocket costs of the attack. They reported that for a subset of 75 first-time attacks with negative abnormal returns, the total shareholder wealth loss was $104 billion, whereas the direct out-of-pocket costs that they could identify (e.g., investigation and remediation costs, legal penalties, and regulatory penalties) were only $1.2 billion. Kamiya et al. found that the excess loss is higher when the attack decreases sales growth more and lower when the board pays more attention to risk management before the attack. They also showed that an attack decreases a firm's risk appetite because it beefs up its risk management and information technology and decreases the risk-taking incentives of management, whereas successful cyberattacks adversely affect the stock price of firms in the target's industry.

Alan, Karagozoglu, and Zhou (2021) proposed a measure of firm-level cybersecurity risk by applying textual analysis to earnings conference call transcripts of public companies and employed a pattern-based sequence-classification method to determine the proportion of time devoted to issues related to cybersecurity risk during these calls. They investigated the effect of cybersecurity risk on firm-level return volatility and found that firm-level cybersecurity risk is positively correlated to idiosyncratic volatility on the days that earnings conference calls are held. This suggests that the discussion of cybersecurity risk–related issues during earnings conference calls is related to an increase in the component of the volatility that responds only to firm-specific news.

Jiang, Khanna, and Yang (2020) constructed a textual analysis–based measure of cyber risk derived from the risk factors section of 10-K documents (i.e., number of times cyber risk or its related terms are referred to in the risk section). To identify related words and phrases, they used a cybersecurity glossary found on Cyberpolicy.[18] They estimated the ex ante likelihood that a firm would experience a data breach using logistic least absolute shrinkage and selection operator (LASSO) regressions combined with cross-validation. Ranking firms based on this proxy for cyber risk, the authors found that cyber risk influences both investor portfolio choices and stock prices; furthermore, they showed that institutional investors tend to sell stocks with high cyber risk and buy those with low cyber risk; this tendency is stronger during periods with higher data breach concerns. Jiang, Khanna, and Yang reported that a one-standard-deviation increase in cyber risk is associated with a premium of 3.41% per annum.

Michel, Oded, and Shaked (2020) performed an event study using cyberbreach data on publicly traded firms from 2005 to 2017 by conditioning breaches on whether the breach was reported by the mainstream media or announced through other channels. They found that in the period prior to the announcement (reporting) date in the media, the mean abnormal return was negative, reflecting a likely leakage of information. Their results in the period following the announcement date showed that the mean abnormal return was positive, often more than offsetting the previous declines. Michel, Oded, and Shaked found it counterintuitive that, in the period following the breach announcements, the cumulative abnormal returns (CARs) were positive and increasing. Moreover, the authors showed that for all breach types, the CARs for breaches reported in the media were statistically significant in periods both before and after the report date. They found that this observation was in contrast to breaches not announced in the media, for which the CARs were only significant in the period before the announcement date. They concluded that when company management is aware of the likely date of the reporting of the breach, there is statistically significant pure leakage, whereas in the situation in which management is not cognizant of the exact date of the reporting, there is no such leakage.

D'Arcy et al. (2020) proposed and tested a set of hypotheses about the impact that firms' corporate social performance (CSP) strengths and concerns have on the likelihood of experiencing a data breach. They asserted that CSP strengths capture firms' activities related to fair treatment of stakeholders and image-enhancing social expectations (e.g., diversity initiatives, philanthropy, pollution-prevention programs), whereas CSP concerns capture activities that are viewed as socially irresponsible, controversial, dangerous, and/or illegitimate (e.g., poor worker conditions in the supply chain, fines or civil penalties related to the safety of products and services, unfair treatment of employees, environmental harm). In their empirical tests, they used data

[18] Cyberpolicy is a website that allow users to compare insurance quotes and buy multiple insurance policies online. See https://www.cyberpolicy.com/glossary.

from the KLD database to identify CSP strengths and CSP concerns. D'Arcy et al. reported a paradoxical finding that firms with a poor CSP record (i.e., CSP concerns) are no more likely to experience a data breach, whereas those with a positive CSP record (i.e., CSP strengths) in areas that are peripheral to core firm activities (e.g., philanthropy, recycling programs) have an elevated likelihood of breach. D'Arcy et al. suggested that firms that simultaneously have peripheral CSP strengths and high CSP concerns in other areas are at an increased risk of breach. According to the authors, this increased likelihood of breach for firms with seemingly disingenuous CSP records suggests that perceived "greenwashing" efforts that attempt to mask poor social performance make firms attractive targets for security exploitation.

Eling and Wirfs (2019) asserted that one of the impediments in the collection of cyber risk data is the absence of a clear-cut definition of "cyber risk" and chose to use a definition based on how banking supervisors categorize operational (i.e., "operational risks to information and technology assets that have consequences affecting the confidentiality, availability or integrity of information or information systems"). The authors used the peaks-over-threshold method from extreme value theory to identify what they refer to as "cyber risks of daily life" and "extreme cyber risks." They indicated that information technology security incidents typically result in small operational disruptions or minimal recovery costs, but occasionally high-impact security breaches can have catastrophic effects on the firm. They showed that that there is a large number of small losses (the cyber risks of daily life) and a few large ones (extreme cyber risks) leading to high tail value at risk values and a higher tail risk measure. They also found that a high portion of incidents occur in the financial industry, although other operational risks are more balanced, suggesting that the financial industry might be an especially attractive target, although obviously better protected. Eling and Wirfs also reported a U-shaped relation between the loss amount and the number of employees and a U-shape in the tail risk measure, indicating heavier tails for small and large companies.

Literature on Geopolitical Risk

Engle and Campos-Martins (2021) introduced a definition of geopolitical risk that is based on volatility shocks to a wide range of financial market prices and proposed a statistical model for the magnitude of the common volatility shocks to measure this risk. They assumed that geopolitical events affect all countries, asset classes, and sectors and used the term *GEOVOL* to refer to such shocks. The authors developed an econometric approach to estimate the GEOVOL model and presented results based on both simulated and empirical data; furthermore, they compared their results to other geopolitical risk estimates that are constructed using survey and textual analysis methods. According to Engle and Campos-Martins, the GEOVOL model provides a novel explanation for why idiosyncratic volatilities co-move based on a new way to formulate multiplicative factors. They also proposed a new criterion for portfolio optimality that is intended to reduce exposure to geopolitical risk.

Caldara et al. (2020) investigated the effects of unexpected changes in TPU on the US economy with the use of three measures of TPU that are constructed using newspaper coverage, firms' earnings calls, and tariff rates. They found that firm-level and aggregate macroeconomic data reveal that increases in TPU reduce business investment, whereas news and increased uncertainty about higher future tariffs reduce investment and activity.

Hassan et al. (2019), by adapting tools from computational linguistics, constructed a measure of political risk faced by individual US firms based on the share of their quarterly earnings conference calls devoted to political risks and found that the dispersion of this firm-level political risk increases significantly at times with high aggregate political risk. Decomposing their measure of political risk by topic, they also found that firms that devote more time to discussing risks associated with a given political topic tend to increase their lobbying on that topic, but not on other topics, in the following quarter. Hassan et al. showed that their political risk measure varies intuitively over time and across sectors. They also showed that the mean measure of political risk across firms increases significantly around federal elections and is highly correlated with the index of aggregate economic policy uncertainty proposed by Baker, Bloom, and Davis (2016), as well as with a range of sector-level proxies of government dependence used in the literature.

Caldara and Iacoviello (2019) developed an indicator of geopolitical risk based on a count of newspaper articles covering geopolitical tensions and examined its evolution and relation to economic effects. They showed that high geopolitical risk reduces US investment, employment, and the level of the stock market, and when the index is decomposed into threats versus acts components, the adverse effects of geopolitical risk are mostly driven by the threat of adverse geopolitical events. They complemented their aggregate measures with indicators of geopolitical risk at the level of individual firms and showed that investment drops more in industries that are positively exposed to aggregate geopolitical risk and that firms reduce investment in response to higher idiosyncratic geopolitical risk.

Ahir, Bloom, and Furceri (2019) constructed an index of uncertainty for 143 countries using quarterly Economist Intelligence Unit country reports based on the frequency of the word “uncertainty” (and its variants) in each country’s report. They referred to this as the World Uncertainty Index (WUI). They showed that spikes in the WUI tend to be more synchronized within advanced economies and between economies with tighter trade and financial linkages. The level of this uncertainty is significantly higher in developing countries, and it is positively associated with economic policy uncertainty and stock market volatility and negatively associated with gross domestic product growth. Ahir, Bloom, and Furceri also reported that innovations in the WUI predict significant declines in output and that this effect varies across countries and across sectors within the same country; that is, across countries, the effect is larger and more persistent in those with lower institutional quality, whereas across sectors, the effect is stronger in those that are more financially constrained.

MEASUREMENT AND DATA SOURCES

Measuring novel risks is a challenge. This challenge can be attributed to the lack of sufficiently informative data that, in part, may be due to the absence of mandated disclosure requirements or the difficulty in identifying proxies for factors that are not directly observable, which, in part, may be due to the need to expand the tool set of financial economists. Recent academic research suggests that it is a combination of both.

Measures based on novel applications of text and news analytics are used as proxies for novel risks in recent academic research. Various studies have developed measures based on news analytics (i.e., indexes calculated using counts of newspaper articles covering topics related to specific to risk categories), which may also incorporate an assessment of the sentiment in such news coverage.

By drawing on the economic policy uncertainty measure of Baker, Bloom, and Davis (2016), Caldara and Iacoviello (2019) developed their geopolitical risk (GPR) index using an algorithm that computes the share of articles related to geopolitical risks in leading international newspapers published in the United States, the United Kingdom, and Canada. The authors further created two subindexes that separate periods of elevated geopolitical risk due to the realization of adverse events from periods of elevated risk without the realization of the underlying event.

Engle et al. (2020) developed two climate change news indexes: one solely based on counts of news articles in *The Wall Street Journal* (WSJ) that include terms from a corpus of climate change vocabulary and the second being a negative climate change news index (CCNI), which captures the share of news articles in the Crimson Hexagon (CH) database (which covers over 1,000 news outlets, including the WSJ, *The New York Times*, *The Washington Post*, Reuters, BBC, CNN, and Yahoo News) that are about climate change and have been assigned to a negative sentiment category by the data vendor, therefore capturing the time-series effects of climate attention. Whereas Huynh and Xia (2021) used the CCNI, Ilhan, Sautner, and Vilkov (2021) used the negative CCNI developed by Engle et al. (2020).

A few studies have used the Google search volume of terms as a proxy for investors' attention to risk. Ilhan, Sautner, and Vilkov (2021) used Google's search volume index (SVI) for the search topic "climate change." They indicated that search activity on Google plausibly proxies for investor attention to climate risk. Choi, Gao, and Jiang (2020) also used Google's SVI and argued that investor attention, as measured by the volume of Google searches for the topic of "global warming" in international cities with major stock exchanges during abnormally warm months in a particular city. This allowed the authors to investigate investor opinion about climate change much more accurately than survey-based methods because the authors were able to identify that retail investors sell carbon-intensive firms when they experience abnormally high temperatures, and there is a spike in Google search volume.

Numerous studies have developed risk measures using textual analytic methods such as natural language processing (NLP) applied to quarterly earnings conference call transcripts and the quarterly 10-K filing documents. Hassan et al. (2019) developed a firm-specific measure of political risk that quantifies the share of the conversation between conference call participants and firm management that centers on risks associated with political matters. The authors indicated that, rather than a priori deciding on specific words associated with different topics, they distinguished political from nonpolitical topics using a pattern-based sequence-classification method developed in computational linguistics, which they adapted to correlate language patterns used by conference-call participants to that of a text that is either political in nature or indicative of a specific political topic (using an undergraduate political science textbook as a training library). Hassan et al. identified an association with risk simply by the use of synonyms for the words "risk" and "uncertainty" in conjunction with political language; specifically, they counted the number of occurrences of bigrams indicating discussion of a given political topic within the set of 10 words surrounding a synonym for risk or uncertainty on either side and divided by the total number of bigrams in the transcript.

Following the Hassan et al. (2019) methodology, Caldara and Iacoviello (2019) constructed a geopolitical risk measure using earnings call transcripts based on firms' own perceptions and showed that it correlates well with the authors' geopolitical risk (GPR) index, which is based on aggregate news coverage. Caldara et al. (2020) constructed their firm-level TPU measure based on text analysis of transcripts of quarterly earnings calls of publicly listed companies. They initially searched each transcript for terms related to trade policy (TP) and then constructed a TP variable that measured, for each transcript, the frequency of TP words (i.e., the number of mentions divided by the total number of words). Caldara et al. suggested that their initial TP variable proxies for the intensity of TP-related discussions, irrespective of whether they center on risk or uncertainty. As a secondary step that is in accordance with the Hassan et al. (2019) approach, the authors isolated discussions about TPU around terms indicating uncertainty, such as “uncertainty,” “risk,” and “potential,” resulting in the frequency of joint instances of TP and uncertainty terms in each transcript to measure the overall uncertainty around TP perceived by a firm.

Alan, Karagozoglu, and Zhou (2021) also followed the Hassan et al. (2019) methodology to create a measure of firm-level cybersecurity risk by analyzing the text of earnings call transcripts extracted from the Standard and Poor’s Global Intelligence database. By identifying the text surrounding synonyms of words such as “risk/risky” and “uncertain/uncertainty,” the authors were able to extract the portion of earnings call transcript text devoted to the discussion of cybersecurity risk instead of more general matters related to cybersecurity, such as technical issues of how to improve a firm’s cybersecurity. Alan, Karagozoglu, and Zhou used extensive sets of books and texts as training libraries to obtain alternative cybersecurity risk measures and found that the impact of cybersecurity risk on idiosyncratic volatility is robust to alternative measures. Jiang, Khanna, and Yang (2020) used a textual analysis–based measure of cyber risk that they derived from the risk factors section of 10-K documents; however, they only counted the number of times cyber risk or its related terms are referred to in the risk section.

Kölbel et al. (2020) used a complex NLP technique, bidirectional encoder representations from transformers, to quantify the relative importance of climate risk compared to other risks that are disclosed in Item 1.A of a firms’ 10-K reports. They discussed why their approach improves upon earlier studies that quantify climate risks from 10-K reports using a simple bag-of-words approach.

In a novel application of textual analytics, Giglio et al. (2021) developed a measure of perception of climate risk in the housing market by performing a systematic textual analysis of for-sale listings to measure the frequency with which climate-related text (e.g., mentions of hurricanes or flood zones) appeared in the written description of the listed properties. Using the fraction of listings that include such text, the authors constructed their “climate attention index” and found that this index reflects households’ perceptions of the risk of future climate change on the cash flows from real estate in those locations.

Currently, ratings-based approaches are used by various data vendors that specialize in ESG and CSR categories, whereas other vendors capture announcements, news coverage, and disclosures and apply textual analytics methods to process the information. Bansal, Wu, and Yaron (2021) suggested that, although primary advantage of ESG ratings is that they are easy to interpret and are relatively well represented across firms, the drawbacks of rating-based measurement are twofold. According to the authors, the criteria for these ratings are often opaque, leaving much room for analyst discretion and firms’ self-reported information in the process; additionally, rating service providers have different ESG criteria and definitions, which could also change significantly over time as the ratings industry consolidates. They discussed characteristics of several ESG databases. For example, they indicated that RepRisk data captures actual ESG-related negative events reported by a diverse set of media outlets, which, according to the authors, are presumably more objective; furthermore, the events are captured as they are reported, which allows for aggregation at higher frequencies. They suggested that, because negative ESG reporting is relatively rare at the firm level, this designation is less persistent over time than the ratings-based ESG measurements. According to the authors, a drawback of a classification based only on negative ESG incidents is that positive ESG events are less likely to be reported in the media and more likely to be self-reported (e.g., in the database complied by CSRWire). Therefore, Bansal, Wu, and Yaron suggested using textual analytics to quantify improvements in CSR performance, such as reductions in negative quantities (e.g., emissions levels or violations of environmental regulations), as well as measuring actual negative ESG events. Another example discussed is the MSCI-ESGSTATS KLD data, which provide ratings for a firm based on all of its ESG-related activities during a calendar year, thereby mapping a large and varied set of ESG activities onto a fixed numerical scale.

Berg, Koelbel, and Rigobon (2020) indicated that ESG rating providers have become influential institutions.[19] Many institutional investors expect corporations to manage ESG issues (Krueger, Sautner, and Starks 2020) and monitor their holdings' ESG performance (Dyck et al. 2019). Berg, Koelbel, and Rigobon suggested that more and more investors rely on ESG ratings to obtain a third-party assessment of corporations' ESG performance, although notable divergence in ESG ratings exists among data providers. They stated that, in the absence of a reliable measure of true ESG performance, the next best thing is to understand what drives the differences between existing ESG ratings. They highlighted the sources of such discrepancies and offered possible avenues to resolve it. They asserted that ESG ratings consist of three basic elements: scope, which denotes all the attributes that together constitute the overall concept of ESG performance; indicators that yield numerical measures of the attributes; and an aggregation rule that combines the indicators into a single rating. According to Berg, Koelbel, and Rigobon, although there is some evidence that clarity about scope and weights can reduce the degree of confusion among ratings discrepancies, improving measurement procedures remains an important research field for the future.

Combining the discussion presented by Bansal, Wu, and Yaron (2021) and the results documented by Berg, Koelbel, and Rigobon (2020), it is possible to conclude that ratings-based measures of novels risks may suffer from biases and inconsistencies that may further complicate the management of these risks. Because the majority of ratings-based measures are used by research in ESG risk, climate change risk, and cybersecurity risk, the implementation of uniform disclosure requirements (to be set by policymakers) and development of more consistent standards for ratings-based measures (to be set by industry associations, academic researchers, and other financial market participants) becomes more important.

Baldauf, Garlappi, and Yannelis (2020) used a measure of beliefs about climate change from the Yale Climate Opinion Maps 2016.[20] The authors indicated that the Yale Climate opinion survey provides, at the county level, survey evidence of how respondents answer questions, including whether they believe that climate change is happening; whether they believe that climate change is human caused; whether they believe that there is scientific consensus on whether climate change is happening; and whether they will be personally affected by climate change. The findings of Berg, Koebel, and Rigobon (2020) on ESG rating discrepancies spearheaded the "The Aggregate Confusion Project" at the MIT Sloan Sustainability Initiative.[21] The Volatility and Risk Institute at the NYU Stern School of Business leads projects on geopolitical and climate change risk measurements.[22] It is worth noting that various academic institutions have substantial initiatives focusing on the measurement of novel risks and providing guidance for regulatory and policy standards while being sources of new data and methodologies for industry practitioners.

[19] Berg, Koelbel, and Rigobon stated that ESG ratings are also referred to as sustainability ratings or CSR ratings; therefore, they used the terms ESG ratings and sustainability ratings interchangeably.

[20] https://climatecommunication.yale.edu/visualizations-data/ycom-us-2016/.

[21] https://mitsloan.mit.edu/sustainability-initiative/aggregate-confusion-project.

[22] https://vlab.stern.nyu.edu/welcome/climate; https://vlab.stern.nyu.edu/welcome/georisk.

FUTURE RESEARCH DIRECTIONS

This section synthesizes future research directions covering ESG risk and climate change risk.

Bansal, Wu, and Yaron (2021) indicated that the variability of investor preference for individual ESG categories is an interesting area for future research that could examine the investor preference channel with disaggregated data on individual investments and ESG fund flows. They suggested that, as investors possibly learn more about ESG and CSR and become more informed about the relation between ESG and stock prices in general, the unexplained performance difference and its time variability may gradually change. Given the recent trends in individual investors' access to electronic trading (e.g., a notable increase in the use of app-based platforms) and in a social media–driven approach to trading (e.g., the unprecedented surge in the prices of *meme stocks*), it is possible that investor preferences in ESG categories and SRI approaches will rapidly change. Increased social media coverage of firms' activities and stock price reactions could have a negative impact on portfolio management and, thus, may require regulatory changes sooner than anticipated.

Giglio, Kelly, and Stroebe (2021) provided a compelling research agenda for climate finance, in which they stated that "on the empirical side, there is substantial scope for improvements of the measures of climate risk exposure in different asset classes, and, in particular, for equity assets." According to the authors, increased disclosure by firms, due either to new regulatory requirements or investor demands, is likely to provide new opportunities to measure financial exposure to various types of climate risks; however, in the absence of new data disclosed directly by firms, Giglio, Kelly, and Stroebe suggested that more creative use of already existing data, such as satellite imagery or text from 10-K statements or earnings calls, can further be processed to improve climate risk exposure measures.

Giglio et al. (2021) indicated that their research provides a transparent and portable framework to show how the insights of modern asset pricing theory can be used together with inputs from a physical model of climate change to inform the appropriate discount rates for investments in climate change abatement. They attributed their modeling approach to new avenues of research that combine the physical elements of climate change (e.g., tipping points, increasing ocean levels) with the likely response of economic activity (e.g., technological innovation, geographic relocation of production)

Blasberg, Kiesel, and Taschini (2021) found that the transition risk factor is a relevant determinant of CDS spreads, but this relation varies substantially across industries. Kölbel et al. (2020), in addition to finding that CDS spreads respond to climate-risk disclosures, presented evidence that only the transition risks are being priced, not the physical risks of climate change, suggesting that the CDS market responds distinctively to transition and physical risks. The results of these studies, which are derived only from the CDS market, suggest that further research may be needed to examine whether and how transition and physical climate risks are incorporated in asset prices in different markets. Findings of this new research direction would likely be critical for climate policy recommendations.

Engle et al. (2020) discussed multiple directions for future research on financial approaches to managing climate risk and asserted that, due to the long-run and non-diversifiable nature of climate risk, standard futures or insurance contracts in which one party promises to pay the other in the event of a climate disaster are difficult to implement. Krueger, Sautner, and Starks (2020) indicated that, despite the growing empirical evidence that investors should take climate considerations into account, integrating climate risks into the investment process can prove challenging, with investment tools and best practices being not well established yet. As an example, Krueger, Sautner, and Starks suggested that many market participants, including institutional investors, find climate risks difficult to price and hedge, possibly because of their systematic nature, a lack of disclosure by portfolio firms, and challenges in finding suitable hedging instruments.

Painter (2020) asserted the importance of understanding how long-term climate change risk is priced in financial markets and suggested that financial consequences of climate change come in four general forms: production risk, reputation risk, regulatory/litigation risk, and physical risk. The author highlighted as an important question whether and how much investors price climate change risk when this risk cannot be easily addressed. Further empirical evidence addressing the question raised by Painter may have significant policy and regulatory implications.

Barnett, Brock, and Hansen (2020) suggested there are established research methodologies for measuring current risks from asset prices; however, measuring changes in expectations about long-run future risks is very challenging. Although asset prices should reflect (in present value terms) investors' view of the uncertainty about future cash flows, measuring the impact of novel risks on asset prices necessitates new methods. Further complicating understanding of the impact of long-run climate change risk on volatility of asset prices is the model uncertainty mentioned by Barnett, Brock, and Hansen. Borrowing from approaches to model risk management, future research may investigate the implementation of stress testing for various novel risks, not for just climate change risk, based on scenarios that differ by, for example, industry and/or regions, as well as for different risk factors.

FUTURE REGULATORY AND POLICY DIRECTIONS

This section synthesizes future regulatory and policy directions covering ESG risk, climate change risk, and cybersecurity risk.

Barber, Morse, and Yasuda (2021) found that investors' WTP varies considerably and investigated what attributes of investors affect investors' WTP for impact. They found that investors facing political and/or regulatory pressure and those benefiting from political or local goodwill exhibit a higher WTP for impact, whereas laws that discourage the sacrifice of financial returns for impact may reduce the WTP for impact. Therefore, it may be possible to structure regulatory policies to increase investor, especially institution investor, engagement with firm management to allow capital markets to drive investments toward reducing the effects of novel risks.

Chen, Dong, and Lin (2020) reported that the Sustainability Accounting Standards Board has developed industry standards to distinguish material and immaterial ESG issues from an investor viewpoint. The authors suggested that these standards have meaningful predictive power over future financial performance. Consequently, it may be possible to create standards for other novel risks as long as uniform disclosure requirements are established and data vendors, policymakers, and industry associations coordinate their efforts.

Ilhan et al. (2019) reported that many institutional investors believe climate risk reporting is as important as traditional financial reporting and that it should be mandatory and more standardized. According to the authors, however, these institutional investors also view current quantitative and qualitative disclosure on climate risks as being insufficient and imprecise. Krueger, Sautner, and Starks (2020) suggested that a major challenge to investors can be the uncertainty of the time horizon over which climate risks will materialize; therefore, the authors evaluated investors' views on the horizons over which they expect climate risks to materialize financially. Despite the potential horizon uncertainty, respondents to the authors' survey did not view climate risks as a theme of the distant future. Less than 10% believed that climate risks will materialize only in 10 years or more, whereas 50% stated that climate risks related to regulation have already started to materialize. This view should encourage policymakers and regulators to increase their engagement with academic researchers and industry organizations to implement uniform disclosure standards that would enable production of actionable data and measurement methods for managing novel risks.

Eling and Wirfs (2019) stated that understanding the properties and behavior of cyber risk is vital for the provision of insurance and the estimation of risk capital and that policymakers and regulators need to develop sound policies for the treatment of this novel risk category. They asserted that the modeling and pricing of cyber insurance policies are the main impediments to the insurability of cyber risks. Referring to sparse cyber risk data, the authors suggested that generation of more data and profound analyses of cyber risk constitute an important area of future work. Their assertions support the need to establish standardized and uniform disclosure requirements for cybersecurity risk.

Michel, Oded, and Shaked (2020) indicated that the SEC regularly analyzes any abnormal trading activity prior to announcements of mergers and acquisitions, and, for decades, it has been well known that insider trading activity may take place prior to these announcements. Based on their findings, Michel, Oded, and Shaked suggested that regulators should also consider a routine trading history analysis of the stock of companies that have been breached and that the focus of regulators' attention should be the several weeks prior to the breach announcement.

Lubin (2021) suggested that information asymmetries and underwriting challenges limit the ability of insurers to properly price stand-alone cyber policies and set appropriate premiums, and the lack of consensus around security standardization, ambiguous coverage schemes, and policy questionnaires limit the effective use of cyber insurance. The author asserted that there is a need for legal reforms as well as agency regulation and public–private partnership in developing the framework for cybersecurity insurance markets.

Flammer, Toffel, and Viswanathan (2021) indicated that shareholder activism fills the gap in the absence of regulatory disclosure requirements; however, Ilhan et al. (2019) suggested that institutional investors, who would be the main climate activists, responded in the authors' survey that climate risk reporting is as important as traditional financial reporting and should be mandatory and more standardized. It is possible that, with the help of academic research centers like the NYU's Volatility Institute, the MIT's Sloan Sustainability Initiative, and the NYU Institute for Policy Integrity, policymakers and industry associations would establish comparable, specific, and decision-useful disclosure measures and encourage data vendors to create benchmarks and use indexes developed in academic research to evaluate the increased disclosure quality.

CONCLUSIONS

In a broader sense, novel risks arise from environmental-, governance-, healthcare-, social responsibility–, sustainability-, and technology-related shortcomings of or challenges faced by firms as well as the uncertainty caused by potential domestic and global regulatory policy responses. Novel risk may be considered an evolving concept; that is, a risk factor that used to be novel becomes part of traditional risks as its measurement and management enter established practices. Therefore, ESG risk, climate change risk, cybersecurity risk, and geopolitical risk should not be considered as an exhaustive list of current or future novel risks in financial markets.

Measuring novel risks is a challenge. This challenge can be attributed to the lack of sufficiently informative data that may be due, in part, to the absence of mandated disclosure requirements or the difficulty in identifying proxies for factors that are not directly observable—which, may be due, in part, to the need to expand the tool set of financial economists. Recent academic research suggests that it is a combination of both.

Although the recent announcements made by the SEC during the first quarter of 2021 highlight the importance of ESG risk and climate change risk, as well as how rapidly the regulatory and policy framework is evolving for these risks, the recent ransomware attacks during May 2021 targeting a major US energy distributor and a major US food processor increased the potential vulnerabilities from cybersecurity risk. These developments have been taking place as the financial markets process the impact of COVID-19 pandemic, which has been affecting the world since February 2020 (as of the writing of this article in August 2021), thus bringing pandemic risk to the forefront of risk taxonomy and heightening sensitivity to geopolitical risk as the perfect storm of novel risks seems to converge on economies across the globe.

Recent academic literature suggests that there are parallels among ESG risk, climate change risk, cybersecurity risk, and geopolitical risk in terms of measurement challenges, including but not limited to emerging data and measurement methods; similarities in terms of their insufficient, noncomparable, less-specific, and non-decision-useful disclosures; and the potential interaction between these risks. Establishment of consistent disclosure policy and reporting requirements and improvement in measuring the impact of these novel risks on asset prices, volatility, and global financial stability is at the forefront of contemporary financial economics and portfolio management.

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Foundations of Climate Investing: How Equity Markets Have Priced Climate-Transition Risks

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KEY FINDINGS

- The authors identified economic transmission channels showing how regulatory policies and green technology influence financial markets. In developed markets outside the United States, more carbon-efficient companies experienced stronger performance over a seven-year study period. They found companies' green revenue share was clearly associated with higher earnings growth and relatively better stock performance within a given sector.
- Next, they looked at the relationship between companies' climate-transition risk profiles and their valuation levels, finding that carbon-intensive companies experienced declining valuation in terms of price-to-book ratios than their less carbon-intensive sector peers—suggesting that markets have discounted the book value of carbon-intensive companies during the study period. In contrast, companies with significant green revenues saw their price-to-earnings ratios increase relative to their sector peers.
- Companies' earnings growth and stock performance was directly related to their greenhouse gas emissions. Using five MSCI low carbon transition categories, the authors found that the riskiest category (stranded assets) had the weakest performance and the solutions category the strongest during the study period. Although most performance differences were explained by the industry factor, there was a significant stock-specific return that showed a strong correlation to companies' climate transition-risk profile.

ABSTRACT

Countries have set varying targets to reduce greenhouse gas emissions in line with the Paris Agreement's goal of keeping the increase in global average temperatures to well below 2°C. In this article, the authors examine to what extent climate risk has been priced into equity markets and whether climate change can be modeled using a typical risk model structure. They develop the fundamental economic transmission channels to explain the potential impact of climate change on equity prices, including empirical evidence for climate policies and green technology as financial risk drivers. They also study the impact of climate-transition risk on valuation levels and trends. They conclude with a discussion of how to measure and categorize companies' climate-risk exposures and how to integrate climate-transition risks into risk models.

TOPICS

*ESG investing, security analysis and valuation, tail risks**

*All articles are now categorized by topics and subtopics. View at PM-Research.com.

Under the 2015 Paris Agreement, global political leaders adopted a goal of limiting the increase in global average temperatures to well below 2°C above preindustrial levels. To achieve this objective, countries defined a national emission reduction path—nationally determined contributions (NDCs)—which ultimately will be mapped onto different sectors and individual companies. Countries' ambitions for reducing greenhouse gas (GHG) emissions, as reflected in their NDCs, vary significantly, as shown in Exhibit 1.

With respect to the 2015 NDCs, the European Union has the most ambitious target. We estimate that its NDC effectively represents a 50% to 60% reduction on 2030 BAU emissions. In contrast, the comparable US pledge corresponds to an estimated 30% to 40% reduction. In emerging markets (EMs), we observe even lower ambitions. For example, China's NDC translates to an estimated 10% to 20% emissions reduction as compared with 2030 BAU emissions. In 2021, the Biden administration updated its pledge to cut emissions by 50% until 2030. However, because this announcement came after the end of our study period, we rely on the 2015 pledges in this article.

Many corporations will have to adjust their operations and/or their products and services to meet their countries' NDCs and future climate policies. Some companies, such as BP, Ford Motor, and CEMEX, already have set ambitious net-zero goals. These policy changes may pose risks to the holdings of global investors. How can they best evaluate these risks? Investors also might ask whether climate risks are already fully priced into financial markets. To the extent that companies' business models are visibly exposed to transition risks (e.g., a shift to a low-carbon economy) or physical risks (e.g., extreme weather conditions), have markets completely reflected those risks?

The scope of this article is to understand the extent to which climate risk has been priced into equity markets and whether climate change can be modeled using a typical risk model structure, exemplified in the following formula:

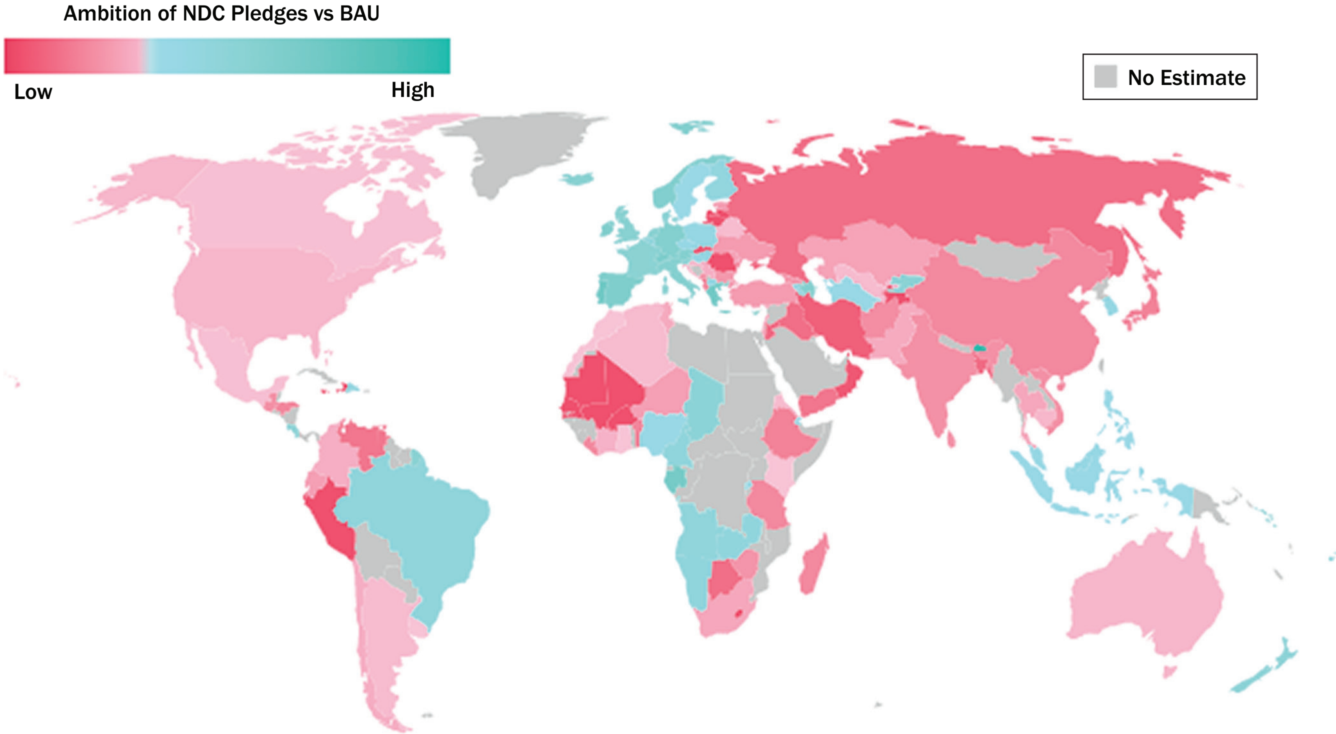
$$\textit{Financial climate risk impact} = \textit{Climate risk exposure} \times \textit{Climate risk driver}$$

We address three key areas in this article:

1. **Economic drivers of climate change:** We identified economic transmission channels within a standard discounted cash flow model showing how regulatory policies and green technology influence financial markets. For example, in developed markets (DMs) outside the United States, more carbon-efficient companies experienced stronger stock-price performance over a seven-year study period. In contrast, in EMs, less carbon-efficient companies fared better across the study period, although more carbon-efficient companies performed better in recent years, which was also true for the United States. This finding lends support to the Porter hypothesis (Porter and van der Linde 1995) in DMs but not in EMs.
2. **Valuation levels:** Next, we compared companies' climate-transition risk profiles to their valuation levels. Carbon-intensive companies experienced greater declines in valuation in terms of price-to-book ratios (P/B) than did their less-carbon-intensive sector peers, suggesting that markets have discounted the book value of carbon-intensive companies during the study period. In contrast, companies with significant green revenue saw their price-to-earnings ratios (P/E) increase relative to their sector peers. Companies' earnings growth and stock performance were directly related to their GHG emissions. Using five MSCI low carbon transition (LCT) categories, we found that the riskiest category (stranded assets) had the weakest performance and the solutions category had the strongest during the study period. Although most performance differences were explained by the industry factor, there was

EXHIBIT 1

Normalized Relative Target Level of NDCs per Region



NOTES: Data reflecting the pledged GHG goals found in the NDCs submitted to the 2015 COP21 conference in Paris, sourced from NDC Registry. To make the NDCs comparable, MSCI ESG Research rebased them in terms of reduction of countries' GHG emissions as a percentage of countries' respective 2030 business-as-usual (BAU) emissions, which reflect the emissions trajectory of the country without any climate policy. Note that member countries are expected to submit new NDCs during 2021.

SOURCE: MSCI ESG Research.

a significant stock-specific return that showed a strong correlation to companies' climate-transition risk profile.

3. **Risk models:** When we included LCT scores in a standard risk model, we found a positive return attached to the climate-transition risk profile, which has accelerated over the past two years. The performance was particularly strong in the two categories at the tails: stranded assets and solutions. In contrast, in the largest category, composed of companies with neutral exposure, the observed stock-price and earnings impact was small.

Our study adds to existing research in two ways. First, instead of just looking for correlations between companies' carbon emissions and stock performance, we analyzed and identified the economic transmission channels that can explain a causal relationship between climate-transition risk drivers on one hand and financial effects on the other hand. Second, we analyzed the extent to which the pricing of climate risk has changed or accelerated after the 2015 Paris Agreement.

In the next section, we summarize the data and methodologies used for our empirical analysis. We then develop the fundamental economic transmission channels to

EXHIBIT 2
Climate Descriptors Used in the Study

Descriptor	Definition
Carbon Intensity	The amount of Scope 1 and 2 GHG (direct emissions and electricity use) in tons of CO_2-equivalent (tCO_2e) per $1 million of sales.
Scope 3 Carbon Intensity	The amount of Scope 3 GHG emissions in tCO_2e per $1 million sales, based on MSCI's Scope 3 Estimation Model, generated by a company's supply chain. This covers all 15 categories of upstream and downstream Scope 3 emissions, as defined by the Greenhouse Gas Protocol. Details on the methodology are provided by Hadjikyriakou, Bokern, and Klug (2020).
Reserve Intensity	Potential GHG emissions in million tCO_2e embedded in companies' coal, oil, and gas reserves per $1 million market capitalization.
Green Revenue Share	The share (in percent) of a company's revenue derived from alternative energy, energy efficiency, and green building.
Carbon Beta	A measure of the sensitivity of a company's stock price to (European) CO_2 price movements. Technically, this is the beta regression coefficient of the residual return from the MSCI GEMLT risk model on the price returns of the allowances traded under the European Union Carbon Emission Trading Scheme (EU ETS).
LCT Score	A measure of a company's climate-transition risk arrived at by aggregating Scope 1, 2, and 3 emissions, avoided emissions, and the quality of companies' climate management into a score between 0 (highest risk) and 10 (lowest risk/highest opportunity).
LCT Category	A category assigned to a company that highlights the predominant transition risks and opportunities that the company is most likely to face. The LCT category is based on the LCT score. There are five LCT categories: stranded assets, product transition, operation transition, neutral, and solutions. Details are provided by Badani et al. (2019).

SOURCE: MSCI.

explain the potential impact of climate change on equity prices, including empirical evidence for climate policies and green technology as financial risk drivers. We also study the impact of climate-transition risk on valuation levels and trends. We follow with a discussion of how to measure and categorize companies' climate-risk exposures and how to integrate climate-transition risks into risk models.

DATA AND METHODOLOGY

We use the descriptors shown in Exhibit 2 to characterize companies' climate change profiles as a basis for our analysis[1] (descriptors come from MSCI climate data and metrics).

Missing data values were omitted in the analysis universe, except for the factor return regression in which missing LCT scores were replaced by 0.[2]

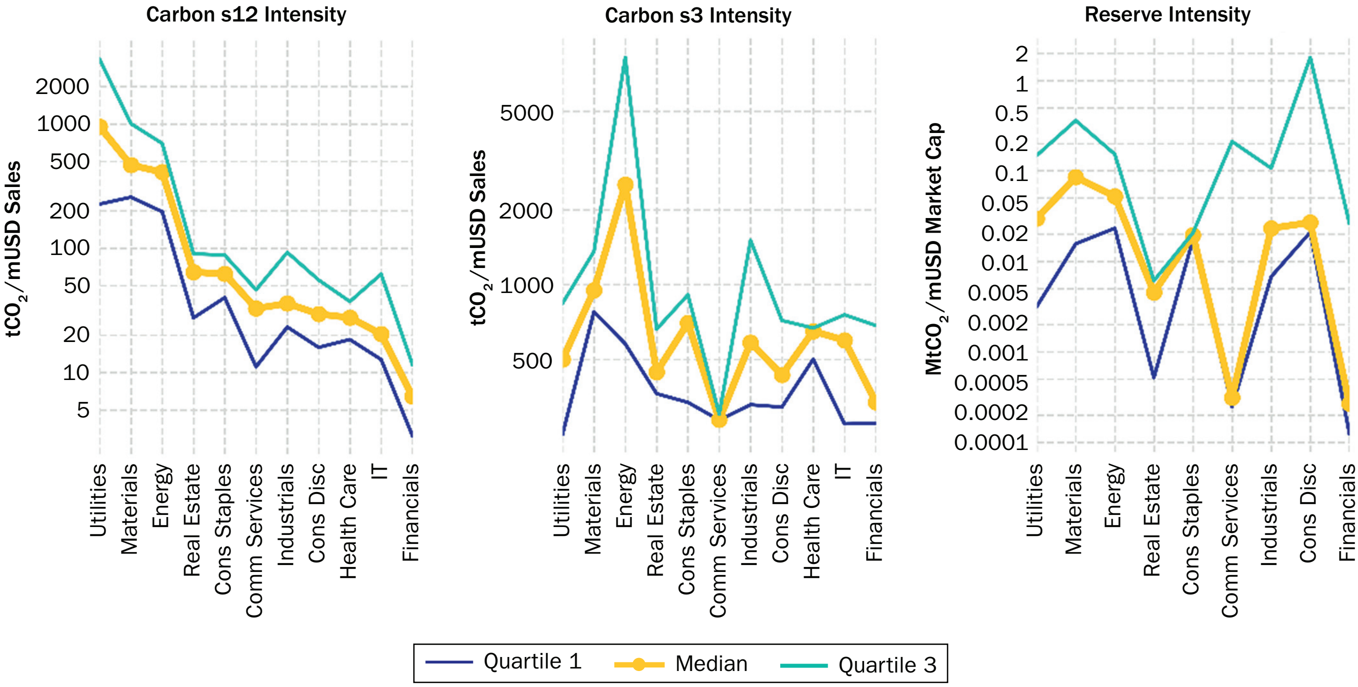
Emissions-Related Sector Exposures

Which sectors have the greatest exposure to carbon risk? We assessed median levels of these descriptors across Global Industry Classification Standard (GICS)

[1] The descriptors are all data fields proprietary to MSCI ESG Research LLC.
[2] See Exhibit 17.

EXHIBIT 3

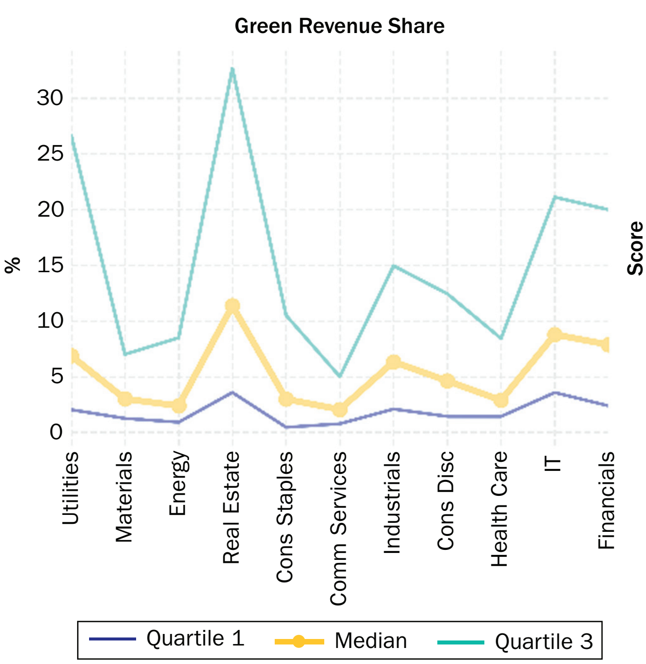
Distribution of Emission Indicators per GICS Sector



NOTES: Data from October 31, 2014, (carbon intensities) or January 31, 2010 (reserve intensity) to January 31, 2021. Note that the healthcare and IT sectors do not have reserve intensity data. For each sector, we show the 25th, 50th, and 75th percentiles of monthly sector averages over the sample period.

EXHIBIT 4

Distribution of Green Indicators per GICS Sector



NOTES: Data are from November 30, 2015 (green revenue share) or December 31, 2014 (low carbon patents score) to January 31, 2021. For each sector, we show the 25th, 50th, and 75th percentiles of monthly sector averages over the sample period.

sectors.[3] The indicators can be grouped into carbon footprint indicators, climate change readiness (or green) indicators, and price-sensitivity (or risk) indicators. We ordered sector-specific results by decreasing emission intensity—from the highest (utilities) to the lowest (financials).

We had different historical data available for the different descriptors. To provide statistically significant results, we used the longest available history for each descriptor in our simulations, which means the time periods shown in our study vary depending on which descriptors were used.

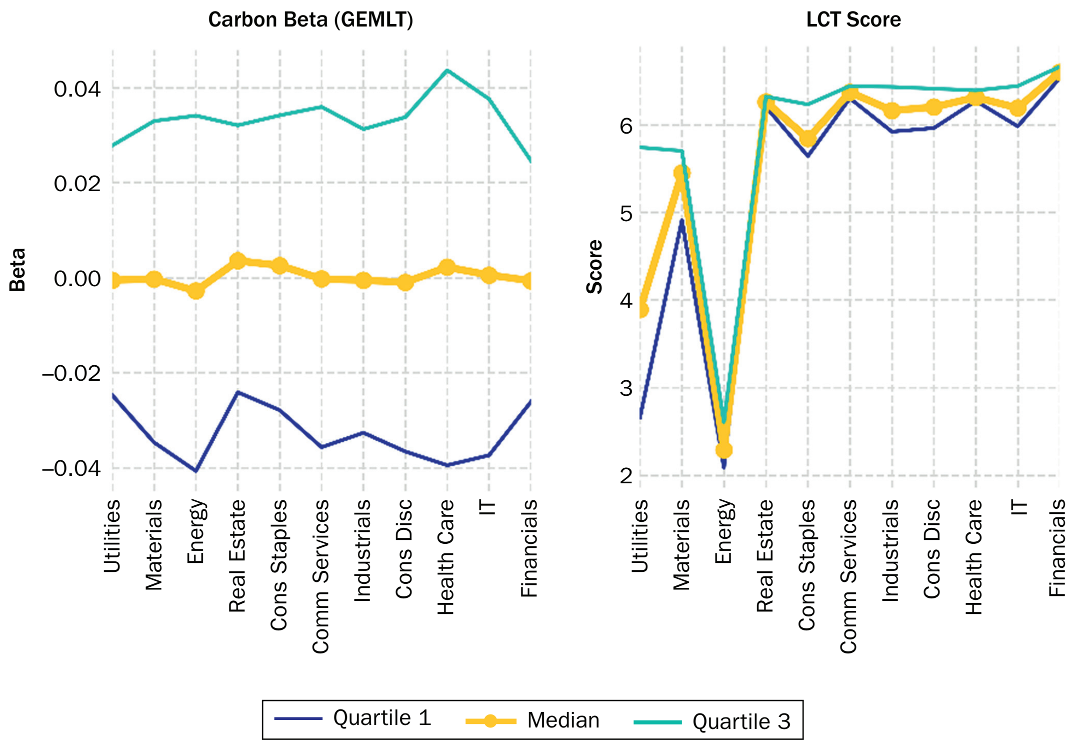
Exhibit 3 illustrates that the utilities, materials, and energy sectors provided the highest levels of emissions and fossil fuel reserves. (Some companies in other sectors also had fossil fuel reserves in related group subsidiaries.)

Interestingly, the three most carbon-intensive sectors are also among the sectors holding most of the patents related to green technology—alongside the IT and industrials sectors (Exhibit 4)—suggesting that these companies are seeking to change their business models.

[3] GICS is the global industry classification standard jointly developed by MSCI and Standard & Poor's.

EXHIBIT 5

Distribution of Climate-Transition Risk Indicators per GICS Sector



NOTES: Data are from July 31, 2012 (carbon beta) or October 31, 2013 (LCT score) to January 31, 2021. For each sector, we show the 25th, 50th, and 75th percentiles of monthly sector averages over the sample period.

Carbon beta values—a market-implied proxy for how dependent companies are on the price of carbon emissions—were small across all sectors (see Exhibit 5), but not unreasonably so, considering that carbon beta shows the impact on residual returns after stripping out the impact on returns of common factors including industry and countries. The energy sector had the lowest (most negative) median value for carbon beta, indicating that the residual returns of this sector were the most negatively affected by an increase in (European) carbon prices.

Data Transformation

We normalized the data to address the skew in the distribution for some of the variables so that a higher numerical value always corresponds to a more climate-friendly company profile. All carbon emission–related variables were transformed onto a logarithmic scale, and we flipped the sign, effectively making them a measure for carbon efficiency. Companies' green revenue shares were also transferred to a log scale.

DRIVERS AND TRANSMISSION CHANNELS OF TRANSITION RISK

In *Risk, Uncertainty, and Profit*, University of Chicago economist Frank H. Knight explained 100 years ago that *risk* is present when the set of potential future events is known and occurs with measurable probability; *uncertainty* is present when the complete set or likelihood of future events is indefinite or incalculable (Knight 1921).

Efficient markets can be expected to price risk efficiently, but the same may not hold for uncertainty owing to unknown probabilities of future events or incomplete knowledge about the set of future states of the economic system.

Although climate change is largely referred to as a risk in the public debate, in reality it is an uncertainty because the probability distribution of climate change and the political development to tackle it are largely unknown. However, the ability to price risks becomes more certain as risks become more defined. For example, the 2015 Paris Agreement and subsequent commitments by different countries to cut emissions have provided markets with very tangible and therefore priceable pieces of information.

In this section, we explore the economic transmission channels that explain how policies and technology drive the process of turning uncertainty into priceable risk information and how these channels can be verified empirically. We focus on two drivers—government policies and green technology—because they are very prominent in the public and academic debate on climate change (United Nations Environment Programme Finance Initiative 2019). However, in practice there may be many other drivers, such as a shift in consumer preferences; however, these are beyond the scope of our analysis.

Climate Policy as a Climate-Transition Risk Driver

Policies and regulations are the political key drivers for countries implementing NDCs. To gain a theoretical understanding of the economic transmission channels from climate-related policies to priceable financial market impact, we looked at integrated assessment models (IAMs), which outline pathways for the transition of the global economy to a low-carbon economy. For instance, in June 2020 the Network for Greening the Financial System (NGFS) published a set of climate scenarios using three IAMs (GCAM, MESSAGEix-GLOBIOM, and REMIND-MAgPIE).[4] These models combine economic aspects, land use, energy, and climate systems in a consistent quantitative framework to model cost-efficient decarbonization pathways. These scenarios describe the policy-induced reduction of emissions as a key driver to climate change, implying increasing operational and cost impacts on companies, which we summarize in Exhibit 6.

We now look for empirical evidence supporting this hypothetical transmission channel.

Given the regional differences in the ambitiousness of countries' NDCs, we examine the relationship between regions and climate-related stock price performance.[5] We are especially interested in differences between DMs and EMs and, within DMs, between the United States and the rest of DMs. Therefore, we used three regional subsets of the MSCI ACWI IMI universe: a US index (MSCI USA IMI), a DM non-US index (MSCI World ex USA IMI), and an EM index (MSCI EM IMI). For each of these benchmarks, we divided the universe sector by sector into Scope 1 and 2 carbon-efficiency quintiles on a monthly basis and compared the performance difference between the top and the bottom quintiles, as well as the difference in earnings growth (Exhibit 7).

Carbon-efficient companies in the MSCI World ex USA Index experienced superior stock performance and earnings growth. In contrast, in EMs, the most carbon-efficient companies showed slight underperformance compared with less carbon-efficient companies and similar levels of earnings growth over time. In the United States, results were mixed: More carbon-efficient companies showed lower earnings growth

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[4] The models are described in some detail in the NGFS technical documentation (NGFS 2020). Further model documentation is available at https://www.iamcdocumentation.eu/index.php/IAMC_wiki.

[5] See Exhibit 1.

EXHIBIT 6

Hypothetical Transmission Channel of Climate Policies

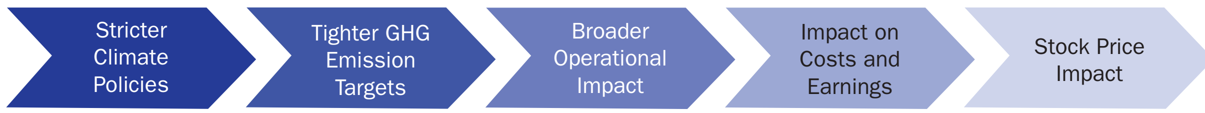
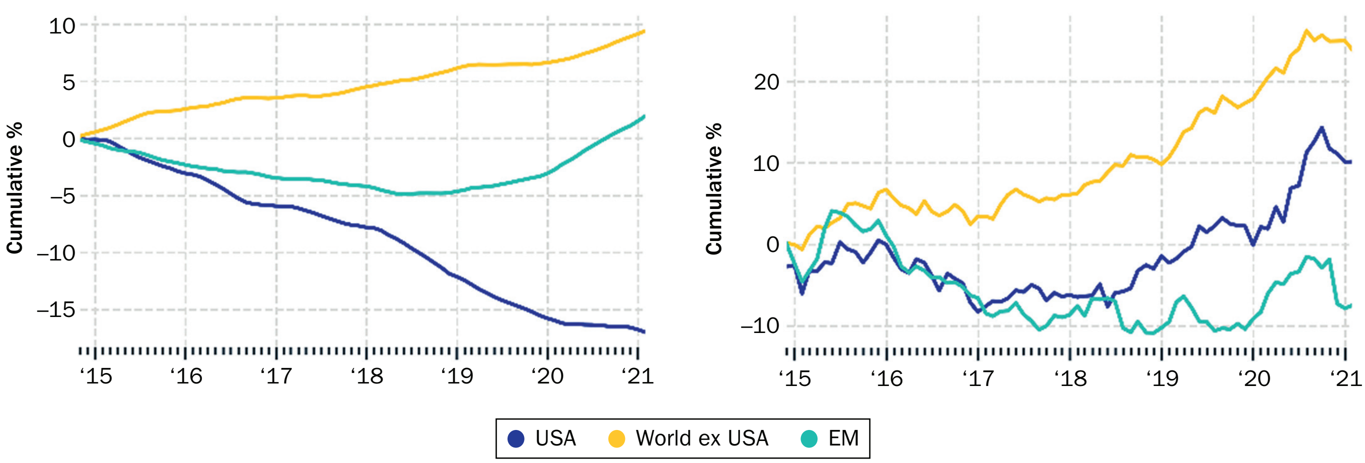


EXHIBIT 7

Top versus Bottom Carbon Efficiency Quintiles



NOTES: Differences in earnings-per-share (EPS) growth are shown in Panel A; stock returns are charted in Panel B. Data are from October 31, 2014 to January 31, 2021. EPS growth is taken from the GEMLT model and uses five-year smoothing.

but slightly better performance, albeit clearly below the MSCI World ex USA Index returns. From the time of Donald Trump's election as the US president in November 2016, more carbon-efficient companies in the United States underperformed their less carbon-efficient peers for about two years; since mid-2018, however, their stocks have rebounded and subsequently outperformed.

In DMs (excluding the United States), the outperformance of more carbon-efficient companies was driven by the majority of companies in the sample. This is apparent in the cumulative specific return contribution of the lowest and highest quintiles in carbon efficiency shown in Exhibit 8. In the United States, the top carbon-efficient quintile of companies outperformed.[6] In EMs, the opposite was true; in other words, the majority of top-quintile companies showed a negative specific return.

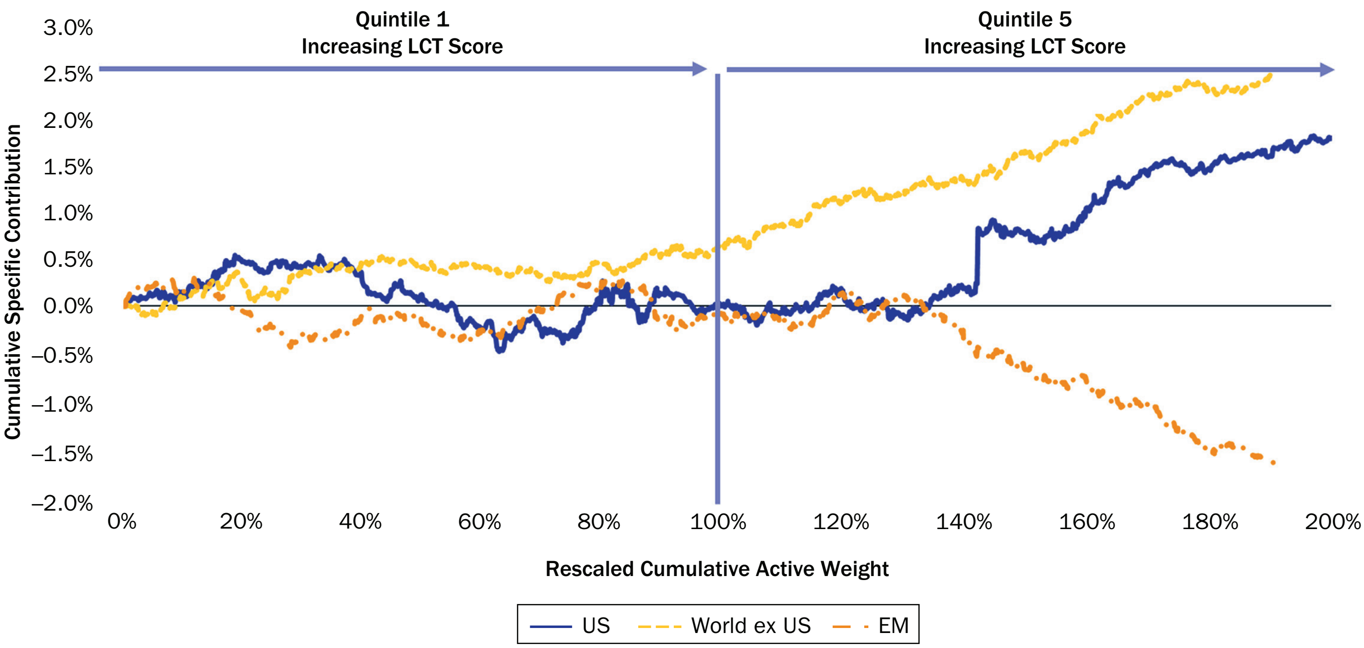
Carbon efficiency has been more financially relevant in DMs (excluding the United States) than in the United States and EMs. This observation is consistent with DMs' stronger political commitment to a low-carbon economy, especially the European Union's 2018 pledge to become carbon-neutral by 2050. This echoes our map in Exhibit 1 that shows that Europe had the most ambitious climate change agenda and EM the least.

It is worth noting the relationship between firms' environmental performance and financial performance since the advent of environmental policies in Western countries in the 1970s (Spicer 1978). The Porter hypothesis (Porter and van der Linde 1995) suggests that strict environmental regulation can result in innovation among

[6] The large stock-specific return in the United States was due to GameStop.

EXHIBIT 8

Cumulative Specific Return versus Cumulative Active Weight



NOTES: Data are from October 31, 2014 to January 31, 2021. The jump in the United States (around the 140% mark) is entirely due to GameStop's performance in January 2021.

polluting firms. That hypothesis has been reformulated into a weak form (environmental regulation may lead to innovation but not necessarily to better financial performance) and a strong form (environmental regulations may lead to better financial performance; Ambec et al. 2011). The Porter hypothesis has given rise to a stream of empirical research with generally inconclusive results (Dechezlepretre and Kruse 2018). As a result, more recent research has tended to focus more on the question of the circumstances under which the Porter hypothesis may hold (Albertini 2013).

The lack of conclusive results may be explained by the regional difference in performance that we observed in Exhibits 7 and 8. Our findings lend support to the Porter hypothesis for DMs but not for EMs, where the level of technical readiness and the political framework are not yet transforming the local economy toward decarbonization to the same extent.

Carbon Emission Costs' Impact on Earnings and Stock Returns

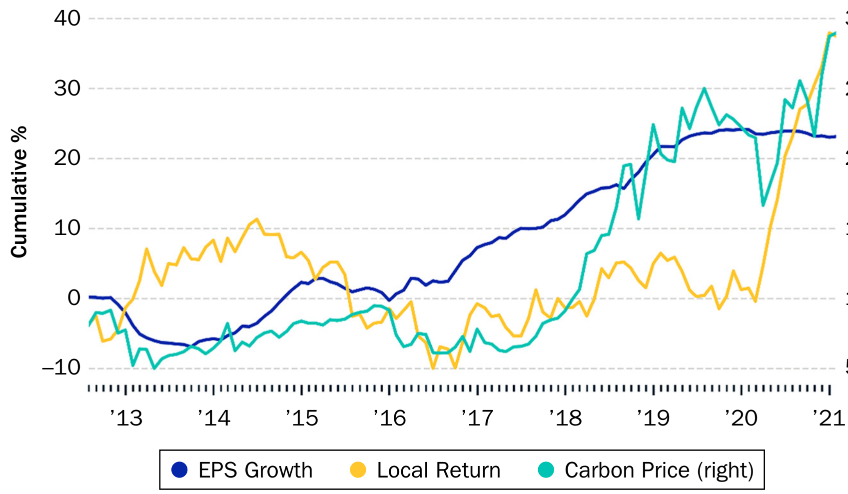
To validate the hypothetical climate transmission channel, we assessed whether emission-related costs showed an impact on earnings and stock performance (the last step in the transmission channel).[7] Given that the EU ETS constitutes the largest carbon trading system worldwide, we used the prices of the EU ETS allowances (EUA).

We examined the most carbon-intense sectors in Europe—utilities, energy, and materials—and ordered companies in each sector according to their sensitivity to

[7] In a separate study, we examined whether climate-related events led to an immediate change in stock prices. However, the results were mixed because some events (e.g., the 2015 Paris Agreement) might have been anticipated by markets. Thus, we are focusing solely on the last step of our transmission model in this section.

EXHIBIT 9

Top- versus Bottom-Quintile Performance of Carbon Beta



NOTES: Data are from July 31, 2012 to January 31, 2021. Universe: utilities, energy, and materials sectors within the MSCI Europe Index. EPS growth is taken from the GEMLT model and uses five-year smoothing. The carbon price is proxied by the daily EEX EUA futures settlement price in euros.

the EUA price (measured by the carbon beta) into top quintiles (most positive price sensitivity) and bottom quintiles (most negative price sensitivity).

Exhibit 9 shows the top versus bottom performance in term of earnings growth and stock performance compared with the European carbon price for the three carbon-intense sectors. During the study period, we saw that companies with more positive or less negative carbon price sensitivity showed a positive earnings growth trajectory, closely aligned with the price increase of carbon. We also found that those companies' stocks have outperformed since 2016, albeit with some time lag when compared with the earnings-growth trajectory.

These findings support the last step in the transmission channel: In exposed sectors, the European carbon price was a cost factor associated with companies' earnings and, ultimately, their stock price. A broad selection of literature has found similar results. For instance, Tian et al. (2016) found a negative association between European carbon prices and returns of stocks of carbon-intensive utilities and a positive association with the returns of stocks of cleaner utilities.

Green Technology as Climate-Transition Risk Driver

The development and rollout of green technology is another key component of the transition to a net-zero economy and a core part of the inner workings of IAMs. Although IAMs produce scenarios at a macroeconomic level, we are interested in the implications for firm performance—in other words, at the microeconomic level. We evaluate green technology's role in a hypothetical transmission channel (Exhibit 10).

In our analysis, we used companies' share of green revenue as a proxy for their involvement in green technology.[8] Green revenue share indicates the extent to which companies have monetized green technology and allows us to test the second half of the transmission channel.

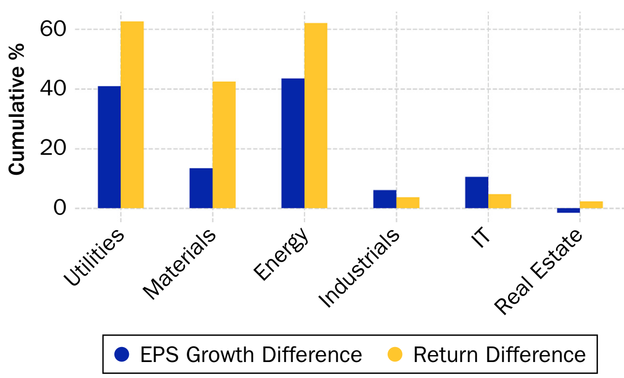
[8] Green revenue has been used in previous research, such as that by Dechezlepretre, Martin, and Mohnen (2017), Kruse et al. (2020), and Kruse, Mohnen, and Sato (2020).

EXHIBIT 10

Hypothetical Transmission Channel of Green Technology

EXHIBIT 11

Top Quintile in Green Revenue Share versus Bottom Quintile



NOTES: Data are from November 30, 2015 to January 31, 2021. EPS growth is taken from the GEMLT model and uses five-year smoothing.

To test the hypothesis of whether green revenue may be financially relevant, we sorted companies in each GICS sector according to their share of green revenue and compared the upper quintiles against the lowest quintiles in terms of both earnings growth and stock performance (Exhibit 11). We observed that, within sectors with significant green revenue, companies with a high share of green revenue showed significantly higher earnings growth than their sector peers with a low green revenue share, except for the real estate sector, where differences were negligible. In addition, this earnings growth advantage was also associated with higher stock performance in all sectors (except real estate, which showed no earnings growth difference).

Overall, our findings suggest that involvement in green technology as proxied by green revenue was clearly accompanied by stronger relative stock performance, which provides empirical support for the transmission channel in Exhibit 10 during our study period. Our findings are in line with those of Kruse et al. (2020), who found that utilities with higher proportions of green revenue tended to have higher profit margins, which led to higher relative valuation levels.

Next, we probe deeper into the financial impact on stock valuation levels and stock-price performance.

VALUATION EFFECTS OF CLIMATE TRANSITION

Now that we have found support for the economic transmission channels, we take a closer look at whether equity markets repriced stock of companies based on climate considerations. We address two questions:

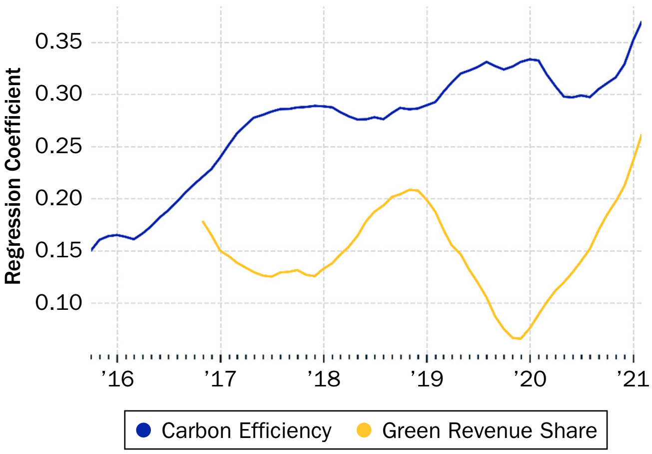
1. Whether firms' climate-transition risk profiles had an impact on their valuation levels during the study period
2. Whether this impact has changed over time—in other words, have we observed any empirical evidence for a shift in investors' preferences or risk aversion

To address the first question, we tested whether lower GHG emissions or higher green revenue shares were associated with higher P/B and P/E ratios in a standard regression model. To address the second question, we assessed the trends in the regression coefficients over time.

First, we regressed companies' P/B and P/E ratios versus their carbon efficiency and green revenue share as explanatory variables. We ran a monthly regression

EXHIBIT 12

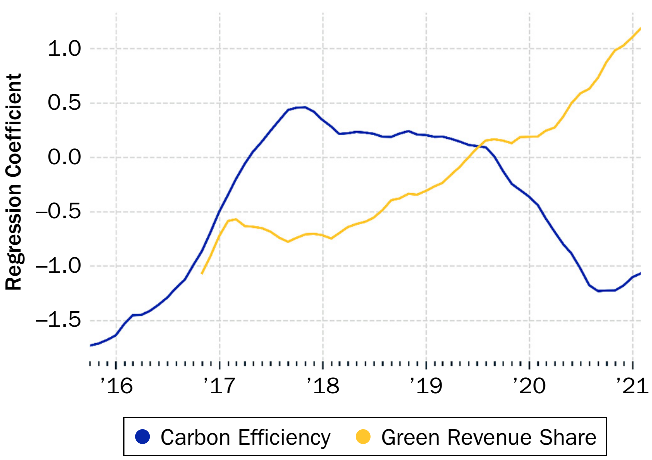
P/B Regression Coefficients



NOTES: Data are from October 31, 2014 to January 31, 2021. This exhibit shows the rolling 12-month average of the cross-sectional regression coefficient of companies' P/B to carbon efficiency and green revenue share. All regressors are z-scored and winsorized at ±3.

EXHIBIT 13

P/E Regression Coefficients



NOTES: Data are from October 31, 2014 to January 31, 2021. This exhibit shows the rolling 12-month average cross-sectional regression coefficient of companies' P/E to carbon efficiency and green revenue share. All regressors are z-scored and winsorized at ±3.

within MSCI ACWI IMI using regions, sectors, and style factors (size, momentum, growth, earnings variability, profitability, residual volatility) and oil-price sensitivity as control variables.[9] The 12-month moving averages of the cross-sectional regression coefficients for P/B and P/E are shown in Exhibits 12 and 13, respectively.

In the P/B analysis (Exhibit 12), we found that more carbon-efficient companies tended to have higher valuation levels and showed an increasing trend in their relative valuation levels. On the other hand, for companies' green revenue shares, the regression coefficient was volatile without as clear a trend as that found for carbon efficiency.

For the P/E analysis (Exhibit 13), the picture is almost the opposite: The carbon efficiency regression coefficients for Scope 1 and 2 emissions were volatile without a clear trend and flipped signs several times during the study period. On the other hand, the green revenue share coefficient showed a clear positive trend, going from a negative to a positive valuation effect during the study period.

These findings are in line with those of previous academic studies. For instance, from 2011 to 2015 (prior to the Paris Agreement), Berkman, Jona, and Soderstrom (2019) found that a measure of climate risk was negatively associated with Tobin's Q measures for US nonfinancial firms and positively associated with the cost of capital.[10] Similarly, Atanasova and Schwartz (2019) investigated North American oil firms from 1999 to 2018 and found that an increase in their reserves was negatively associated with those firms' Tobin's Q measures, especially in countries with more-stringent climate policies—leading the authors to conclude that markets penalized the valuation of companies with reserves growth.

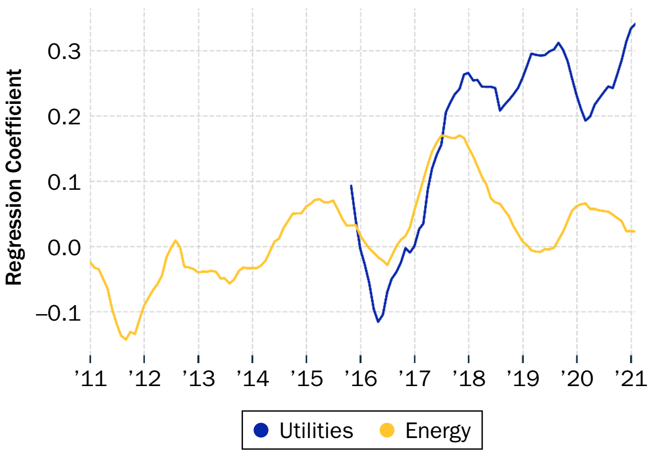
The difference between the P/B and P/E analysis is worth highlighting: P/B is a more backward-looking analysis because book value represents past earnings and past buildup of companies' balance sheets. The fact that our P/B regression showed a more significant trend for carbon efficiency could mean that, during the study period, investors became increasingly skeptical as to whether the book value of companies heavily reliant on carbon-intensive activities is sustainable in the long run. In other words, investors may have become more risk-averse toward potentially stranded assets

[9] Style factors were selected based on their correlation with P/B and P/E variables. We also tested other control sets, which always included regions and sectors; only the list of style factors varied. The smaller control set contained the size factor, and the larger control set contained all style factors except those directly correlated with the dependent variable (i.e., B/P and P/E).

[10] The ratio of a firm's enterprise value to the book value of its assets.

EXHIBIT 14

P/B Regression on Reserve Efficiency: Utilities and Energy Coefficients



NOTES: Data are from October 31, 2014 (utilities) or January 31, 2010 (energy) to January 31, 2021. This exhibit shows the 12-month rolling average of the cross-sectional regression coefficient of companies' P/B to reserve efficiency in selected sectors.

on companies' balance sheets and started to discount companies' book values in their pricing of equities.

To probe deeper, we regressed companies' P/B versus companies' reserve efficiency for the energy and utilities sectors—the sectors that hold most of the fossil fuel reserves. The regression coefficient showed a clear upward trend over time for both sectors (Exhibit 14), providing further evidence for financial markets building a discount into P/B valuation levels.

In contrast, the P/E analysis is a more forward-looking view of how markets price companies' future business potential. Here, green revenue share was the strongest trend indicator, meaning investors were increasingly willing to pay higher valuation multiples for companies with more green revenue, which could be in line with expectations for larger future earnings.

MODELING AND MEASURING FINANCIAL TRANSITION RISK

We will now explore how to integrate climate-transition risks into financial risk models.

Measuring and Categorizing Transition Risk Exposure

We can proxy and categorize companies' transition risk profile by combining risk exposure (climate policy risk) and opportunity exposure (green technology) using standardized indicators such as companies' GHG emissions. We used companies' LCT scores as a comprehensive measure for transition risk. The score aggregates companies' risks due to direct emissions (Scope 1, Scope 2), risks due to their upstream supply chain (Scope 3 upstream emissions), and risks inherent in their products and services (Scope 3 downstream emissions). The LCT scores take into account companies' green opportunity exposure by measuring avoided emissions from green technology in Scope 3 emissions and companies' climate-transition risk management.

Next, we assess the extent to which companies' aggregate climate-transition exposures (proxied by their LCT scores) may explain stock performance. We integrated the LCT score into a standard equity risk model (MSCI GEMLT) to measure performance effects and to control for other systematic factors.

In addition, the LCT score is used to categorize companies' transition risk exposure into five LCT categories within MSCI ACWI IMI (Exhibit 15). We observe that the largest group on both measures was the neutral category, whereas the two most extreme categories—stranded assets and solutions—were the smallest.

To assess whether these emission-based categories adequately described companies' climate-transition risk, we ran a stock performance and earnings growth analysis of the LCT categories on the MSCI ACWI IMI universe using hypothetical equal-weighted portfolios with monthly rebalancing (Exhibit 16).

The two highest-risk categories (stranded assets and product transition) underperformed significantly, whereas solutions companies outperformed in terms of both stock performance and earnings growth. In fact, the relative stock performance of the different categories was in the exact same order as for the LCT categories.

EXHIBIT 15

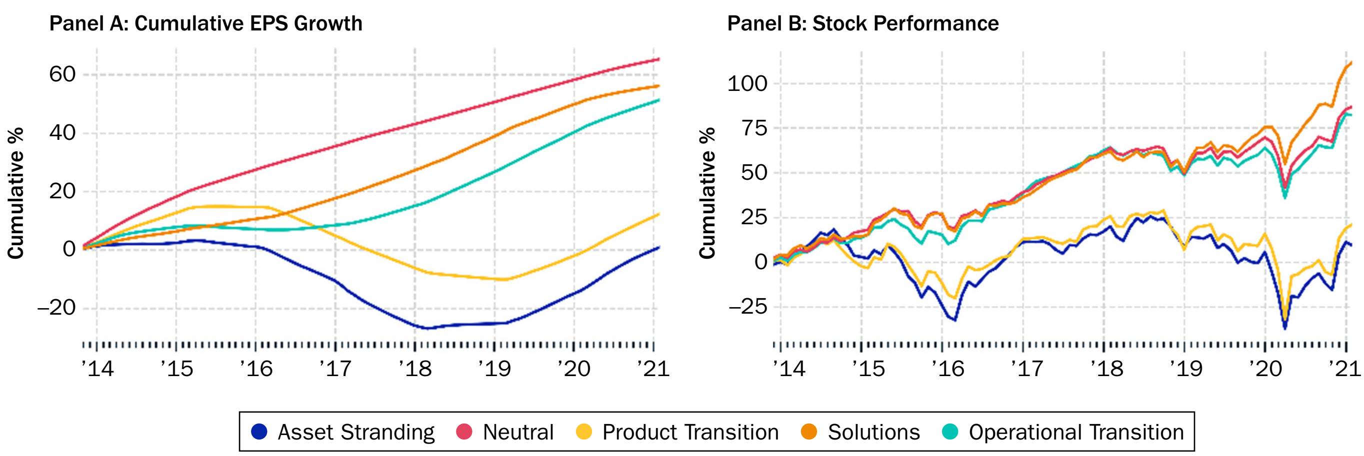
Breakdown of MSCI ACWI IMI into Climate-Transition Categories

LCT Category	Description	No. of Stocks	Weight
Asset Stranding	Potential to experience stranding of physical or natural assets owing to regulatory, market, or technological forces arising from low-carbon transition	75	1%
Product Transition	Reduced demand for carbon-intensive products and services; winners and losers are defined by the ability to shift product portfolio to low-carbon products	483	10%
Operational Transition	Increased operational and capital cost owing to carbon taxes and investment in carbon emissions mitigation measures, leading to lower profitability of companies	1,013	9%
Neutral	Limited exposure to low-carbon transition risk; companies could face physical risk or indirect exposure to transition risk via lending or investment operations	5,539	74%
Solutions	Potential to benefit through the growth of low-carbon products and services	304	3%

NOTE: Data are from October 30, 2013 to January 31, 2021.

EXHIBIT 16

Stock Performance and Earnings Growth Analysis of the LCT Categories



NOTES: Data are from October 31, 2013 to January 31, 2021. EPS growth is taken from the GEMLT model and uses five-year smoothing.

Integrating Transition Risk Exposure into Risk Models

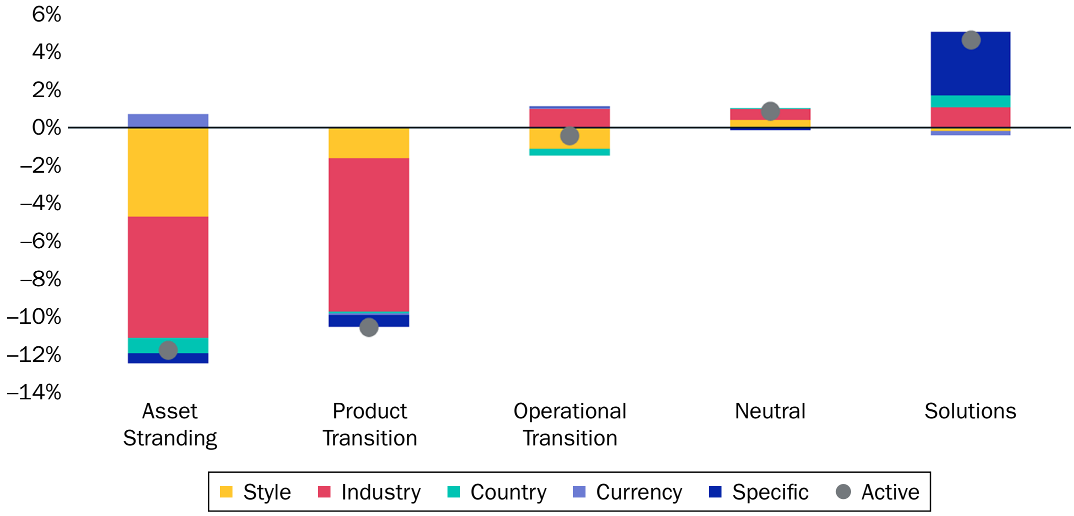
As a third step, we conducted a performance attribution to see the extent to which these performance results were due to common factors. To be precise, we measured the active performance of each LCT category (long leg) against the MSCI ACWI IMI (short leg). Both legs were equally weighted, with monthly rebalancing.

The results in Exhibit 17 show again the monotonic relationship between LCT categories and performance, from stranded assets to solutions companies. For the higher-risk LCT categories (stranded assets and product transition), most of the underperformance was explained by the industry factor, which is in line with our earlier findings that direct and indirect emissions are very concentrated in a few sectors and consequently in a few industries. In addition, the stranded assets category showed a significant performance contribution from equity style factors, especially the momentum factor.

In addition, there has been a significant stock-specific performance contribution—especially in the solutions LCT category. The specific return contribution is important

EXHIBIT 17

Active Performance Attribution (equally weighted)



NOTE: Data are from October 31, 2013 to January 31, 2021.

because it indicates the return not explained by common equity factors. To what extent can these specific returns be explained by differences in companies' LCT scores? To address this question, we sorted companies in each LCT category (the long leg) in increasing order of LCT score and plotted the cumulative specific return over the cumulative portfolio weight for each category (Exhibit 18).

Specific returns were most significant in the solutions category: We found a convex curve, which means that solutions companies with higher LCT scores had higher stock-specific returns than solutions companies with lower LCT scores. The stranded assets category also showed a strong degree of convexity in the cumulative return curve, with lower LCT scores showing negative stock-specific returns and higher LCT scores showing positive specific returns.[11]

We also observed a certain degree of convexity in the cumulative specific return curves for the product transition and operational transition categories in the lower half of the curve, whereas they were closer to a linear relationship at the upper end of the LCT score range in those categories. On the other hand, stocks in the neutral LCT category showed relatively little aggregate stock-specific return and no convexity. Overall, this shows that the stock-specific returns that can be attributed to the LCT scores were very concentrated in the categories most exposed to climate transition risk, in line with our intuition.

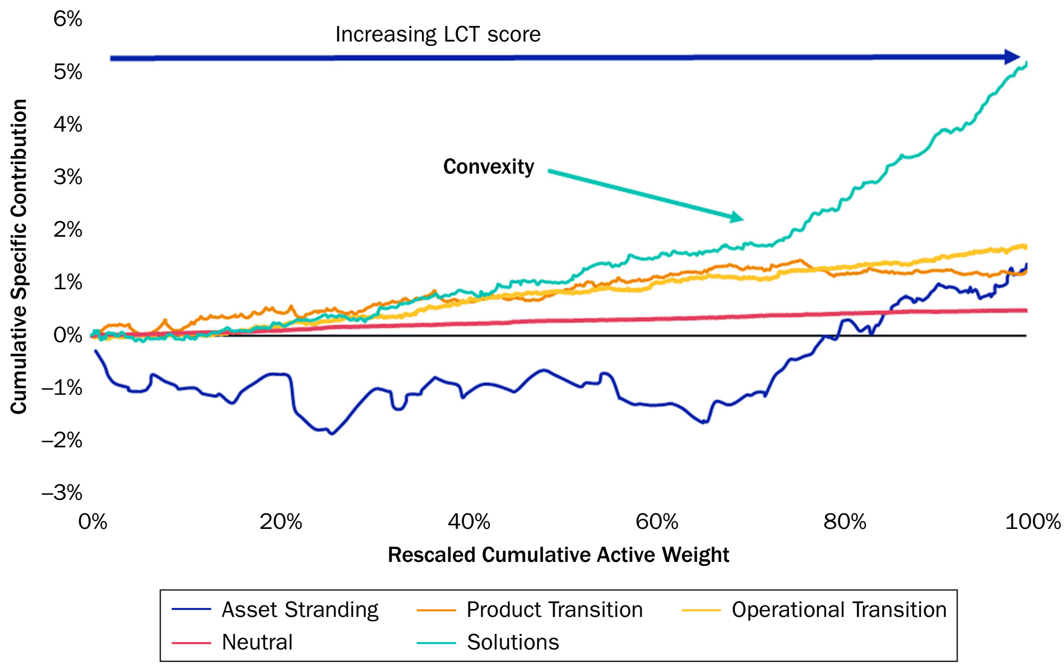
Could companies' climate-transition risk profiles (as measured by their LCT scores) serve as an additional equity risk driver? To assess this question, we included LCT scores as a hypothetical driver in the factor-return estimation of the MSCI GEMLT model to obtain the return associated with the LCT score—in other words, the return after taking into consideration all existing factors in the GEMLT model.

The resulting cumulative returns associated with the LCT score are shown in Exhibit 19 and are quite intuitive: Overall, LCT scores showed a positive return that was relatively small in the first half of the study period but accelerated substantially during the last two years of the study period. The growing

[11] This finding explains why the aggregate stock-specific return for the stranded assets category in Exhibit 9 was quite small: Positive and negative stock-specific returns were offsetting each other.

EXHIBIT 18

Cumulative Specific Return over Cumulative Portfolio Weight



NOTE: Data are from October 31, 2013 to January 31, 2021.

EXHIBIT 19

Cumulative Returns of the LCT Score

NOTE: Data are from October 31, 2013 to January 31, 2021.

strength of LCT scores may provide additional support for the policy- and technology-related transmission channels in Exhibits 6 and 10 because climate-related policies and technology have increased since the Paris Agreement was adopted in late 2015.

The improved value of LCT scores provides support for the idea that, during the study period, climate-transition risk had been a price factor, alongside traditional equity style factors. However, price impact was mainly concentrated in the most exposed LCT categories, whereas there was little stock price impact in the largest neutral category. This finding is in line with that of Goergen et al. (2019), who found that a "carbon risk factor" existed between 2010 and 2017, as measured by an indicator for companies' transition risk that used GHG emissions and ESG variables. Our findings contrast, however, with those of Bolton and Kacperczyk (2020), who found that carbon-intense companies outperformed their greener peers from 2005 to 2018 using a global equity universe. The authors termed this a "carbon premium."

Our study is more focused on the time after the Paris Agreement. Our analysis suggests that the increasing price discount of carbon-intense companies after the Paris Agreement went hand in hand with a relative decline in earnings and stock performance for those companies. In all three sectors, we saw very clear stock-price outperformance related to high versus low LCT scores. In the utilities and materials sectors, higher LCT scores also were associated with relatively higher earnings growth.

How Climate-Transition Risks Materialized

We can draw four key conclusions from these results:

1. Although emissions data are typically reported with a significant time lag, our analysis shows that companies' total emissions profile as measured by the LCT score and LCT category provided a meaningful way to proxy and categorize their transition-risk exposure, as shown by differences in earnings growth and stock performance. This may be because companies' involvement in carbon-intensive activities or climate solutions does not change over short periods of time; emissions and green revenue reported some months ago have provided a good proxy for companies' transition-risk exposure. For financial risk models, this means that companies' emissions profiles represent the climate transition-risk exposure, rather than the climate-risk driver. The results also support the Bank of International Settlement's suggestion that providing a firm-level green rating based on a company's total emissions profile could provide a useful signal to investors (Ehlers, Mojon, and Parker 2020).
2. Transition risk was not uniformly distributed across MSCI ACWI IMI: The financial impact was mainly concentrated in the two smallest and most extreme categories (asset stranding and solutions), whereas the impact was small in the neutral LCT category (accounting for 74% of the benchmark by market capitalization).
3. For asset stranding and solutions, there was a strongly nonlinear relationship between companies' LCT scores and stock-specific returns, which suggests that companies' emissions profiles provided a relevant stock-price factor alongside common style factors.
4. The financial effects of climate-transition risk appeared continuously over time and have accelerated significantly since 2019, which mirrors the findings of Giese, Lee, and Nagy (2021), who found climate risk to be a long-term "erosion risk." This finding can be explained by the economic transmission channels, which shows how policies and technology potentially drove the process of transforming climate uncertainty into priceable pieces of climate risk information over time.

From a financial risk management perspective, investors may want to consider that the observed financial erosion process may continue as climate policy, green technology, and financial markets evolve. Financial climate stress scenarios, as proposed by the Task Force on Climate-related Financial Disclosure (TCFD), may help simulate or extrapolate a continuation of the observed financial erosion path into the future.[12]

Future research may focus on whether the observed acceleration in stock-price impact continues and the extent to which the financial impact may spread more broadly to the neutral LCT category. Researchers may also explore whether there are additional economic transmission channels that can potentially drive financial effects, such as climate-related shifts in consumer behavior.[13]

[12] TCFD recommendations for disclosing climate-related risks, June 2017.

[13] Existing literature also looked at other financial aspects of climate transition risk, such as systematic risks in equity markets (Monasterolo and De Angelis 2020), tail risks (Ilhan, Sauntner, and Vilkov 2021), and the influence of climate-related disclosure on financial performance (Matsumura, Prakash, and Vera-Muñoz 2014).

CONCLUSION

We identified two economic transmission channels that help explain how climate policies and green technology may transform climate uncertainty into tangible risk parameters priceable by financial markets. Looking for empirical evidence, we found regional differences in NDCs to be associated with regional differences in financial performance: In DMs (excluding the United States), we saw the biggest relative performance advantage during our seven-year study period for more carbon-efficient companies versus their less carbon-efficient sector peers in terms of stock-price and earnings growth. In contrast, EMs had less carbon-efficient companies outperform their greener sector peers during the entire study period (although performance improved in the past two years), which was in line with less-ambitious NDCs in EMs. The United States sat in the middle of these extremes.

We also found that climate transition has shifted during the study period: Carbon-intensive companies have seen a relative downward trend in their P/B valuation, which means markets started to effectively discount book values that can be linked to carbon-intensive activities. In contrast, companies with high exposure to green revenue have seen their P/E rise, which means investors were willing to pay an increasing premium to gain exposure to technology that has the potential to replace the existing carbon-intensive infrastructure.

Companies across the five LCT categories (stranded assets, product transition, operational transition, neutral, and solutions) showed very different stock-performance and earnings-growth patterns. Although most of the performance difference was explained by the industry factor, we found a significant stock-specific performance contribution associated with differences in companies' GHG emissions. This performance contribution was particularly strong in the most extreme risk categories: stranded assets (highest risk) and solutions (lowest risk/highest opportunity). We were also able to attribute intersectoral performance differences among the most carbon-efficient and the least carbon-efficient quintiles to differences in green revenue. We also found that the LCT score provided a positive return when used in GEMLT, which increased in the past two years, providing additional evidence that climate-transition risk should be considered as an additional risk factor.

Furthermore, we found clear evidence that climate-transition risk unfolds in the shape of erosion risk, rather than event risk. This finding provides empirical support for conducting climate stress scenarios as one way to extrapolate the observed financial erosion path into the future.

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The Market Measure of Carbon Risk and its Impact on the Minimum Variance Portfolio

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KEY FINDINGS

- Measuring carbon risk is different if we consider a fundamental-based approach by using carbon intensity metrics or a market-based approach by using carbon betas.
- Managing relative carbon risk implies overweighting of green firms, whereas managing absolute carbon risk implies having zero exposure to the carbon risk factor. The first approach is an active management bet, whereas the second is an immunization investment strategy.
- Both specific and systematic carbon risks are important when building a minimum variance portfolio and justify combining fundamental and market approaches to carbon risk.

ABSTRACT

Like environment, social, and governance investing, climate change is an important concern for asset managers and owners and a new challenge for portfolio construction. Until now, investors have mainly measured carbon risk using fundamental approaches, such as with carbon intensity metrics. Nevertheless, it has not been proven that asset prices are directly affected by these fundamental-based measures. In this article, the authors focus on another approach, which consists of measuring the sensitivity of stock prices with respect to a carbon risk factor. In the authors' opinion, carbon betas are market-based measures that are complementary to carbon intensities or fundamental-based measures when managing investment portfolios; carbon betas may be viewed as an extension or forward-looking measure of the current carbon footprint. In particular, they show how this new metric can be used to build minimum variance strategies and how it affects portfolio construction.

TOPICS

*ESG investing, portfolio construction, tail risks, fundamental equity analysis**

According to Mark Carney (2019), climate change is one of the big current challenges faced by the financial sector, with the goal to accelerate the transition to a low-carbon economy. This transition concerns all financial institutions: central banks, commercial banks, insurance companies, asset managers, asset owners, and so on. Among the several underlying topics, climate change risk management will be one of the pillars of future regulation to ensure financial sector resilience to tail risk.

*All articles are now categorized by topics and subtopics. View at PM-Research.com.

Because risk management must concern both physical and transition risks (Carney 2015), how to incorporate climate change when managing banks' credit portfolios is not obvious. The question is how climate change affects issuers' default probability. The same issue arises when we consider stock and bond portfolios of asset managers and owners.

We must understand how asset prices react to climate change. Thus, we must develop new risk metrics to assess the relationship between climate change and asset returns. However, we face data collection issues when we consider this broad subject. Therefore, we focus here on carbon risk because it is the main contributor to climate change[1] and we have more comprehensive and robust data on carbon metrics at the issuer level.

The general approach to managing an investment portfolio's carbon risk is to reduce or control the portfolio's carbon footprint (e.g., by considering CO_2 or CO_{2e} emissions). This approach assumes that carbon risk will materialize and that having a portfolio with a lower exposure to CO_2 emissions will help to avoid some future losses. The main assumption of this approach is that firms that currently have high carbon footprints will be penalized in the future in comparison with firms that currently have low carbon footprints. In this article, we use an alternative approach. We define carbon risk from a financial point of view, and we assume that the carbon risk of equities corresponds to the market risk priced in by the stock market. This carbon financial risk can be decomposed into a common (or systematic) risk factor and a specific (or idiosyncratic) risk factor. Because identifying the specific risk is impossible, we focus on the common risk factor that drives carbon risk. The objective is then to build a market-based risk measure to manage the carbon risk in investment portfolios. This is exactly the framework proposed by Görgen et al. (2019) in their seminal paper.

In this framework, the carbon financial risk of a stock corresponds to its price sensitivity to the carbon risk factor. This carbon beta is a market-based relative risk and may be viewed as an extension or forward-looking measure of the carbon footprint, in which the objective is to be more exposed to green firms than to brown ones. In this case, this is equivalent to promoting stocks with a negative carbon beta over stocks with a positive carbon beta. This approach of relative carbon risk differs from the approach of absolute carbon risk, which is measured at the stock level by the absolute value of the carbon beta, because absolute carbon risk considers both large positive and negative carbon beta values to incur a financial risk that must be reduced. This is an agnostic or neutral method, contrary to the first method, which is more related to investors' moral values or convictions.

Since the 2008 Global Financial Crisis, institutional investors have widely used minimum variance (MV) strategies to reduce their equity investments' market risk. Although the original idea of these strategies was to reduce the portfolio's volatility, today the goal of MV strategies is to manage the largest financial unrewarded risks and not just volatility risk. This is why sophisticated MV programs also include idiosyncratic valuation risk, reputational risk, and so on. In this context, incorporating climate risk into MV portfolios is natural. Therefore, we propose a two-factor model that is particularly adapted to this investment strategy and show that the solution depends on whether we would like to manage relative or absolute carbon risk.

THE MARKET MEASURE OF CARBON RISK

To manage a portfolio's carbon risk, carbon risk needs to be measured at the company level. There are different ways to measure this risk, including the fundamental

[1] This implies that we consider transition risks, not physical risks.

and market approaches. In this article, we favor the second approach because it provides a better assessment of the impact of climate-related transition risks on each company's stock price. Moreover, the market-based approach allows us to mitigate the issue of a lack of climate change–relevant information. In what follows, we present this latest approach by using the mimicking portfolio for carbon risk developed by Görgen et al. (2019). We compare this seminal approach with a simplified approach, which consists of using direct metrics such as carbon intensity. Once carbon betas are computed, we can analyze the carbon risk of each company priced in by the stock market and compare it with the carbon intensity, which is the most frequently used fundamental-based measure of carbon risk. We also discuss the difference between relative and absolute carbon risk.

Measuring Carbon Risk

Measuring a company's carbon risk using the carbon beta of its stock price was first proposed by Görgen et al. (2019). In what follows, we summarize their approach and test alternative approaches. Moreover, we suggest using the Kalman filter to estimate the dynamic carbon beta of stock prices.

The Carima approach. The goal of the carbon risk management (Carima) project, developed by Görgen et al. (2019), is to develop "a quantitative tool in order to assess the opportunities of profits and the risks of losses that occur from the transition process." The Carima approach combines a market-based approach and a fundamental approach. The carbon risk of a firm or a portfolio is measured by considering the dynamics of stock prices, which are partly determined by climate policies and transition processes toward a green economy. Nevertheless, a prior fundamental approach is important to quantify carbon risk. In practical terms, the fundamental approach consists of defining a carbon risk score for each stock in an investment universe using a set of objective measures, whereas the market approach consists of building a brown minus green (BMG) carbon risk factor and computing the risk sensitivity of stock prices with respect to this factor. Therefore, the carbon factor is derived from climate change–relevant information from numerous firms.

In the Carima approach, the BMG factor is developed using a large amount of climate-relevant information provided by different databases. In the following, we detail the methodology used by the Carima project to construct the BMG factor. Two steps are required to develop this new common risk factor: (1) the development of a scoring system to determine whether a firm is green, neutral, or brown and (2) the construction of a mimicking factor portfolio for carbon risk that has a long exposure to brown firms and a short exposure to green firms. The first step consists of defining a brown green score (BGS) using a fundamental approach to assess the carbon risk of different firms. This scoring system uses four environment, social, and governance (ESG) databases over the period from 2010 to 2016: Thomson Reuters ESG, MSCI ESG ratings, Sustainalytics ESG ratings, and the Carbon Disclosure Project (CDP) climate change questionnaire. Overall, 55 carbon risk proxy variables are retained. Each variable is transformed into a dummy derived with respect to the median, meaning that 1 corresponds to a brown value and 0 corresponds to a green value.

Görgen et al. (2019) then classified the variables into three different dimensions that may affect the stock value of a firm in the event of unexpected shifts toward a low-carbon economy: (1) value chain, (2) public perception, and (3) adaptability. The value chain dimension mainly deals with current emissions, and the adaptability dimension reflects potential future emissions determined in particular by emission reduction targets and environmental research and development (R&D) spending. Three scores are created and correspond to the average of all variables contained in each dimension: the value chain (VC), public perception (PP), and nonadaptability (NA).

It follows that each score has a range between 0 and 1. Görgen et al. (2019) proposed defining the BGS using the following equation:

$$\mathrm{BGS}_i(t) = \frac{2}{3}(0.7 \cdot \mathrm{VC}_i(t) + 0.3 \cdot \mathrm{PP}_i(t)) + \frac{\mathrm{NA}_i(t)}{3}(0.7 \cdot \mathrm{VC}_i(t) + 0.3 \cdot \mathrm{PP}_i(t)) \quad (1)$$

The higher the BGS value, the browner the firm.

The second step consists of constructing a BMG risk factor. Here the Carima project considers an average BGS for each stock that corresponds to the mean value of the BGS over the period in question, 2010–2016. The construction of the BMG factor follows the methodology of Fama and French (1992), which consists of splitting the stocks into six portfolios: small green (SG), small neutral (SN), small brown (SB), big green (BG), big neutral (BN), and big brown (BB).

The return of the BMG factor is defined as follows:

$$R_{\mathrm{bmg}}(t) = \frac{1}{2}(R_{\mathrm{SB}}(t) + R_{\mathrm{BB}}(t)) - \frac{1}{2}(R_{\mathrm{SG}}(t) + R_{\mathrm{BG}}(t)) \quad (2)$$

where the returns of each portfolio are value weighted.

Alternative approaches. Because the Carima approach is based on 55 variables from four ESG databases, it may be complicated for investors and academics to reproduce the BMG factor of Görgen et al. (2019). This is why Roncalli et al. (2020) proposed several proxies that may be easily computed. They used the same approach to build the BMG factor, but replaced the BGS with simple scoring systems using a single variable. Among the different tested factors,[2] Roncalli et al. (2020) showed that the Carima BMG factor is highly correlated to two BMG factors based on (1) the carbon intensity derived on the three scopes (Trucost dataset) and (2) the MSCI carbon emissions exposure score (MSCI 2020). In Exhibit 1, we report the cumulative performance of these two factors and the Carima factor. We observe that the three factors are very similar and highly correlated. On average, we observe that brown firms slightly outperformed green firms from 2010 to 2012. The cumulative return then fell by almost 35% because of the unexpected path in the transition process toward a low carbon economy. From 2016 to the end of the study period, brown firms created a slight excess performance. Overall, the best-in-class green stocks outperform the worst-in-class green stocks over the study period, with an annual return of 2.52% for the Carima factor, 3.09% for the carbon intensity factor, and 4.01% for the factor built with the carbon emissions exposure score.

Estimation of the carbon beta. Görgen et al. (2019) and Roncalli et al. (2020) tested several models to estimate the carbon beta by considering different sets of risk factors, including market, size, value, and momentum risk factors. Although Görgen et al. used a static approach by assuming that the carbon beta is constant over the period, Roncalli et al. proposed a dynamic approach by assuming that the betas are time varying. This is more realistic because carbon betas may evolve with the introduction of a climate-related policy, a firm's environmental controversies, a change in the firm's environmental strategy, increased incorporation of carbon risk into portfolio strategies, and so on. In what follows, we consider the dynamic approach with a two-factor model.

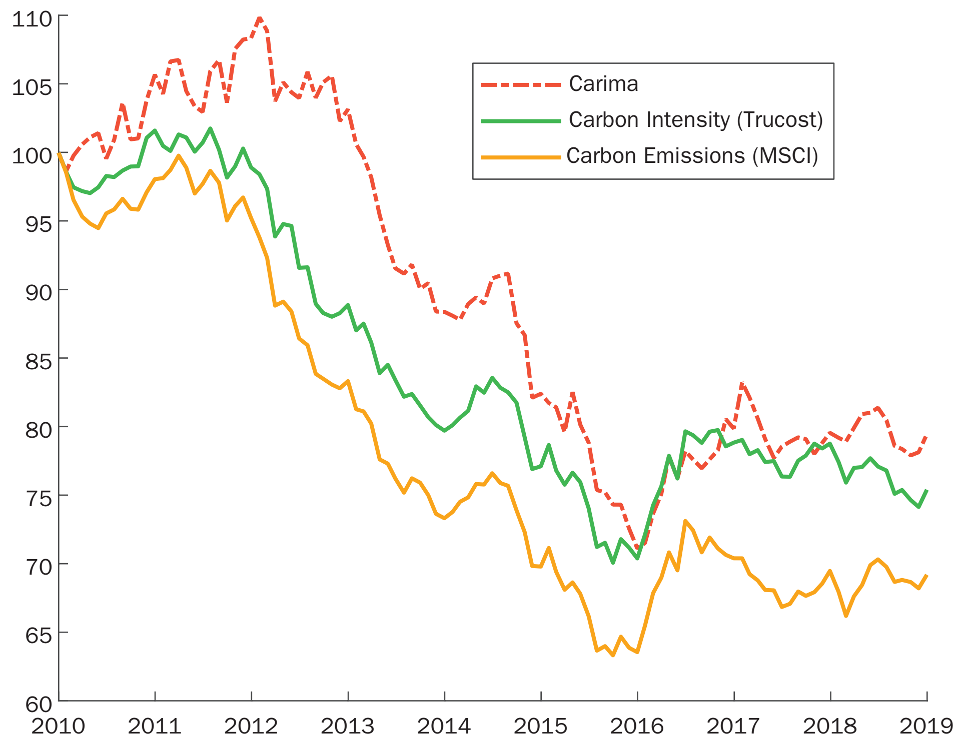
Let $R_i(t)$ be the monthly return of stock i at time t. We assume that

$$R_i(t) = \alpha_i(t) + \beta_{\mathrm{mkt},i}(t)R_{\mathrm{mkt}}(t) + \beta_{\mathrm{bmg},i}(t)R_{\mathrm{bmg}}(t) + \varepsilon_i(t) \quad (3)$$

[2] To build these factors, they considered the stocks that were present in the MSCI World index during the 2010–2018 period.

EXHIBIT 1

Cumulative Performance of the BMG Factors



where $R_{mkt}(t)$ is the return of the market risk factor, $R_{bmg}(t)$ is the return of the BMG factor, and $\varepsilon_i(t) \sim \mathcal{N}(0, \tilde{\sigma}_i^2)$ is white noise. The alpha component and the beta sensitivities follow a random walk:

$$\begin{cases} \alpha_i(t) = \alpha_i(t-1) + \eta_{alpha,i}(t) \\ \beta_{mkt,i}(t) = \beta_{mkt,i}(t-1) + \eta_{mkt,i}(t) \\ \beta_{bmg,i}(t) = \beta_{bmg,i}(t-1) + \eta_{bmg,i}(t) \end{cases} \quad (4)$$

where $\eta_{alpha,i}(t) \sim \mathcal{N}(0, \sigma^2_{alpha,i})$, $\eta_{mkt,i}(t) \sim \mathcal{N}(0, \sigma^2_{mkt,i})$, and $\eta_{bmg,i}(t) \sim \mathcal{N}(0, \sigma^2_{bmg,i})$ are three independent white noise processes.

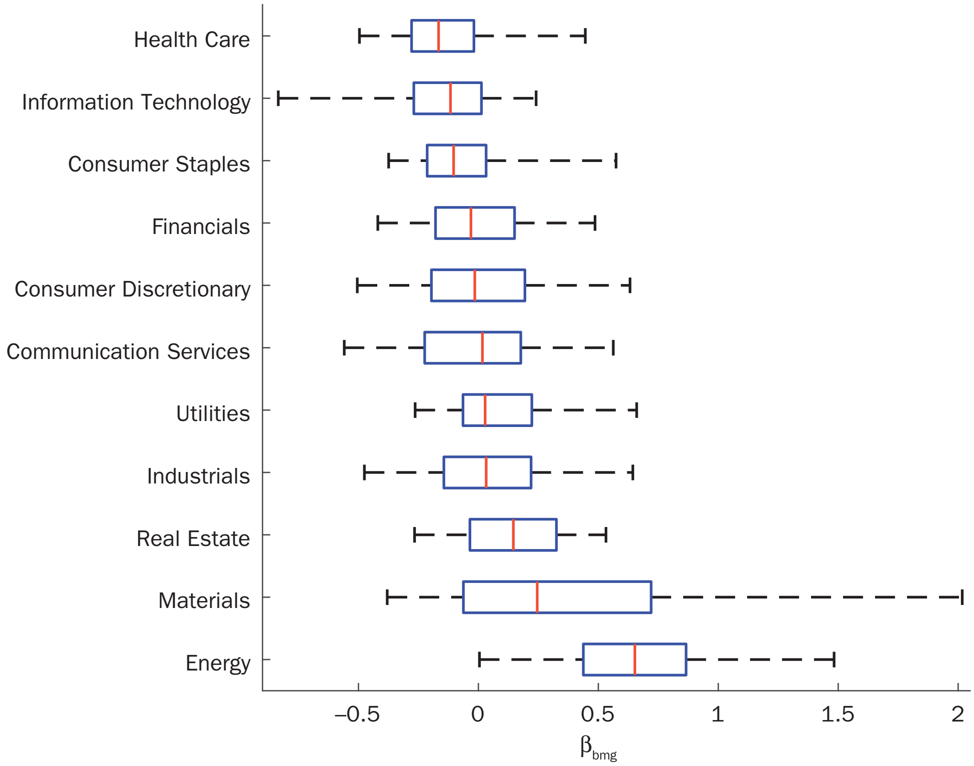
In the sequel of the article, we use the Carima factor to estimate the carbon beta. For the market factor, we use the time series provided by Kenneth French on his website. We estimate $\alpha_i(t)$, $\beta_{mkt,i}(t)$, and $\beta_{bmg,i}(t)$ for the stocks that belong to the MSCI World index between January 2010 and December 2018[3] using the Kalman filter (Fabozzi and Francis 1978). Moreover, we scale the Carima risk factor so that it has the same volatility as the market risk factor over the entire period, implying that the magnitude of the carbon beta $\beta_{bmg,i}(t)$ may be understandable and comparable to the magnitude of the market beta $\beta_{mkt,i}(t)$.

The average carbon beta of a stock is 0.05, which is close to zero, whereas the monthly variation of the carbon beta has a standard deviation of 6.24%. If we consider

[3] More precisely, we only consider the stocks that were in the MSCI World index for at least three years during the 2010–2018 period, and we take into account only the returns for the period during which the stock is in the MSCI World index.

EXHIBIT 2

Box Plots of the Dynamic Carbon Betas at the End of 2018



the market beta, the figures become, respectively, 1.02 and 5.45%. Therefore, the time volatility of the carbon beta is larger than that of the market beta.

In Exhibit 2, we report the Global Industry Classification Standard sector analysis of the carbon sensitivities at the end of December 2018. The box plots provide the median, quartiles, and 5% and 95% quantiles of the carbon beta. We notice that, on average, the energy, materials, and real estate sector have a positive carbon beta,[4] whereas the other sectors have a neutral or negative carbon beta. The results differ slightly from those obtained by Görgen et al. (2019) and Roncalli et al. (2020), who provided a sector analysis by considering a constant carbon beta over the period 2010–2018.

The average carbon beta $\beta_{bmg,\mathcal{R}}(t)$ for region $\mathcal{R}$ at time t is calculated as follows:

$$\beta_{bmg,\mathcal{R}}(t) = \frac{\sum_{i\in\mathcal{R}} \beta_{bmg,i}(t)}{\mathrm{card}\mathcal{R}}$$

In Exhibit 3, we report $\beta_{bmg,\mathcal{R}}(t)$ for several MSCI universes at the end of each year: World (WD), North America (NA), EMU, Europe-ex-EMU (EU), and Japan (JP). Whatever the study period, the carbon beta $\beta_{bmg,\mathcal{R}}(t)$ is positive in North America, which implies that American stocks are negatively influenced by an acceleration in the transition process toward a green economy. The average carbon beta is always negative in the Eurozone. Overall, the Eurozone always has a lower average carbon beta than the

[4]This is in line with the findings of Bouchet and Le Guenedal (2020), who demonstrate that credit risks are more material in the energy and materials sectors. Therefore, the market perceives these sectors as the entry point for systemic financial carbon risks.

EXHIBIT 3

Relative Carbon Risk by Region (end of year)

Year	WD	NA	EMU	EU	JP
2010	–0.02	0.13	–0.47	–0.16	0.02
2011	–0.04	0.11	–0.48	–0.14	–0.07
2012	–0.04	0.05	–0.32	–0.04	–0.13
2013	–0.02	0.07	–0.21	0.05	–0.22
2014	–0.04	0.01	–0.21	–0.02	–0.14
2015	0.00	0.04	–0.20	0.05	–0.08
2016	0.02	0.10	–0.21	0.01	–0.09
2017	0.03	0.12	–0.23	–0.03	–0.04
2018	0.06	0.10	–0.08	0.07	–0.02

world as a whole, whereas the opposite is true for North America. Nevertheless, the negative sensitivity of European equity returns has dramatically decreased since 2010, and the BMG betas are getting closer for North America and the Eurozone.

Absolute versus Relative Carbon Risk

In the previous paragraph, the relative carbon risk of a stock i at time t is measured by its carbon beta value:

$$\mathcal{RCR}_i(t) = \beta_{\text{bmg},i}(t)$$

A majority of investors will prefer stocks with a negative carbon beta over stocks with a positive carbon beta. However, an investment portfolio with a negative carbon beta is exposed to the risk that brown firms will outperform green firms. In this case, reducing the portfolio's carbon risk means having a carbon beta as close as possible to zero. This is why we introduce the concept of absolute carbon risk, which is equal to the absolute value of the carbon beta:

$$\mathcal{ACR}_i(t) = \left|\beta_{\text{bmg},i}(t)\right|$$

Exhibit 4 presents the sector analysis of the absolute carbon risk at the end of December 2018. From this point of view, utilities is the sector least exposed to absolute carbon risk, whereas the energy and materials sectors are the most exposed.

$\mathcal{ACR}_i(t)$ is also a pricing magnitude measure of the carbon risk. Let us consider an investment universe with two stocks. We assume that $\beta_{\text{bmg},1}(1) = 0.5$ and $\beta_{\text{bmg},2}(1) = -0.5$. On average, the relative carbon risk is equal to zero, whereas the absolute carbon risk is equal to 0.5. One year later, we obtain $\beta_{\text{bmg},1}(2) = 1$ and $\beta_{\text{bmg},2}(2) = -1$. In this case, the relative carbon risk of the investment universe has not changed and is always equal to zero. However, its absolute carbon risk has increased and is now equal to 1. It is obvious that the carbon risk is priced in more in the second period than in the first period.

We have reported the absolute carbon risk by region in Exhibit 5. We notice that the carbon risk was priced in more in 2011 and 2012 because of the pricing magnitude in the Eurozone. In this region, the absolute carbon risk has dramatically decreased from 50% in 2011 to 27% in 2018. More globally, we observe a convergence between the different developed regions. One exception is Japan, where the absolute carbon risk is 50% lower than in Europe and North America.

Comparison between Market and Fundamental Measures of Carbon Risk

ESG rating agencies have developed many fundamental measures and scores to assess a firm's carbon risk. For instance, the most well known is the carbon intensity $\mathcal{CI}_i(t)$, which involves scopes 1, 2, and 3. In this article, a firm's carbon risk corresponds to the carbon beta priced in by the financial market. It is not obvious that there is a strong relationship between fundamental and market measures because we may observe wide discrepancies between the market perception of the carbon risk and the carbon intensity of the firm. For instance, the linear correlation between $\mathcal{CI}_i(t)$ and $\beta_{\text{bmg},i}(t)$ is equal to 17.4% at the end of December 2018. If we consider the BMG

EXHIBIT 4

Box Plots of the Absolute Carbon Risk at the End of 2018

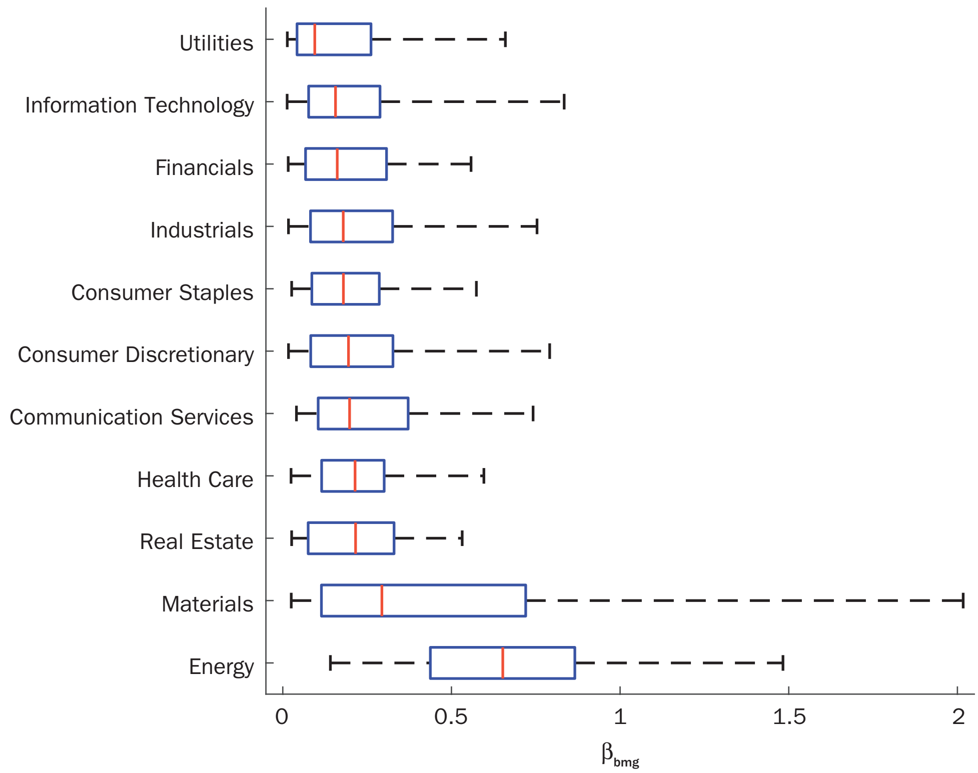


EXHIBIT 5

Absolute Carbon Risk by Region (end of year)

Year	WD	NA	EMU	EU	JP
2010	0.35	0.32	0.50	0.35	0.30
2011	0.34	0.32	0.51	0.32	0.31
2012	0.28	0.24	0.40	0.24	0.27
2013	0.28	0.26	0.31	0.24	0.30
2014	0.27	0.26	0.30	0.24	0.26
2015	0.27	0.29	0.27	0.27	0.20
2016	0.29	0.31	0.30	0.30	0.20
2017	0.27	0.29	0.30	0.28	0.20
2018	0.28	0.29	0.27	0.29	0.20

factor built directly with carbon intensity (Exhibit 1), the correlation increases but remains relatively low—21.4% at the end of December 2018. The relationship between $\mathcal{CI}_i(t)$ and $\beta_{bmg,i}(t)$ is then more complex, as seen in Exhibit 6.

This result is easily understandable because the stock market incorporates dimensions other than carbon intensity to price in the carbon risk. From a fundamental point of view, if the carbon intensity of two firms is equal to 100, they present the same carbon risk. Nevertheless, we know that their risks depend on other factors and parameters. For instance, it is difficult to compare two firms with the same carbon intensity if they belong to two different sectors or countries. The trajectory of carbon intensity is another important factor. For instance, the risk is not the same if one firm has dramatically decreased its carbon intensity in recent years. Moreover, the adaptability issue, the capacity of a firm to transform its business with investments in green R&D, and its financial resources to absorb transition costs (Bouchet and Le Guenedal 2020) are other important parameters that affect the market perception of the firm's carbon risk. Therefore, carbon intensity is less appropriate to describe financial risks than carbon beta. In other words, the carbon beta is an integrated measure of the different fundamental factors affecting a firm's carbon risk.

In Exhibit 7, we report the correlation between $\mathcal{CI}_i(t)$ and $\beta_{bmg,i}(t)$ at the end of December 2018. We note that it is higher in the Eurozone than in other regions.

EXHIBIT 6

Scatter Plot of $\mathcal{CI}_i(t)$ and $\beta_{bmg,i}(t)$ at the End of 2018

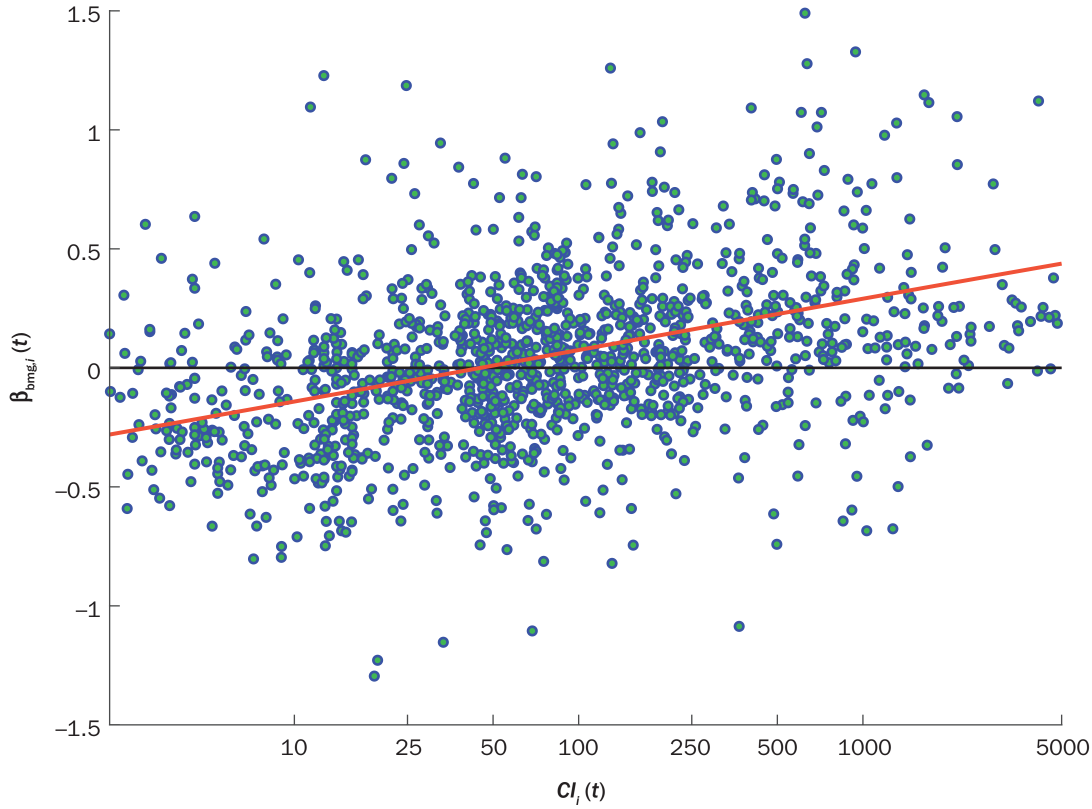


EXHIBIT 7

Correlation (in percent) between $\mathcal{CI}_i(t)$ and $\beta_{bmg,i}(t)$ at the End of 2018

Sector	WD	NA	EMU	EU	JP
Financials	18.2	20.1	29.2	20.9	–1.5
Energy	18.2	17.8	31.8	24.5	3.8
Materials	20.3	24.8	37.2	28.0	5.4
Information Technology	20.4	21.0	34.2	26.1	3.2
Health Care	20.9	21.3	34.5	26.3	4.2
Consumer Staples	21.5	22.3	35.1	26.4	4.3
Communication Services	21.6	22.2	32.2	24.7	6.6
Consumer Discretionary	22.3	23.1	37.8	25.8	2.6
Real Estate	22.4	22.5	34.3	26.1	6.1
Industrials	23.6	23.8	38.7	31.6	8.1
Utilities	26.6	29.8	26.5	26.1	8.4
All Sectors	21.4	22.3	33.8	26.2	4.6

In particular, the correlation in Japan is very low (less than 5%). Moreover, we observe that it differs with respect to the sector. For instance, the financial sector presents the lowest correlation value, certainly because the carbon risk of financial institutions is less connected to their greenhouse gas emissions than their (green and brown) investments and financing programs.

INCORPORATING CARBON RISK INTO MV PORTFOLIOS

There is an increasing interest among fund managers of MV portfolios to take into account carbon risk for two main reasons: First, it is a financial and regulation risk that may negatively affect stock returns; and second, it is highly sought after by institutional investors. In what follows, we show how to incorporate carbon risk into these strategies. In particular, we provide an analytical formula that is useful in understanding the impact of carbon betas on the MV portfolio and the covariance matrix of stock returns. We also discuss the different practical implementations of MV portfolios when we consider market and fundamental measures of carbon risk.

Analytical Results

In this paragraph, we extend the famous formula of the MV portfolio when we complement the market risk factor with the BMG factor. We then illustrate how the MV portfolio selects stocks in the presence of carbon risk.

Extension of the one-factor global minimum variance formula. We consider the global minimum variance (GMV) portfolio, which corresponds to the following optimization program:

$$\begin{aligned} x^* = & \arg\min \frac{1}{2} x^\top \Sigma x \\ & \text{s.t.} \quad \mathbf{1}_n^\top x = 1 \end{aligned} \tag{5}$$

where x is the vector of portfolio weights, and Σ is the covariance matrix of stock returns. In the capital asset pricing model, we recall that

$$R_i(t) = \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \varepsilon_i(t) \tag{6}$$

where $R_i(t)$ is the return of asset i, $R_{\mathrm{mkt}}(t)$ is the return of the market factor, $\varepsilon_i(t) \sim \mathcal{N}(0, \tilde{\sigma}_i^2)$ is the idiosyncratic risk, and $\tilde{\sigma}_i$ is the idiosyncratic volatility. Clarke, de Silva, and Thorley (2011) and Scherer (2011) showed that

$$x_i^* = \frac{\sigma^2(x^*)}{\tilde{\sigma}_i^2}\left(1 - \frac{\beta_{\mathrm{mkt},i}}{\beta^*_{\mathrm{mkt\%}}}\right) \tag{7}$$

where β^*_{mkt} is a threshold and $\sigma^2(x^*)$ is the variance of the GMV portfolio. Therefore, we note that the MV portfolio is exposed to stocks with low specific volatility $\tilde{\sigma}_i$ and low beta $\beta_{\mathrm{mkt},i}$. More precisely, if asset i has a market beta $\beta_{\mathrm{mkt},i}$ smaller than the threshold β^*_{mkt}, the weight of this asset is positive: $x_i^* > 0$. If $\beta_{\mathrm{mkt},i} > \beta^*_{\mathrm{mkt}}$, then $x_i^* < 0$.

Clarke, de Silva, and Thorley (2011) extended Equation 7 to the long-only case, where β^*_{mkt} is another threshold. In this case, if $\beta_{\mathrm{mkt},i} < \beta^*_{\mathrm{mkt}}$, $x_i^* > 0$ and if $\beta_{\mathrm{mkt},i} \geq \beta^*_{\mathrm{mkt}}$, $x_i^* = 0$.

We consider an extension of the capital asset pricing model by including the BMG risk factor:

$$R_i(t) = \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{bmg},i} R_{\mathrm{bmg}}(t) + \varepsilon_i(t) \tag{8}$$

where $R_{\mathrm{bmg}}(t)$ is the return of the BMG factor, and $\beta_{\mathrm{bmg},i}$ is the BMG sensitivity (or the carbon beta) of stock i. Moreover, we assume that $R_{\mathrm{mkt}}(t)$ and $R_{\mathrm{bmg}}(t)$ are uncorrelated.

Roncalli et al. (2020) showed that the GMV portfolio is defined as

$$x_i^* = \frac{\sigma^2(x^*)}{\tilde{\sigma}_i^2}\left(1 - \frac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^*} - \frac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^*}\right) \tag{9}$$

where β_{mkt}^* and β_{bmg}^* are two threshold values. In the case of long-only portfolios, we obtain a similar formula:

$$x_i^* = \frac{\sigma^2(x^*)}{\tilde{\sigma}_i^2}\max\left(1 - \frac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^*} - \frac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^*}; 0\right) \tag{10}$$

but with other values of the thresholds β_{mkt}^* and β_{bmg}^*.

Interpretation of these results. Contrary to the single-factor model, the impact of sensitivities is more complex in the two-factor model. Indeed, we know that $\bar{\beta}_{\mathrm{mkt}} \approx 1$ and $\bar{\beta}_{\mathrm{bmg}} \approx 0$. It follows that β_{mkt}^* is positive, but β_{bmg}^* may be positive or negative.[5] We deduce that the ratio $\frac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^*}$ is an increasing function of $\beta_{\mathrm{mkt},i}$, but the ratio $\frac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^*}$ may be an increasing or a decreasing function of $\beta_{\mathrm{bmg},i}$. The GMV portfolio will then always prefer stocks with low market betas, but not necessarily stocks with low carbon betas. For instance, it may prefer stocks with high carbon betas if β_{bmg}^* is negative.

In the long-only case, a stock is selected if it satisfies the following inequality:

$$\frac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^*} + \frac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^*} \leq 1$$

Therefore, we notice that there is a trade-off between $\beta_{\mathrm{mkt},i}$ and $\beta_{\mathrm{bmg},i}$. Nevertheless, Roncalli et al. (2020) showed that the long-only MV portfolio tends to prefer stocks with low absolute carbon risk.

We recall that the volatility of stock i is equal to $\sigma_i^2 = \beta_{\mathrm{mkt},i}^2\sigma_{\mathrm{mkt}}^2 + \beta_{\mathrm{bmg},i}^2\sigma_{\mathrm{bmg}}^2 + \tilde{\sigma}_i^2$ whereas the covariance between stocks i and j is equal to $\sigma_{i,j}^2 = \beta_{\mathrm{mkt},i}\beta_{\mathrm{mkt},j}\sigma_{\mathrm{mkt}}^2 + \beta_{\mathrm{bmg},i}\beta_{\mathrm{bmg},j}\sigma_{\mathrm{bmg}}^2$. Therefore, choosing stocks with low volatilities implies considering stocks with low values of $\beta_{\mathrm{bmg},i}^2$. In a similar way, removing stocks with high positive correlations implies removing stocks with high values of $\beta_{\mathrm{bmg},i}\beta_{\mathrm{bmg}\,j}$. This explains why the MV portfolio will prefer stocks with low values of $\beta_{\mathrm{bmg},i}$.

Practical Implementations

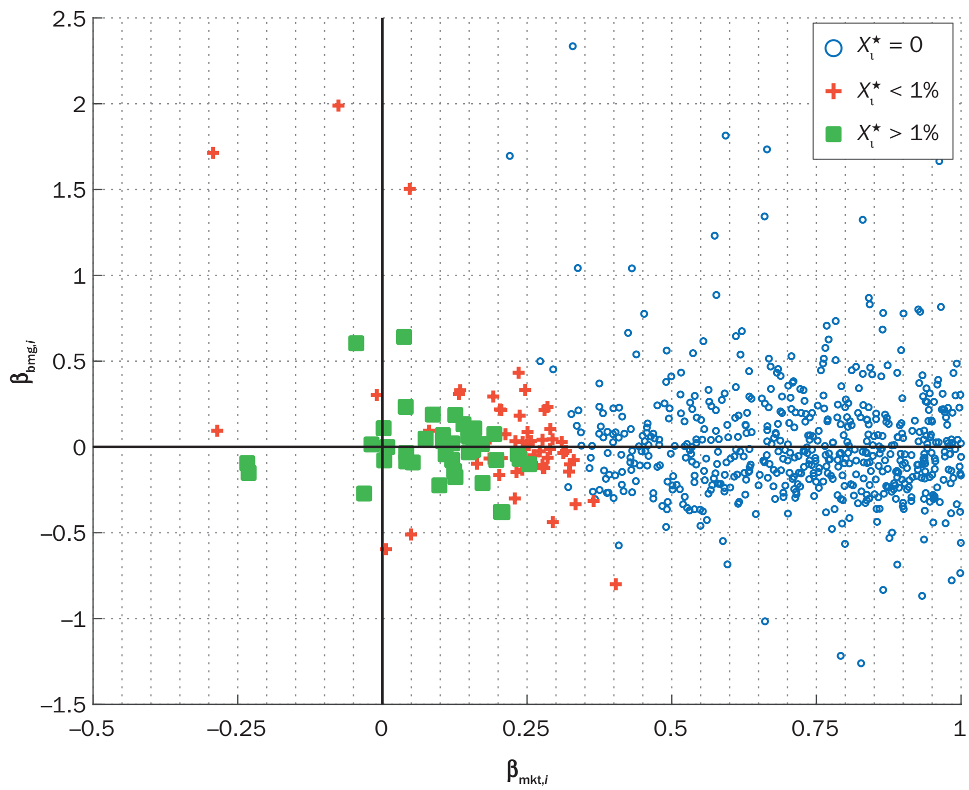
We now apply the previous framework to the MSCI World index at December 2018 and illustrate the difference between absolute and relative carbon risk when we consider the MV portfolio. Moreover, we compare these market-based approaches with implementations of MV portfolios that use fundamental carbon risk metrics.

Impact of carbon risk. In Exhibit 8, we indicate the stocks that make up the MV portfolio with respect to their beta values $\beta_{\mathrm{mkt},i}$ and $\beta_{\mathrm{bmg},i}$. We find that the most important axis is the market beta. Indeed, the market risk of a stock determines whether the stock is included in the MV portfolio, whereas the carbon risk adjusts the weights of the asset. As we can see, the portfolio overweights assets whose market and carbon sensitivities are both close to zero. This solution is satisfactory if the original motivation is to reduce the portfolio's absolute carbon risk, but it is not satisfactory if the objective is to manage the portfolio's relative carbon risk.

[5] Moreover, it generally takes a high absolute value.

EXHIBIT 8

Weights of the Long-Only MV Portfolio



Considering relative carbon risk. To circumvent the previous drawback, we can directly add a constraint in the optimization program:

$$\beta_{bmg}(x) = \sum_{i=1}^{n} x_i \times \beta_{bmg,i} \le \beta_{bmg}^{+} \tag{11}$$

where $\beta_{bmg}(x)$ is the carbon beta of portfolio x, and β_{bmg}^{+} is the maximum tolerance of the investor with respect to the relative carbon risk. We consider the previous example. If we would like to impose a carbon sensitivity of lower than –0.25, we obtain the results given in Exhibit 9. A comparison with Exhibit 8 shows that the MV portfolio tends to select stocks with both a low market sensitivity and a negative carbon beta. Moreover, large weights are associated with large negative values of $\beta_{bmg,i}$ on average.

Managing both market and fundamental risk measures. The previous method is not the standard approach when managing carbon risk in investment portfolios. Indeed, the asset management industry generally considers constraints on carbon intensity measures. Following Andersson, Bolton, and Samama (2016), we can impose individual constraints on the different stocks:

$$x_i = 0 \quad \text{if} \quad \mathcal{CI}_i \le \mathcal{CI}^{+} \tag{12}$$

or we can use a global constraint:

$$\mathcal{WACI}(x) = \sum_{i=1}^{n} x_i \times \mathcal{CI}_i \le \mathcal{WACI}^{+} \tag{13}$$

EXHIBIT 9

Weights of the Constrained MV Portfolio ($\beta^+_{bmg} = -0.25$)

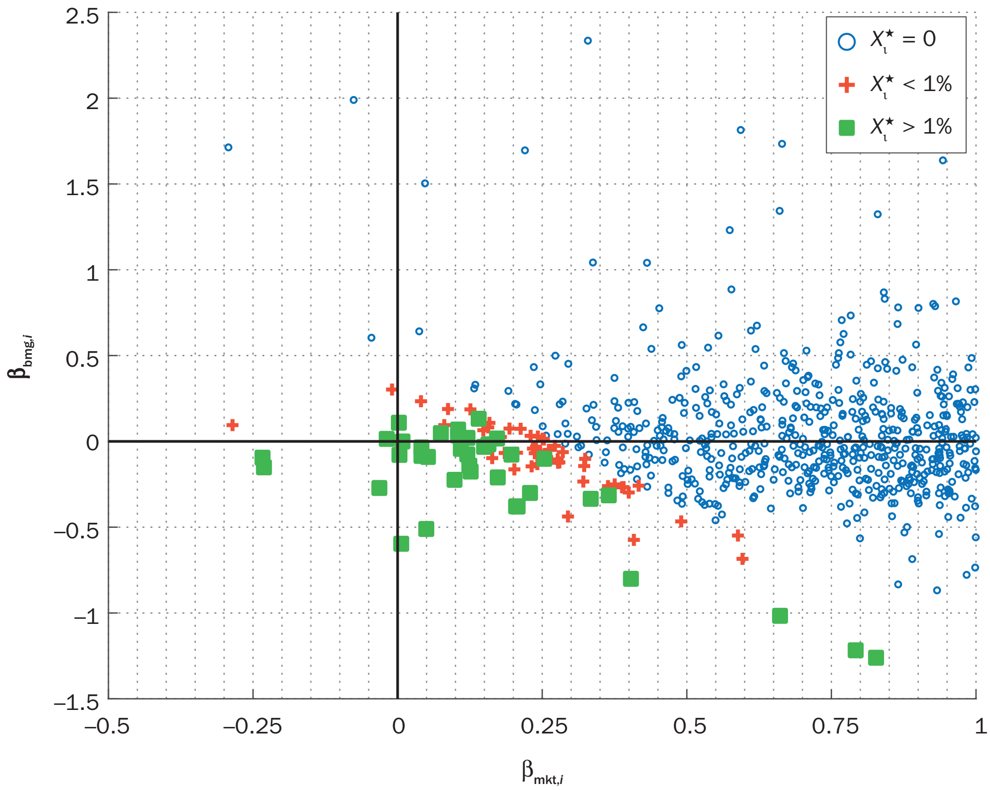


EXHIBIT 10

MV Portfolios with a Relative Carbon Beta Constraint

β^+_{bmg}	$\beta_{bmg}(\mathbf{x})$	$\mathcal{WACI}(\mathbf{x})$	$\mathcal{N}(\mathbf{x})$
	1.43%	538	105
–10.00%	–10.00%	501	100
–20.00%	–20.00%	422	89
–40.00%	–40.00%	289	70

where $\mathcal{CI}_i$ is the carbon intensity of stock i, and $\mathcal{WACI}(x)$ is the weighted average carbon intensity of portfolio x. $\mathcal{CI}^+$ and $\mathcal{WACI}^+$ are the individual and portfolio thresholds that are accepted by investors.

We may wonder whether managing the fundamental measure of carbon risk is equivalent to managing the market measure of carbon risk.[6] A preliminary answer has been provided previously because we have found that the correlation between $\beta_{bmg,i}$ and $\mathcal{CI}_i$ is less than 30% on average. In Exhibit 10, we compute the MV portfolio by considering several threshold values of β^+_{bmg}. We notice that using a lower value of β^+_{bmg} reduces the value of $\mathcal{WACI}(x)$, but $\mathcal{WACI}(x)$ remains very high because some issuers have low common carbon risk but high idiosyncratic carbon risk. We have also reported the number of stocks $\mathcal{N}(x)$ in the MV portfolio. As expected, it decreases when we impose a stronger constraint.

Exhibit 11 is a variant of Exhibit 10 considering a constraint $\mathcal{WACI}^+$ on the portfolio's carbon intensity instead of a constraint β^+_{bmg} on the portfolio's carbon beta. Here, the impact on the portfolio's carbon beta is low when we strengthen the constraint. Indeed, the portfolio's carbon beta $\beta_{bmg}(x)$ is equal to 1.43% when we target a carbon intensity of 500, whereas it drops to 1.33% when the constraint on the carbon intensity is set to 50.

[6] In what follows, we also impose that $\mathcal{CI}^+ = 4{,}000$.

EXHIBIT 11

MV Portfolios with a Carbon Intensity Constraint

$\mathcal{WACI}^+$	$\mathcal{WACI}(x)$	$\beta_{bmg}(x)$	$\mathcal{N}(x)$
500	500	1.43%	105
250	250	1.37%	103
100	100	1.36%	98
50	50	1.33%	82

EXHIBIT 12

MV Portfolios with Carbon Beta and Intensity Constraints

$\mathcal{WACI}^+$	$\mathcal{WACI}(x)$	$\beta_{bmg}(x)$	$\mathcal{N}(x)$	$\mathcal{WO}(x)$
500	430	–20.00%	111	74.65%
250	250	–20.00%	86	75.26%
100	100	–20.00%	79	74.87%
50	50	–20.00%	74	74.99%

These results show that the two optimization problems give two different solutions in terms of carbon risk. Therefore, it makes sense to combine the approaches by imposing two constraints:

$$\begin{cases} \mathcal{WACI}(x) \leq \mathcal{WACI}^+ \\ \beta_{bmg}(x) \leq \beta_{bmg}^+ \end{cases} \tag{14}$$

Moreover, the threshold β_{bmg}^+ allows us to reduce the common carbon risk, but not the idiosyncratic carbon risk. The WACI constraint circumvents this problem. Exhibit 12 presents the results for several values of $\mathcal{WACI}^+$ when β_{bmg}^+ is –20%. For instance, we notice that the WACI constraint is not reached when $\mathcal{WACI}^+ = 500$ and $\beta_{bmg}^+ = -20\%$. The last column of Exhibit 12 corresponds to the portfolio's weight overlap with respect to the optimized portfolio based on the WACI constraint, meaning that we compare the portfolio optimized with the BMG and WACI constraints to the portfolio optimized with the WACI constraint. In this example, we notice that the weight overlap $\mathcal{WO}(x)$ is 75% on average. This means that 25% of the MV portfolio allocation is changed when we add the market carbon constraint $\beta_{bmg}^+ = -20\%$.

CONCLUSION

This article considers the seminal approach of Görgen et al. (2019) to measuring carbon risk. Although many asset managers and owners use carbon intensity, we focus on the carbon beta, which is priced in by the market. The carbon beta is estimated using a two-step approach. First, we build a BMG risk factor. Second, we perform Kalman filtering to obtain the time-varying carbon beta. By considering this dynamic framework, we highlight several stylized facts. We show that this market measure is very different from a traditional fundamental measure of carbon risk, mainly because carbon intensity is not the only dimension that is priced in by the market.

Another important result is the difference between relative and absolute carbon risk. Investors who are sensitive to relative carbon risk prefer stocks with a negative carbon beta over stocks with a positive carbon beta, whereas investors who are sensitive to absolute carbon risk prefer stocks with a carbon beta close to zero. Managing relative carbon risk implies having a negative exposure to the carbon risk factor, whereas managing absolute carbon risk implies having zero exposure to the carbon risk factor. The first case is an active management bet because performance may be negative if brown stocks outperform green stocks. Nevertheless, this approach reduces exposure to firms that face a threat of environmental regulation (Maxwell, Lyon, and Hackett 2000). The second case is an immunization investment strategy against carbon risk. However, this hedging strategy is not widely implemented by institutional and passive investors because of their moral values and convictions; they generally prefer to implement relative carbon risk strategies.

Introducing carbon risk into a MV portfolio is a hot topic among asset managers and owners. Indeed, the goal of an MV portfolio is to build a low-volatility strategy on the equity market. This is achieved by considering a strong risk management approach on several dimensions. Originally, the strategy only focused on the portfolio's volatility. Since the 2008 global financial crisis, it has included other risk dimensions that can burst the equity market, such as credit risk and valuation risk. Climate risk has become another important dimension, especially because MV strategies are massively implemented by ESG institutional investors. In this context, the question of carbon metrics is important. In this article, we show that managing the carbon intensity of MV portfolios has little impact on their carbon beta. The opposite is not true, but the effect of managing the carbon beta on carbon intensity is limited. This is why we propose combining the market and fundamental approaches to carbon risk. Another issue concerns the choice of the market carbon risk measure. We show that the optimization program of an MV portfolio naturally considers absolute carbon risk. However, relative carbon risk can also be an option if the investor's goal is not to hedge the carbon risk but to be a green investor.

ACKNOWLEDGMENTS

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Top-Down Portfolio Implications of Climate Change

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KEY FINDINGS

- The authors assess the top-down cross-asset impact of climate change for strategic asset allocation in both optimistic and pessimistic scenarios.
- The top-down analysis suggests that growth-oriented assets, such as equities, would be directly affected by climate change. Their return would decline in the pessimistic scenario, with significant differences across countries.
- Using these strategic return expectations, a top-down climate risk–aware portfolio would tilt away from regions and assets that are expected to be adversely affected, particularly certain emerging markets, for better risk-adjusted returns.

ABSTRACT

This article reviews the significant progress in academic research on economic impact of climate change and explores the implications for expected returns and strategic portfolio allocation across major public asset classes. There have been numerous efforts to measure the environmental impact within a broader environment, social, and governance framework with a focus on microeconomic and firm-level implications. In this article, the authors assess the impact of climate change on long-term expected returns across asset classes from a top-down macroeconomic perspective. They use well-accepted climate risk scenarios to assess the potential impact of alternative climate scenarios on economic growth, inflation, and asset returns for major asset classes. Finally, they design hypothetical portfolios given these top-down assumptions and explore portfolio allocation implications.

TOPICS

*ESG investing, legal/regulatory/public policy, tail risks, portfolio construction**

*All articles are now categorized by topics and subtopics. **View at PM-Research.com**.

Climate change is no longer a hypothetical risk: Our planet is warming at an accelerating pace. Rising levels of greenhouse gases in the atmosphere contribute to increased temperatures across the globe. Absent meaningful political, economic, or technological changes, the warming trend will continue. Moreover, as temperatures climb, feedback effects may cause acceleration at an even more rapid pace.

The impacts of climate change are likely to affect many aspects of human life, including the global economy. Environmental changes throughout the remainder of this century, as well as political responses to these changes, will undoubtedly influence economic trends worldwide. From the perspective of a long-term investor, climate change is a source of considerable uncertainty.

The transition to a sustainable economy in possible climate change scenarios poses both significant risks and opportunities for investors' portfolios. The path of climate change remains unclear: It is dependent on regulatory, governmental, and societal actions, and so it is hard to predict when and how climate externalities will be fully reflected in economic outcomes and market prices.

Our goal is to quantitatively assess the impact of climate change on expected returns and strategic portfolio allocation across major public assets. Our article first reviews the significant progress in academic and policy research on this topic. To date, there have been efforts to measure the environmental impact to firms within a broader environment, social, and governance (ESG) framework. Various sources may help investors assess their exposure to environmental or climate risk, with a focus on microeconomic and firm-level implications.[1] We suggest that this bottom-up focus can be complemented by evaluating the top-down and cross-asset implications of climate change to provide a fuller picture of the impacts of climate change for long-term investors. Our article assesses the impact of climate change on long-term expected returns across asset classes from a top-down macroeconomic perspective. We use those estimates in well-accepted risk scenarios to assess the potential impact of alternative climate scenarios on economic growth, inflation, and asset returns for major asset classes. Finally, we design hypothetical portfolios given our top-down assumptions.

THE ECONOMIC IMPACTS OF CLIMATE CHANGE

Economic risks from climate change can be bifurcated into two categories: physical risks and transition risks (Grippa, Schmittmann, and Suntheim 2019). Physical risks include the actual economic costs of extreme weather events, or the net impact of gradual changes to the climate, and can involve business disruption, asset destruction, or reduction in productivity.

Transition risks reflect the financial impact of changes to regulation and policies from transitioning to a more sustainable economy. These can involve changes to technology or consumer preferences, or additional costs of production due to policy changes (Exhibit 1). For example, a rapid and ambitious transition to lower emissions standards would result in a sizable amount of unextracted fossil fuel reserves (McGlade and Elkins 2015). Such stranded assets have potentially systemic consequences for the financial system and investors alike.

Evolution of Climate Scenarios

To assess the future economic impacts of climate change, we start with plausible climate change scenarios. Representative concentration pathways (RCPs) and shared socioeconomic pathways (SSPs) are two frameworks used to describe these scenarios. Researchers combine RCP and SSP scenarios to project their findings onto future economic outcomes.

RCPs are standardized emissions scenarios created by the Intergovernmental Panel on Climate Change (IPCC) to exogenously prescribe the future flow of emissions. They are labeled according to the overall amount of heating, known as *radiative forcing*, measured in watts per square meter that will be generated by the year 2100. In this article, we use data from the IPCC's book-end scenarios, RCP 2.6 (optimistic) and

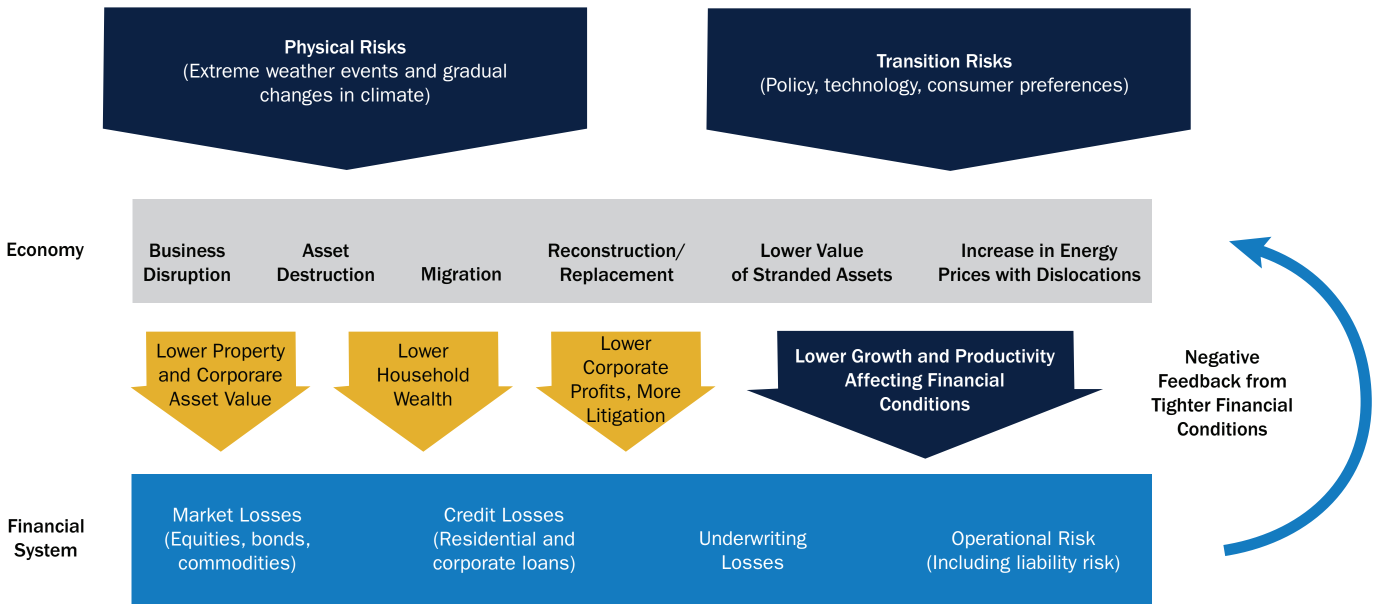
[1] Examples include MSCI, Sustainalytics, and so on.

EXHIBIT 1

Climate Change Will Result in Physical and Transitional Economic Costs (IMF)

Physical and Transition Risks

The Risks from Climate Change to the Economy have Two Basic Channels, but Many Potential Impacts



NOTE: Accessed March 9, 2021.

SOURCE: Grippa, Schmittmann, and Suntheim (2019).

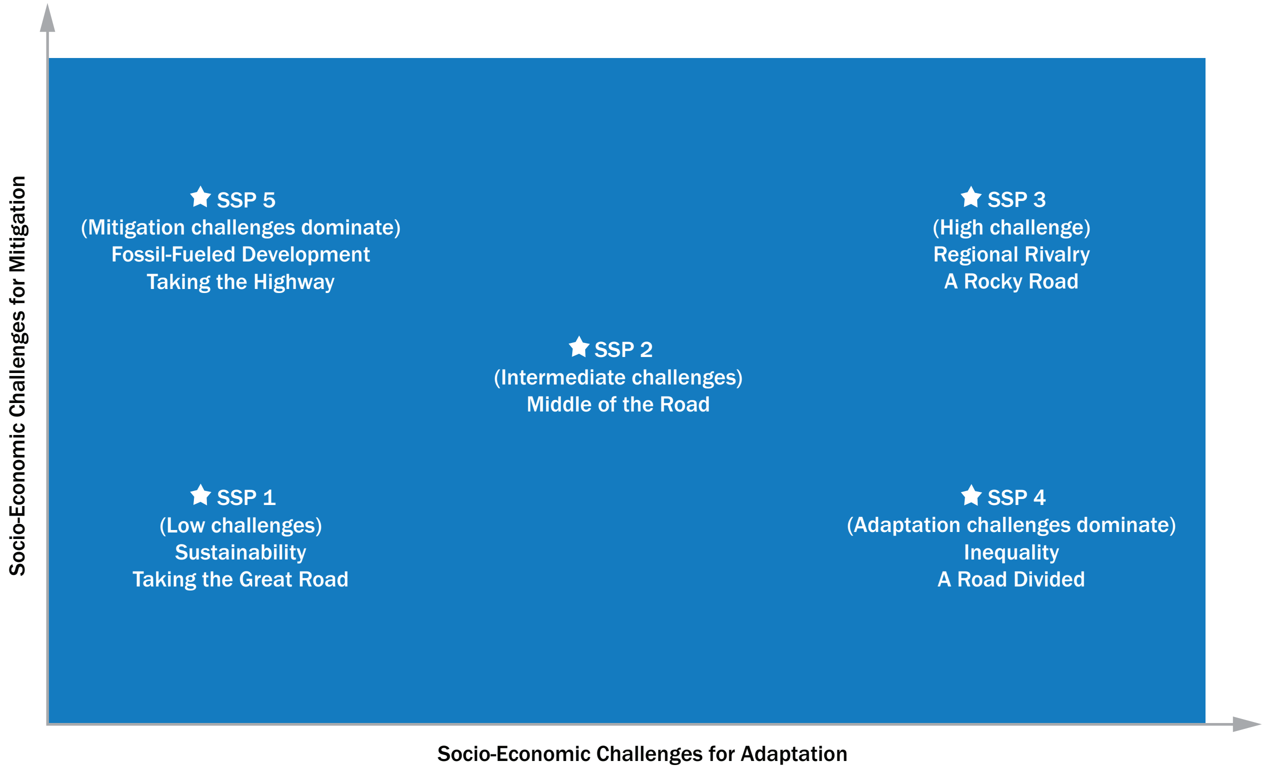
RCP 8.5 (pessimistic). The optimistic scenario presumes the lowest level of warming, with CO_2 emissions declining immediately to less than one-third of the current levels by 2050 and becoming net-negative during the 2080s. It assumes that signatory countries adhere to the Paris Agreement and that those goals are achieved. The pessimistic scenario presumes the largest level of warming, with CO_2 emissions nearly doubling from their current levels by 2050 and continuing to rise thereafter. This scenario assumes that no mitigating policy or societal changes take place.

Scientists developed a second set of assumptions to describe the evolution of future economic paths: SSPs incorporate ways in which society as a whole—not just individual economies—may choose to respond to the future temperature increases described in RCP scenarios. The SSPs are based on five narratives, as depicted in Exhibit 2:

- sustainable development with low challenges to mitigation and adaptation (SSP 1)
- middle-of-the-road development with medium challenges to mitigation and adaptation (SSP 2)
- regional rivalry with high challenges to mitigation and adaptation (SSP 3)
- inequality with low challenges to mitigation and high challenges to adaptation (SSP 4)
- fossil-fueled development with high challenges to mitigation and low challenges to adaptation (SSP 5).

EXHIBIT 2

SSPs on the Mitigation and Adaptation Spectrum



NOTE: For illustrative purposes only.

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Macroeconomic Impacts of Climate Change

Academics and policymakers take two main approaches to estimating the relationship between climate and economic variables. Both structural models and reduced-form models use historical data under various climate path scenarios to project potential future economic costs. Given the long-term nature of the costs from climate change, there is necessarily a considerable amount of uncertainty in these estimates.

Structural models include integrated assessment models (IAMs), which combine standard structural economic mode with simple climate models. IAMs can be used to derive estimates of the impact of emissions on climate variables, such as temperature, rainfall, and sea levels (Nordhaus 1992; Tol 1997; Stern 2006). Climate outcomes are related to a set of functions that calculate economic damages at a regional and global level. The appeal of IAMs is that they can incorporate separate channels for physical risks and transition risks and can provide answers to questions about climate change costs and adjustment mechanisms. However, many criticize the assumptions made by a tractable general equilibrium model regarding a complex issue, which weakens the authority of the answers provided by IAMs.[2]

[2] Criticisms include the following: assumptions about the damage functions (impacts of climate change on the economy) and discount rates (e.g., how to adjust for climate-related risk) (Ackerman et al. 2009; Pindyck 2013; Stern 2016); the absence of an endogenous evolution of the structures of production (Acemoğlu et al. 2012; Pottier, Hourcade, and Espagne 2014; Acemoğlu, Ozdaglar, and Tahbaz-Salehi 2015); unrealistic assumptions about well-functioning capital markets and rational expectations (Keen 2019); the emphasis on relatively smooth transitions to a low-carbon economy; and the quick return to a steady state following a climate shock (Campiglio et al. 2018).

By contrast, more modern reduced-form empirical analyses use real-world data and careful econometric measurement. As opposed to IAMs, which seek to answer all questions comprehensively, these studies tend to be limited in scope, focusing on topics such as growth or inflation individually (Burke, Hsiang, and Miguel 2015; Kahn et al. 2019). Reduced-form panel models seek to learn from historical experiences. They do not identify explicitly physical or transition costs; rather, they project a future economic transition path similar to the last 50 years and then extrapolate climate change from weather variations using a distributed lag approach. Overall, reduced-form panel estimates provide results up to an order of magnitude greater than the typical damage functions included in IAMs (Ricke et al. 2018).[3]

It is important to note that certain events, such as rising sea levels or ocean acidification, have no recent historical precedent from which to draw inference. These unprecedented events will almost certainly have significant, negative net economic consequences, which suggests that even the latest studies may still be underestimating the economic impact of global warming.

Panel studies also focus exclusively on measured market gross domestic product (GDP); as such, they do not incorporate several nonmarket climate change effects, such as the loss of biodiversity. Nor can the reduced-form panel approach separately identify the costs of adaptation. The need to invest in noncarbon infrastructure may boost GDP in the short run—especially in rich, advanced economies—without necessarily adding to the productive capital stock, resulting in weaker long-term productivity growth and a potentially lower level of output in the future.

In this article, we rely on estimates of the economic impact of climate change provided by Kahn et al. (2019) for our optimistic scenario and by Burke, Hsiang, and Miguel (2015) for our pessimistic climate scenario. Kahn et al. studied the long-term impact of climate change on economic activity across 174 countries from 1960 to 2014. They found that per capita real output growth is adversely affected by persistent changes in temperature above or below its historical norm but that this effect is relatively muted in both RCP 2.6 (optimistic) and RCP 8.5 (pessimistic) scenarios.

In the pessimistic scenario, we use alternate estimates from Burke, Hsiang, and Miguel, whose modeling approach considered increased material economic costs from climate change in RCP 8.5/SSP 5 scenarios, as illustrated in Exhibit 3.[4] Their estimates determined an historical sweet spot for productivity growth based on temperature levels; they then assessed the impact of various climate change scenarios on such growth.

Both sets of researchers primarily measured the economic cost of physical risks and did not explicitly model transition costs. These estimation procedures may, however, capture some transition costs, to the extent that climate change mitigation policies adopted in their historical sample periods have already affected growth. In addition, these scenarios primarily examine the direct impact of temperature changes on economic activity. They do not attempt to model second- or higher-order effects, which would include climate change–induced geopolitical changes. This problem is outside of our range of focus.

Economic Impact of Climate Change on Population Growth

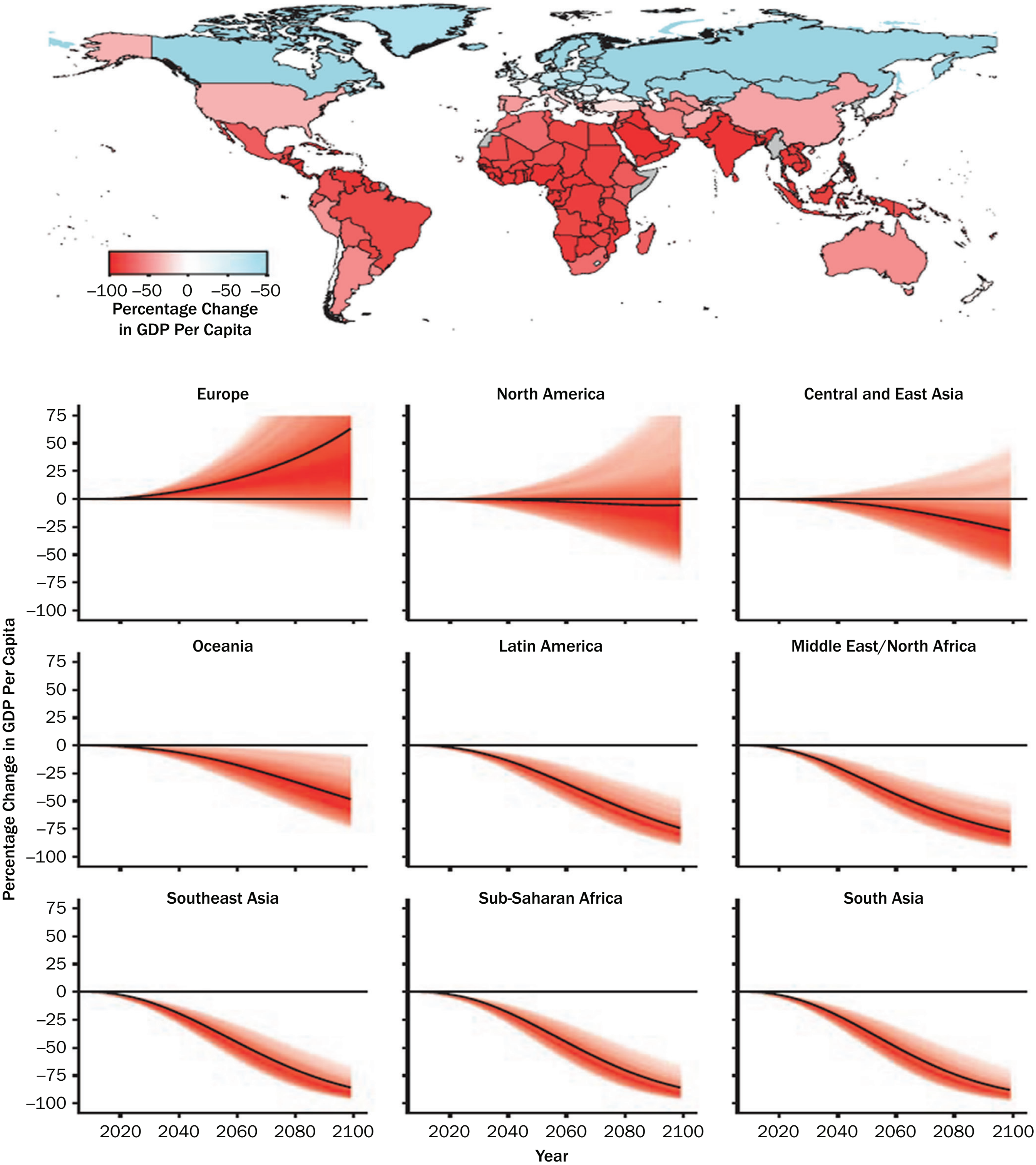
In addition to the impact on GDP per capita, climate change can affect aggregate GDP via a population growth channel. Carleton et al. (2020) analyzed data from 41

[3] Building on the estimates of Burke, Hsiang, and Miguel (2015), Ricke et al. (2018) estimated that the social cost of carbon may be as high as $430 per ton, well outside the estimates typically used for investment appraisal discussed by Auffhammer (2018).

[4] Burke, Hsiang, and Miguel (2015) only provided estimates for the pessimistic scenario.

EXHIBIT 3

Projected Effect of Temperature Changes on Regional Economies



NOTES: Burke, Hsiang, and Miguel (2015) showed that overall economic productivity is nonlinear in temperature for all countries, with productivity peaking at an annual average temperature of 13°C and declining strongly at higher temperatures. The relationship is globally generalizable, unchanged since 1960, and apparent for agricultural and nonagricultural activity in both rich and poor countries. (They share the full data and replication code at http://web.stanford.edu/~mburke/climate/data.html.)

SOURCE: Burke, Hsiang, and Miguel (2015). Accessed March 9, 2021.

countries that cover 55% of the global population over 50 years. They uncovered a U-shaped relationship, in which extreme cold and hot temperatures increase mortality rates, especially for the elderly. This relationship is flattened by both higher incomes and adaptation to local climate (e.g., robust heating systems in cold climates and cooling systems in hot climates). They found that, under a pessimistic emissions scenario (i.e., RCP 8.5 and SSP 3), the total mortality burden of climate change is projected to be 85 death equivalents per 100,000 at the end of the century. This relative decrease in population is forecast to cost roughly 3.2% of the global GDP at the end of the century. These empirically grounded estimates of the costs of climate-induced mortality risks substantially exceed available estimates from leading structural models.

Impact of Climate Change on Central Bank Policy Rates and Inflation

Central banks and regulators are increasingly recognizing that climate change can be a source of major systemic financial risk. The Network for Greening the Financial System (the Network) was formed in 2017 by major central banks and supervisors, including the European Central Bank and US Federal Reserve, to coordinate work on climate and green finance issues. The Network's December 2020 survey (Network for Greening the Financial System 2020) found increasing and shared awareness of climate-related risks among central banks, even if concrete actions have been limited so far, given the complexity of the matter.

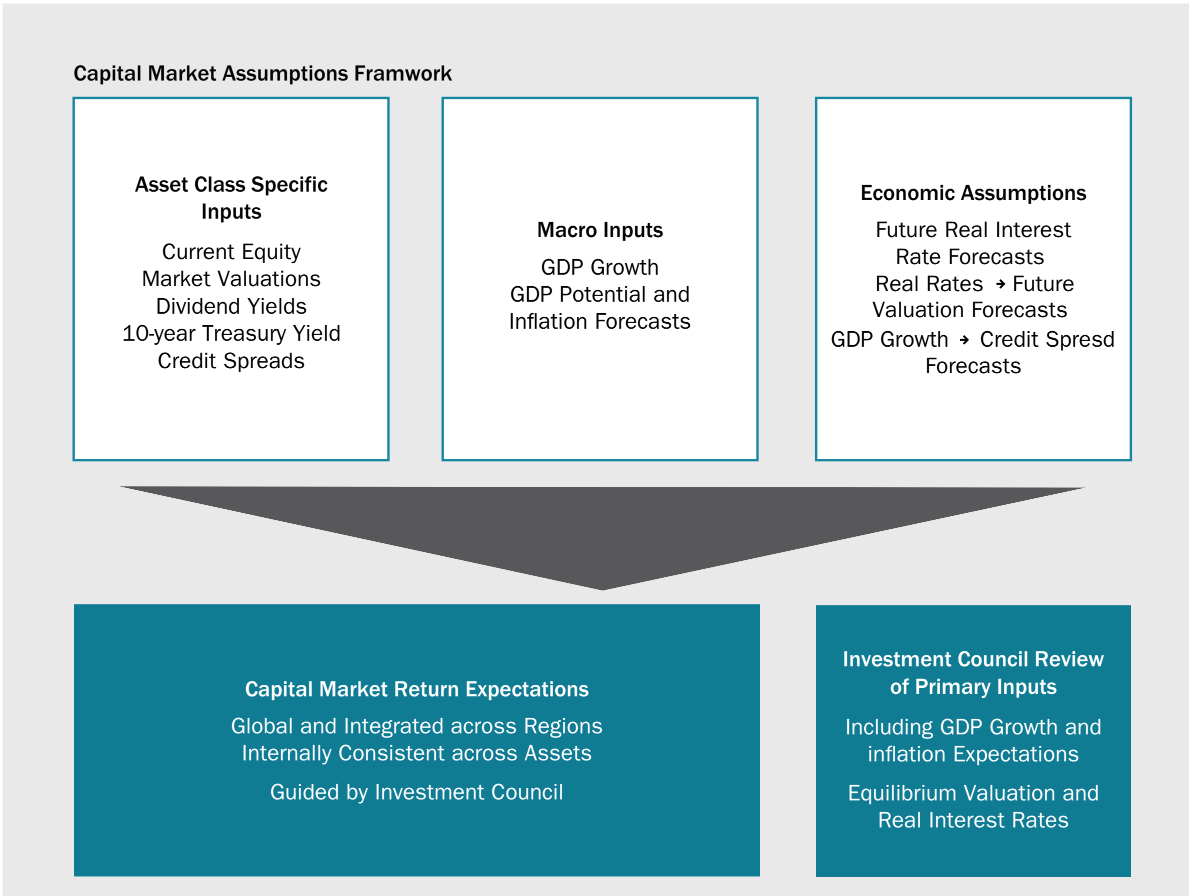
Climate change will likely create additional uncertainty around inflation and policy interest rates. Broadly speaking, issues that require modeling upgrades and that are of genuine interest for monetary policy include (1) the estimation of the impact of climate change on the natural interest rate, (2) the identification and propagation of climate-related physical shocks to price stability, and (3) the impact of transition policies on price stability.

Current research suggests that the impact of climate change on inflation is unclear. It may create supply and demand shocks that pull inflation and output in opposite directions, generating a trade-off for central banks between stabilizing inflation and stabilizing output fluctuations (Bolton et al. 2020). Climate-related events are also likely to affect monetary policy through supply-side and demand-side shocks, thereby affecting central banks' price stability mandate. Supply-side shocks can include pressures on the supply of energy and agricultural products that are particularly prone to sharp price adjustments and increased volatility (McKibbin et al. 2017). The frequency and severity of such events may well increase, affecting supply through more or less complex channels.

Relatively few studies have analyzed the impact of climate-related shocks on inflation, but some indicate that food prices tend to increase in the short term following natural disasters and extreme weather events. (Heinen et al. 2017; Parker 2018; Debelle 2019). Demand-side shocks could be related to mortality or growth impacts of climate change, particularly over the longer term. Shocks to long-term demand are not always easy for central banks to disentangle from the business cycle, which can make them more difficult to respond to.

In recent years, central banks have struggled with monetary policy adjustments when interest rates are low. Typically, central banks estimate the real rate of interest consistent with stable inflation when the economy is growing at full employment. The estimation of this natural interest rate (NIR) is one element that helps define the monetary policy stance (accommodative, neutral, or restrictive), given a country's position in the economic cycle. The effect of climate change on the NIR, via various drivers, is ambiguous (Bertram et al. 2020). If an economy with a low NIR is struck by more frequent, severe climate-induced natural disasters, this could imply that, all else being equal, the central bank is more likely to hit the effective lower bound on

EXHIBIT 4
CMA Framework



NOTE: For illustrative purposes only.

SOURCE: QMA.

policy interest rates. The central bank would thus have less scope to use conventional tools, such as cutting policy rates, to respond to economic shocks, potentially prolonging economic downturns.

INCORPORATING CLIMATE SCENARIOS IN LONG-TERM CAPITAL MARKET ASSUMPTIONS

Capital market assumptions (CMAs) underpin the long-run outlook for strategic allocations in multi-asset portfolios. We use the methodology of Aiolfi, Tokat-Acikel, and Johnson (2020) as our baseline framework for generating consistent 10-year return projections across the capital markets. Their process begins with asset class fundamentals and macroeconomic assumptions at the country level, decomposing local return expectations into three broad categories: income, growth, and valuation adjustments, as shown in Exhibit 4.

We can incorporate the impacts of climate change into these CMAs. Because they have a 10-year horizon, and the impacts of climate change are expected to be much longer, we supplement the Aiolfi, Tokat-Acikel, and Johnson (2020) methodology with steady-state, or equilibrium, estimates for asset class returns. We assume that the economy is chugging along at its long-term pace and all other asset prices have adjusted in these steady-state estimates. For instance, short-term real interest rates were driven negative in most developed countries because central banks provided monetary stimulus to encourage a recovery from the COVID-19 epidemic in 2020. This cannot be a steady-state expectation in a well-functioning economy over the long term, however. In our steady-state framework, short-term real interest rates are assumed to return to historical levels. Changes in these rates flow through our models into expectations for bond and equity returns. In addition, we assume that asset prices are fairly valued. Although asset classes can be cheaply (expensively) valued in the market in the shorter term, these valuation effects are removed from the steady-state CMAs.[5]

Steady-state CMAs provide expectations for returns after the initial 10-year horizon. To estimate returns at a fixed point in the future; for example, 80 years into the future (to the year 2100), we combine 10-year CMAs with steady-state CMAs to produce long-term CMAs. We calculate long-term return estimates as a weighted average using one-eighth the CMA return forecast and seven-eighths the steady-state return forecast. (See the Appendix.)

Growth and Inflation Impacts

Climate change is expected to have a significant long-term global macroeconomic impact. Thus, assumptions related to economic growth and inflation are a good starting place for analysis. In long-term CMAs, we construct macroeconomic assumptions using long-term economic growth and inflation estimates from the International Monetary Fund (IMF).[6] We take a simple comparative statics approach and model the impact of climate change as a delta on baseline growth expectations, considering both optimistic and pessimistic scenarios.

As stated previously, we base the optimistic scenario on estimates from Kahn et al. (2019) for RCP 2.6. Recall that under this scenario, there is a global effort to constrain the growth in carbon dioxide, which keeps temperatures from rising significantly from current levels.

Kahn et al. (2019) provided estimates for the cumulative impact on GDP growth per capita at different horizons for each country. From this information, we calculate the annualized percentage change in GDP per capita over 30-year and 80-year horizons (i.e., by the year 2050 and 2100, respectively). Given the inherent uncertainty in the impacts of climate change on population growth, we leave these assumptions unchanged.[7] Adding the expected GDP per capita loss to our initial growth estimates over the relevant horizon leaves us with climate change–adjusted growth assumptions. The impacts from climate change in the optimistic scenario only result in small changes from our baseline forecasts, as can be seen in Exhibit 5.

The pessimistic scenario is based on estimates from Burke, Hsiang, and Miguel (2015). We use their RCP 8.5 data for the temperature path and SSP 5 for the societal response path. Under RCP 8.5, little to no effort is made to constrain increasing levels of carbon dioxide, which puts upward pressure on global temperatures.

[5] Other adjustments include setting the yield curve slope at 10 years equal to half of potential growth, setting the current spread equal to the equilibrium spreads, setting default rates to their long-term levels, and removing mean reversion. Asset return estimates require corresponding adjustments.

[6] Aiolfi, Tokat-Acikel, and Johnson's (2020) 10-year CMAs initially use 10-year economic growth and inflation estimates from the IMF. The steady-state CMAs do not modify these assumptions, leaving them effectively unchanged in the long-term estimate.

[7] As discussed previously herein in "Economic Impact of Climate Change on Population Growth."

EXHIBIT 5

Annualized Percent Change in Long-Term Real GDP Forecasts

	Kahn et al. (2019)		Burke, Hsiang, and Miguel (2015)	
Country	RCP 2.6 by 2050/2100	RCP 8.5 by 2050/2100	RCP 8.5 by 2050	RCP 8.5 by 2100
United States	–0.02	–0.11	–0.13	–0.50
United Kingdom	0.00	–0.03	0.22	0.39
France	0.00	–0.05	0.11	0.10
Germany	0.01	–0.02	0.31	0.54
Italy	0.00	–0.07	–0.07	–0.33
Spain	0.01	–0.06	–0.23	–0.69
Japan	–0.03	–0.11	0.14	–0.48
Switzerland	–0.04	–0.12	0.48	0.88
Australia	0.00	–0.06	–0.32	–0.83
Canada	–0.02	–0.12	0.74	1.39
Brazil	0.00	–0.08	–0.80	–1.93
China	0.02	–0.05	–0.18	–0.60
Korea	–0.03	–0.11	0.07	0.00
Taiwan	0.02	–0.05	–0.18	–0.60
India	–0.02	–0.10	–1.14	–2.75
South Africa	0.00	–0.07	–0.46	–1.20

NOTES: As of March 9, 2021. Figures and information provided are estimates subject to change. Neither of these two papers estimate the impact of climate change on Taiwan specifically. The estimate for China is used instead.

SOURCE: Prepared by the authors using data from Kahn et al. (2019) and Burke, Hsiang, and Miguel (2015).

SSP 5 assumes fossil-fueled development with high challenges to mitigation and low challenges to adaptation. This scenario provides estimates of GDP per capita both with and without climate change, from which we extract annualized GDP per capita losses over the relevant horizons. Compared to our optimistic results, the pessimistic scenario shows larger temperature increases that are expected to have a larger impact on economic growth. Moreover, this economic impact is highly nonlinear in the pessimistic estimates, but not so for the optimistic ones.

Whereas Kahn et al. (optimistic) took an empirical approach, based on the historical effects of temperature on growth, Burke, Hsiang, and Miguel (pessimistic) took a more structural approach, seeking a sweet spot for temperatures and their corresponding impacts. They found that rising temperatures will more negatively affect countries near the equator but that climate change may have a modest positive impact on more temperate countries closer to the poles. In addition, the pessimistic results suggest that as the horizon lengthens, some countries will experience a greater deterioration in economic growth. Thus, we focus on the 2100 horizon for our pessimistic scenario. As mentioned earlier, we assume no change in population growth.

Exhibit 5 provides a comparison of our assumptions of long-term GDP growth impacts from climate change. Although the values in Exhibit 5 may not look large in absolute value, compounding these values over 80 years, particularly in the pessimistic scenario, leads to very large cumulative changes. For instance, the –2.75% difference in Indian per capita GDP growth is –90% compounded over 80 years.[8]

In contrast to assumptions for economic growth, we make no change to inflation assumptions. Although central banks are beginning to consider the impact of climate

[8] $(1 + -2.75\%)^{80} - 1 = -89.3\%$.

EXHIBIT 6

GDP Growth and Inflation Expectations in Optimistic and Pessimistic Scenarios

	Baseline/Optimistic Climate Scenario		Pessimistic Climate Scenario	
Country	GDP Growth	Inflation	GDP Growth	Inflation
United States	1.49	2.19	0.99	2.19
United Kingdom	1.03	1.76	1.42	1.76
France	1.10	1.21	1.20	1.21
Germany	1.00	1.62	1.54	1.62
Italy	0.34	1.07	0.01	1.07
Spain	1.08	1.38	0.39	1.38
Japan	0.35	0.77	–0.13	0.77
Switzerland	1.00	0.61	1.88	0.61
Australia	1.93	1.99	1.10	1.99
Canada	1.37	1.73	2.76	1.73
Brazil	1.45	3.09	–0.48	3.09
China	5.46	2.47	4.86	2.47
Korea	2.18	1.51	2.18	1.51
Taiwan	1.98	1.21	1.38	1.21
India	5.60	3.91	2.85	3.91
South Africa	1.14	4.34	–0.06	4.34

NOTES: Figures and information provided are estimates subject to change. Neither of these two papers estimate the impact of climate change on Taiwan specifically. The estimate for China is used instead. Data as of March 9, 2021.

SOURCE: Prepared by the authors using data from Kahn et al. (2019) and Burke, Hsiang, and Miguel (2015).

change on inflation and interest rates, it is still early days for clear assumptions on either one. Moreover, as described previously, we found little agreement in the academic literature on how to handle the impact of climate change on inflation. It is generally acknowledged that climate change will likely create additional uncertainty around inflation and interest rates.

Exhibit 6 compares our growth and inflation expectations in both optimistic and pessimistic scenarios for major developed and emerging countries. Because the optimistic assumption calls for minimal economic impact from climate change, we use our baseline assumption for this scenario. The pessimistic scenario uses estimates from Burke, Hsiang, and Miguel (2015). These growth and inflation expectations feed into our steady-state return expectations for equities, bonds, and other asset classes.

Asset Return Expectations

Next, we measure the impact these changing economic assumptions have on our CMAs. Exhibit 7 shows our long-term CMAs for major public asset classes over a long-term horizon in optimistic and pessimistic climate change scenarios.

Global Fixed Income[9]

Bond return forecasts in our framework are largely predicated on income and valuation factors. At a given maturity point, the forecast income return for a government bond will consist of the average expected coupon yield over the forecast horizon, as well as proceeds from bonds maturing to lower yields. Changes in yield at a given

[9] Forecasts may not be achieved and are not a guarantee or reliable indicator of future results.

EXHIBIT 7

Expected Geometric Returns in Optimistic and Pessimistic Climate Scenarios

	Expected Geometric Return (%), Q4 2020		
	Impact of Climate Change		
Asset	Optimistic LT CMAs	Pessimistic LT CMAs	Change
Cash	1.27	1.27	0.00
US Treasury	3.69	3.69	0.00
US Treasury 1–3 Year	2.73	2.73	0.00
Global Treasury Hedged	3.01	3.01	0.00
US AGG	3.96	3.85	–0.11
Global AGG Hedged	2.95	2.88	–0.06
US IG	4.79	4.64	–0.15
US HY	5.96	5.61	–0.35
US TIPS	3.77	3.77	0.00
US Equities	7.83	7.40	–0.44
UK Equities Unhedged	7.27	7.62	0.34
Europe ex-UK Equities Unhedged	6.71	7.04	0.33
Japan Equities Unhedged	5.66	5.24	–0.43
Developed International ex-US Equities Unhedged	6.67	6.80	0.14
EM Equities Unhedged	9.80	9.08	–0.72
Global Equities Unhedged	7.74	7.42	–0.32
US REITs	7.04	7.04	0.00
Developed REITs Unhedged	7.04	7.04	0.00
Commodities	1.33	1.33	0.00
60/40 Portfolio	5.82	5.63	–0.19

NOTE: As of March 9, 2021.

SOURCE: Prepared by the authors.

maturity point over the forecast horizon determine the necessary valuation adjustments. If yields are forecast to rise (fall) over the next 10 years, the valuation adjustment will be negative (positive). Using sovereign yields as a starting place, expected returns for fixed-income credit indexes include any additional income expected from an average credit spread yield over comparable government bonds, adjusted for expected default and downgrade losses over the forecast horizon. We then calculate the valuation adjustment for expected changes in spreads.

When we consider long-term steady-state bond forecasts, we assume that real interest rates have already stabilized at their equilibrium level, significantly higher than current levels. Furthermore, the slope of 10-year government yields is also fixed at roughly half of the economy's potential growth rate. As a result, sovereign yields are expected to be higher and more stable, which means stronger returns in the steady state. Credit benefits from the same forces that affect sovereigns. We assume that default rates match long-term rates, rather than varying with business cycles.

Although our longer-term, steady-state returns are significantly more attractive for many segments of the fixed-income market than our outlook over the next 10 years, our methodology leaves little room for an impact from climate change on sovereign bonds.[10] In the steady state, the return for sovereign bonds is driven by real equilibrium interest rates and compensation from inflation. The real equilibrium interest rates are assumed to be stable in the steady state. In line with the literature summarized previously, we keep interest rates unchanged in climate change scenarios—there are many ways that climate change might influence real equilibrium rates, but the direction is unclear. Similarly, as discussed earlier, inflation over long periods of time is primarily driven by central banks. It is unclear how inflation should change in different climate scenarios. Leaving both real equilibrium rates and inflation unchanged in the climate change scenarios keeps nominal sovereign returns unchanged, as well.

Corporate bonds and other, riskier debt instruments pose a thornier problem. The return on riskier debt can be split up between the return on safer, sovereign bonds and the premium earned from accepting additional risk of defaults. Ten-year CMAs primarily focus on the impact of defaults in a business cycle. For instance, a poor economy currently with high defaults might see stabilization in the future. However, the steady state is the primary driver of returns in our climate change scenarios. In the steady state, we assume a constant default rate, essentially ignoring normal business cycle variation. To account for a higher default rate in the climate scenario, we assume that a climate shock hits US and global fixed-income indexes. Riskier segments of the market, such as high-yield debt, are assumed to be hit harder by the shock than the aggregate. We also modestly lower the assumption for the recovery rate on investment-grade and high-yield debt. As a result, high-yield bonds have lower returns in the climate scenario than in our long-term CMAs. Investment-grade and aggregate bonds also have lower returns, although they are affected more modestly.

Another way to incorporate the impact from climate change is to consider credit migration, whereby some firms face a greater probability of being downgraded from their current ratings while the default rates within credit rating buckets remains unchanged. For instance, if firms that are rated BBB+ are downgraded to BBB, aggregate default rates will rise, even if the default rate of BBB+ and BBB-rated firms remains unchanged.

Equities[11]

Consistent with other long-term asset class forecasts, our equity forecasts are based on income, growth, and valuation considerations. To build the income component of our equity forecasts, we calculate each country's expected income contribution based on current and anticipated levels of dividend yield, as well as the expected returns attributable to buyback activity (positive) or net positive share issuance (negative). Because our forecast is focused on the long term, our earnings growth assumptions are centered on broad macroeconomic indicators consistently available across countries, including both economic growth and inflation.

Steady-state returns are primarily driven by income and growth. From the perspective of the steady state, valuations drop away as asset prices are assumed to have moved to equilibrium values. Because valuations are expensive based on historical standards in most countries, the 10-year CMA equity forecasts are depressed relative to steady-state estimates.

In contrast to our fixed-income forecasts, our equity forecasts are sensitive to long-term economic growth and thus are directly affected by the climate change

[10] Sovereign bonds for countries with significant credit risks, such as emerging markets, may be affected in a way we do not capture here. In an extreme scenario, a country economy devastated by physical risks of climate change would require higher rates of return to compensate for the higher risks of lending to that country. See PGIM (2021).

[11] Forecasts may not be achieved and are not a guarantee or reliable indicator of future results.

scenarios. Weaker (or stronger) economic growth assumptions strongly affect weaker (or stronger) earnings growth forecasts, flowing into a weaker (or stronger) equity forecast. For instance, the pessimistic climate scenario forecasts modestly lower growth in US GDP per capita. Although the United States has substantial geographical diversity (Bozeman, Montana, will be affected by climate change differently than Miami, Florida), productivity growth in warmer regions will slow by more than the pickup from warming in colder regions. As a result, our models predict both slowing earnings growth and weaker equity returns in the United States.

The impact of climate change on Japanese equity returns is consistent with that in the United States. However, European equity returns are expected to be modestly positive. In contrast to the United States and Japan, European countries may expect either a mildly negative impact of climate change on growth (e.g., Italy or Spain) or a modestly positive one, especially for higher latitude countries such as Germany, Switzerland, and Norway. Because the countries that benefit from climate change are larger in the index than those that are hurt by it, the net impact is positive.

Compared to developed markets, the impact of climate change on emerging-market equity returns has larger cross-sectional variation. With already elevated temperatures in India, future global warming is forecast to have a significant negative impact on equity returns over the long term. Brazil and South Africa are also expected to be negatively affected, whereas China and Taiwan may experience more modest drags. However, the effect on the temperate climate in Korea is more mixed. Aggregating the impact across all emerging market countries by market capitalization reveals a net negative impact.

It is important to note that transition costs, which are not explicitly modeled here, also differ across countries. Countries that assume technology leadership in the transition to a sustainable economy may improve their economic growth. The International Renewable Energy Agency, an intergovernmental organization that supports transition to sustainable energy, published a new report on progress in various countries in 2019.[12] This report concluded that China has a leading position in manufacturing, innovation, and deployment of renewable energy technologies. It is the greatest location for renewable energy investment, accounting for more than 45% of the global total in 2017. The United States, Japan, and the European Union are also making progress on renewable energy, whereas many emerging countries are lagging behind. Progress on renewables will increase energy independence, reduce vulnerability to energy price shocks, and potentially change the balance of power among countries.

Real Assets[13]

We include commodities, real estate investment trusts (REITs), and Treasury inflation-protected securities (TIPS) as real assets in our CMAs.

The return forecast for commodities is compiled for each sector individually and then aggregated. Our model incorporates spot forecasts, roll yield, and collateral returns linked to real rates and inflation forecasts. Commodity forecasts incorporate global growth in the spot forecast. When the global economy is running hot (cool), this results in higher (lower) forecasts for commodities. However, the economy is assumed to be chugging along at the same potential growth rate in the steady state. This implies that growth (contraction) in commodity demand is matched by growth (contraction) in commodity supply. As a result, climate change is assumed to have no impact on commodity returns. Mitigation responses to climate change are likely to affect individual commodities in different ways at the micro level. For example,

[12] Global Commission on the Geopolitics of Energy Transformation (2019).

[13] Forecasts may not be achieved and are not a guarantee or reliable indicator of future results.

certain industrial metals that are used in green energy production will likely command higher prices, whereas fossil fuel prices will likely suffer from low demand alongside wider use of electric cars.

The methodology for forecasting REIT returns corresponds with our approach for equities. As with equities, the valuation component falls out in the steady state. This leaves the considerable income of REITs and income growth. In contrast to equities, our model assumes that REIT income growth is proportional to inflation. Because our climate scenario leaves global inflation unchanged, the return for REITs is left unchanged. Individual REITs may face varying levels of physical risk from climate change based on their location, which is beyond the scope of our macro aggregate level of analysis.

TIPS are modeled with a framework similar to US Treasury yields. We expect a correspondingly higher return from TIPS in the steady state due to higher, stable, real interest rates. Similar to Treasuries, there is no impact on TIPS in our pessimistic climate change scenario.

Asset Risk Expectations

In addition to the expected return impacts articulated so far, we believe that climate change will create higher volatility for capital markets in affected countries. Countries that face more material environmental challenges will face higher uncertainty in terms of both physical risks and transitional risks. Although there are significant externalities from other countries' actions, the costs of dealing with these risks will be borne by local economies and societies. We incorporate this increased volatility with a simple heuristic: If the impact on GDP growth is negative in a given country, the volatility of that country's equities is increased by the same percentage. We then aggregate at regional and global levels. Exhibit 8 shows our volatility assumptions for climate change in optimistic and pessimistic scenarios.

PORTFOLIO ALLOCATION IMPLICATIONS OF CLIMATE CHANGE

Future climate change scenarios pose significant risks and potential opportunities for investors. Investors who view climate change as a credible risk have demonstrated various responses to this challenge. Some tilt their portfolio away from investments that may be exposed to potential negative consequences. Others engage in activism, influencing management behavior or financing new green projects. Although the physical risks of climate change are negative for most investments, the transition to a sustainable economy will also create advantageous circumstances for investors.

Although we have not yet quantitatively modeled opportunities that will benefit from the transition to a sustainable economy, it is generally accepted that the energy, utilities, materials, and industrials sectors will feel the greatest impact.[14] Transition Pathway Initiative (TPI), a global initiative led by asset owners, issued a 2020 State of Transition Report stating that

1. Nearly 40% of the world's biggest and most emissions-intensive public companies are demonstrably unprepared for the transition to a low-carbon economy.
2. More than 80% of companies remain off-track for Paris Accord targets. Companies and countries that can make this transition successfully may be major beneficiaries.

[14] Ibid. 12.

EXHIBIT 8

Expected Long-Term Volatility in Optimistic and Pessimistic Climate Scenarios

	Expected Vol. (%), Q4 2020 Impact of Climate Change		
Asset	Optimistic LT CMAs	Pessimistic LT CMAs	Change
Cash			
US Treasury	9.23	9.23	0.00
US Treasury 1–3 Year	3.81	3.81	0.00
Global Treasury Hedged	13.83	13.83	0.00
US AGG	8.79	9.03	0.24
Global AGG Hedged	9.24	9.43	0.20
US IG	9.70	10.01	0.31
US HY	10.78	11.40	0.62
US TIPS	9.96	9.96	0.00
US Equities	15.94	16.83	0.89
UK Equities Unhedged	15.61	15.61	0.00
Europe ex-UK Equities Unhedged	14.70	14.70	0.00
Japan Equities Unhedged	16.87	18.14	1.27
Developed International ex-US Equities Unhedged	13.31	13.31	0.00
EM Equities Unhedged	24.75	26.57	1.82
Global Equities Unhedged	19.68	20.49	0.80
US REITs	16.88	16.88	0.00
Developed REITs Unhedged	21.12	21.12	0.00
Commodities	15.91	15.91	0.00
60/40 Portfolio	13.72	14.17	0.45

NOTE: As of March 9, 2021.

SOURCE: Prepared by the authors.

We primarily explore the first option in this article, namely how to tilt a portfolio away from climate change risks. To measure these risks, we rely on the reduced-form economic estimates discussed previously. Our estimates predominantly capture physical costs and cannot separate physical and transition risks. Nevertheless, the macroeconomic implications of the physical risks of climate change are expected to lead to adverse growth outcomes. In our analysis, we find that certain asset classes and countries are more vulnerable than others. Our analysis will be informative for an asset allocator who believes that climate risks are credible and wants to reduce the impact of potentially adverse outcomes.

Our portfolio analysis focuses on a growth-oriented investor benchmarked against a policy portfolio consisting of 70% equities (45% US stocks, 15% developed ex-US stocks, and 10% emerging markets stocks), 20% fixed income (US aggregate bonds), and 10% real assets (2% TIPS, 5% REITs, and 3% commodities). The investor evaluates expected portfolio performance on the basis of the Sharpe ratio, the portfolio's return in excess of the risk-free rate divided by the portfolio's standard deviation. By optimizing portfolio weights, subject to constraints (±5% standard deviation from the policy portfolio policy,[15] no shorting, no leverage) that maximize the Sharpe ratio, the

[15] For equities and fixed-income asset classes. For real assets (TIPS, REITs, and commodities), deviations of ±2% from the policy portfolio fare allowed.

EXHIBIT 9

Optimal Portfolio in Optimistic and Pessimistic Scenarios for a Growth-Oriented Investor

Asset	Optimistic Portfolio	Pessimistic Portfolio	Difference
US Equities	40.0%	40.0%	0.0%
Developed International ex-US Equities Unhedged	10.0%	18.0%	8.0%
EM Equities Unhedged	13.0%	5.0%	–8.0%
US AGG	25.0%	25.0%	0.0%
US TIPS	4.0%	4.0%	0.0%
US REITs	7.0%	7.0%	0.0%
Commodities	1.0%	1.0%	0.0%

NOTES: As of March 9, 2021. The benchmark policy portfolio has 45% US stocks, 15% developed ex-US stocks, 10% emerging markets stocks, 20% US aggregate bonds, 2% TIPS, 5% REITs, and 3% commodities. We allow for ±5% deviations from the policy portfolio in the Sharpe ratio maximization optimization, subject to these deviations; no shorting and no leverage limit.

SOURCE: Prepared by the authors.

investor will tilt the portfolio toward higher expected return, lower expected standard deviation, or both. Running the optimization for the optimistic scenario, using long-term return expectations and volatilities, the optimal portfolio allocates as follows: 40% US stocks, 10% developed ex-US stocks, 13% emerging market stocks, 25% US aggregate bonds, 4% TIPS, 7% REITs, and 1% commodities. After adjusting return and volatility expectations to incorporate the impacts from climate change, the optimizer increases the developed market ex-US position and reduces the allocation to emerging market equities. This is largely consistent with the impact on returns discussed previously, as well as the increased volatility associated with riskier equity asset classes.

Return assumptions in the pessimistic climate scenario were weaker for emerging markets and stronger, on balance, for developed markets excluding the United States. In fixed income, the return of US aggregate bonds is assumed to be modestly lower in the pessimistic climate scenario, primarily owing to higher defaults among the credits. In addition, return assumptions were left unchanged for assets, resulting in no change in their weights in the optimization.[16]

The portfolio optimized under the optimistic scenario will yield lower returns and higher risk, if the pessimistic scenario is realized. Strategic portfolios that fail to acknowledge the potential return and risk implications of climate change may be more exposed to periods of underperformance.

CONCLUSION

Climate change will affect both the environment and the economy. Such changes throughout the remainder of the century will undoubtedly influence economic trends, as well as the political response to them. From the perspective of a long-term investor, climate change is a source of considerable uncertainty. The transition to a sustainable economy in various climate change scenarios poses significant risks and opportunities for investors' portfolios.

Although we acknowledge the challenges of accurately estimating the size of the potential macroeconomic impact of climate change, it is clear that climate change will have a negative impact on economic growth. This growth impact varies across countries, with the most sizable impact expected in emerging market countries. These countries also seem least prepared to handle the economic, policy, and societal challenges that may be awaiting them. By contrast, implications for the impact of climate change on inflation and interest rates are ambiguous. Although central banks are increasingly recognizing that climate change can be a major source of systemic financial risk, the impact of climate change is uncertain.

[16] This is partially driven by the optimizer enforcing constraints on deviations from the policy portfolio. For instance, US equities are 45% in the policy portfolio, meaning the optimizer can allocate 40%–50% in that asset class. With the allocation at 40% in the optimistic scenario, it cannot go lower in the pessimistic scenario.

Our top-down cross-asset analysis suggests that the most direct impact will be on growth-oriented assets, such as equities and corporate credit. We find that the impact on developed sovereign bonds, REITs, and commodities is likely to be more localized at the micro level of individual securities, rather than at the asset-class level. Using top-down strategic return expectations, a climate risk–aware portfolio would tilt away from regions and assets that are expected to be adversely affected to obtain better risk-adjusted returns.

Our article should be considered an initial attempt to frame a discussion of climate change from the perspective of a strategic portfolio allocator. As our understanding of the physical and transition risks of climate change improves, portfolio allocation implications will also become clearer. Furthermore, although we explored top-down implications of climate change in this article, we believe that combining both bottom-up and top-down views of the economic impacts of climate change would provide the best opportunity to obtain the desired portfolio outcomes.

APPENDIX

CONSTRUCTION OF LONG-TERM CMAS

We construct long-term CMAs by combining 10-year CMAs and steady-state CMAs. Returns are expected to follow the 10-year CMA scenario for the first segment of history and then follow the steady-state CMAs thereafter. One motivation for this structure is that the cheap (rich) might have better (worse) returns over the near-term horizon. However, the longer an investor's time horizon, the less weight they should place on an asset class being cheap or rich today and the more weight they should place on what happens in the steady state.

Because CMAs have a 10-year horizon and we are considering the returns over the next 80 years (to the year 2100), we calculate the long-term returns as a weighted average using one-eighth the CMA return forecast and seven-eighths the steady-state return forecast. Exhibit A1 compares our baseline 10-year CMA return estimates with the steady-state estimates and the long-term CMAs.

CONSTRUCTION OF LONG-TERM VOLATILITY

CMA volatility estimates by Aiolfi, Tokat-Acikel, and Johnson (2020) were constructed based on historical standard deviations over the long-term.[17] To construct steady-state volatility, we rely on the methodology of Cox, Ingersoll, and Ross (1985), whose model links the volatility of interest rates to the square root of interest rates. Higher interest rates are associated with greater volatility in interest rates, just not linearly. In our case, we have volatility estimates over the subsequent 10 years and want to model how those values would change if the return estimates were to change. The steady-state volatility is calculated by scaling the 10-year volatility by the square root of the ratio of the steady-state return to the 10-year return expectation. This approach ensures that if an asset class has a higher return in the steady state, such as would occur due to interest rates rising beyond our typical 10-year horizon, then the volatility is also scaled higher. However, because the scaling uses a square root instead of a linear adjustment, volatility will not

[17] Back to the 1980s for all asset classes, except for emerging markets.

EXHIBIT A1
Long-Term CMA Return Estimates

Asset	10-Year CMAs	Steady State	LT CMAs
Cash	0.46	1.39	1.27
US Treasury	0.77	4.11	3.69
US Treasury 1–3 Year	0.54	3.04	2.73
Global Treasury Hedged	0.58	3.35	3.01
US AGG	1.38	4.33	3.96
Global AGG Hedged	0.87	3.24	2.95
US IG	1.88	5.20	4.79
US HY	3.11	6.37	5.96
US Corp 1–5 Year	1.08	3.75	3.42
US Credit 1–3 Year	0.92	3.50	3.18
US Floating Rate <5 Year	0.94	3.24	2.95
EM Sovereign Dollar Debt	2.32	8.58	7.79
US TIPS	1.00	4.17	3.77
US Equities	5.68	8.14	7.83
US Small Cap	6.18	8.64	8.33
US Mid Cap	5.93	8.39	8.08
US Large Value	5.78	8.24	7.93
UK Equities Unhedged	7.55	7.23	7.27
Europe ex-UK Equities Unhedged	7.01	6.67	6.71
Japan Equities Unhedged	6.58	5.53	5.66
Developed International ex-US Equities Unhedged	7.30	6.58	6.67
EM Equities Unhedged	7.33	10.16	9.80
Global Equities Unhedged	6.29	7.95	7.74
US REITs	5.97	7.19	7.04
Developed REITs Unhedged	5.94	7.19	7.04
Commodities	0.91	1.39	1.33
60/40 Portfolio	4.12	6.07	5.82

NOTE: As of March 9, 2021.

SOURCE: Prepared by the authors.

increase as much as returns in the steady state. This means that the Sharpe ratio will also increase.[18]

Given the steady-state volatility, a similar approach to the one described previously with respect to returns is taken to compute the long-term volatility. The long-term variance is calculated as one-eighth of the 10-year variance plus seven-eighths of the steady-state variance. Taking the square root gives the long-term volatility. Exhibit A2 compares baseline CMA volatility estimates with the steady-state estimates and the long-term CMAs.

[18] When the risk-free rate is 0%. Using a linear adjustment for volatility will ensure that the Sharpe ratio is unchanged in the steady state. However, this would also result in very large and very unreasonable estimates for some asset classes. For instance, US Treasuries would require a 23.4% volatility to keep the Sharpe ratio unchanged, which is not consistent with history, even when yields were at comparable levels to the steady state.

EXHIBIT A2

Long-Term CMA Volatility Estimates

Asset	10-Year CMAs	Steady State	LT CMAs
Cash			
US Treasury	4.55	10.53	9.23
US Treasury 1–3 Year	1.83	4.34	3.81
Global Treasury Hedged	6.54	15.78	13.83
US AGG	5.65	10.02	8.79
Global AGG Hedged	5.44	10.53	9.24
US IG	6.65	11.05	9.70
US HY	8.57	12.26	10.78
US Corp 1–5 Year	3.37	6.28	5.51
US Credit 1–3 Year	2.86	5.58	4.89
US Floating Rate <5Year	2.10	3.90	3.42
EM Sovereign Dollar Debt	9.21	17.68	15.51
US TIPS	5.56	11.35	9.96
US Equities	15.11	18.09	15.94
US Small Cap	19.53	23.09	20.35
US Mid Cap	16.96	20.17	17.78
US Large Value	14.80	17.67	15.57
UK Equities Unhedged	18.04	17.66	15.61
Europe ex-UK Equities Unhedged	17.04	16.63	14.70
Japan Equities Unhedged	20.78	19.05	16.87
Developed International ex-US Equities Unhedged	15.84	15.04	13.31
EM Equities Unhedged	23.85	28.08	24.75
Global Equities Unhedged	19.85	22.31	19.68
US REITs	17.43	19.13	16.88
Developed REITs Unhedged	21.75	23.94	21.12
Commodities	14.58	18.07	15.91
60/40 Portfolio	12.84	15.58	13.72

NOTE: As of March 9, 2021.

SOURCE: Prepared by the authors.

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Geopolitical Risk in Investment Research: Allies, Adversaries, and Algorithms

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KEY FINDINGS

- Analyses of geopolitical risk in an investment context are most effective when formulated in a clear and precisely expressed conceptual framework.
- Considerations of geopolitical risk often act as *defeaters*, overriding potentially compelling market-related reasons for or against a particular investment.
- Quantitative approaches to analyzing geopolitical risk are most useful in the analysis and simulation of the structural relationships between global actors.

ABSTRACT

Geopolitical risk is a driver of just about every type of investment portfolio. However, in practice, most geopolitical research published by investment firms is not informed by international relations theory, giving it a less rigorous, editorial flavor. This article is an attempt to address the latter shortcoming by providing a theoretically grounded framework for analyzing geopolitical risk in an investment context. The first half of the article presents a qualitative framework for analyzing geopolitical risk. The framework uses conceptual tools from international relations theory that can be easily adapted to portfolio management. The second half of the article explores the analysis of geopolitical risk from a quantitative standpoint. The focus of this section is the application of game-theoretic, machine learning, and algorithmic techniques to the study of international relations. The last section of the article briefly addresses the topic of portfolio construction and provides a simple framework for incorporating geopolitical views into the portfolio selection process.

TOPICS

Risk management, global markets, portfolio management/multi-asset allocation, big data/machine learning*

Among non-financial drivers of financial risk, perhaps none is at the forefront of investors' minds more than geopolitical risk. This is due to the fact that markets are governed by institutions that are part of the connective tissue of nation-states, which in turn are the primary actors in international affairs. Accordingly, the interactions of states with one another and important non-state actors can have significant impacts on market performance. The degree to which investment strategies incorporate assessments of geopolitical risk into their investment processes varies, from global macro hedge fund strategies whose investments are driven in

*All articles are now categorized by topics and subtopics. **View at PM-Research.com**.

large part by their managers' views on various geopolitical trends and themes, to purely quantitative strategies in which geopolitical considerations generally play a limited role, if any at all.

Many investment firms have large armies of personnel tasked with forming views and writing commentary on current and prospective developments in world affairs. Although there is no lack of research on geopolitical themes and risks, not all of it is equally valuable to investors. The primary failing of much of the geopolitical research that is produced by investment firms is that it often displays a lack of analytical depth and historical context and is almost never couched within a systematic and theoretically grounded framework for understanding the dynamics within and among geopolitical actors. Rather, many of the geopolitically oriented pieces that are produced by investment firms often read less like research articles and more like op-ed columns with charts. Developing high-quality geopolitical analysis is especially challenging today for a number of reasons. The primary reason is that there are so many potentially impactful geopolitical factors that it is difficult to build thoughtful views on all of them, especially given the resource constraints of most firms. This is directly related to the lack of depth we find in many pieces of geopolitical research. Although firms would generally like to chime in on every current event, most are simply not equipped to do so in a coherent manner.[1]

Given the challenges of uncovering and analyzing the sources and potential impacts of geopolitical risk on investment outcomes, in this article we define and explain the basic dimensions of geopolitics as they pertain to portfolio management. In the first half of the article, we provide a practical yet rigorous conceptual framework for analyzing geopolitical risk that draws from contemporary political theory. Although it is beyond the scope of one article to present a comprehensive methodology that covers every aspect of international affairs, it is nevertheless possible to present an approach to analyzing geopolitics that provides more analytical clarity and investment relevance compared to the prevailing approach to geopolitical analysis in the investment industry.[2] The framework discussed in the first half of the article is qualitative in nature. The concepts presented can be used in a standalone fashion or in combination with the quantitative approaches to analyzing geopolitical risk discussed in the second half of the article. In the latter, our particular emphasis is on game-theoretic and algorithmic approaches to analyzing geopolitical risks; these approaches lend themselves to the structural analysis of the relations between geopolitical actors. From a practical portfolio management standpoint, they are useful in facilitating informed scenario analyses of prospective geopolitical events.

ALLIES AND ADVERSARIES

In the context of portfolio management, we define geopolitical risk as "any potential detriment to a portfolio's positions stemming from political developments within and among states and/or non-state actors." Our starting point is to define our units of analysis by adapting a framework for analyzing international relations provided by Waltz (1959). The framework was originally developed to describe interstate conflict

[1] Compounding the foregoing state of affairs is that many governments (especially in developing and frontier markets) frequently hire so-called 'experts' to write op-ed pieces or research papers articulating a specific political agenda, even if it is factually unfounded. This type of fake analysis has become all too common in recent years.

[2] For a recent survey monograph on various aspects of geopolitical risk and investing, see Klement (2021).

in terms of three levels of analysis[3]: *individual*, *state*, and *interstate*.[4] Here we adopt Waltz's tripartite structure but modify it so that we can use it as a tool to explain the potential sources of geopolitical risk as they pertain to investment portfolios. Before describing the framework in detail, we note that the different levels of analysis are not necessarily mutually exclusive. Indeed, in most cases, each level of analysis will inform portfolio management to a differing degree. As such, assessments of geopolitical risk will generally be made in an all-things-considered manner.

Before developing an overarching framework for conducting geopolitical analysis, it is important to construct what we call a *worldview*.[5] Developing a worldview entails developing a specific theoretical orientation that guides one's research. A worldview includes assumptions about the primary goals of international actors, the fundamental nature of the international system, and so on. It is roughly analogous to the mental models that most investors have regarding the primary drivers of markets. Developing a worldview is a major preoccupation of theorizing in academic international relations research and one whose embrace by investors conducting geopolitical analysis would bring welcome clarity to their ideas.

The major schools of international relations theory provide worldviews that stand in stark contrast to one another. For example, *realism* contends that international relations are primarily a struggle for power between states (the primary unit of analysis) that are attempting to survive in an anarchic world. Realism can be further divided into *defensive realism*, which views states as being primarily concerned with their own security (they are *security maximizers*), whereas *offensive realism* views states as being primarily concerned with the attainment of power, with the ultimate goal of becoming regional hegemons.[6] Realism, especially offensive realism, assumes that states are more concerned with attaining gains relative to other states than with absolute improvement in their well-being. Thus, states are assumed to view international relations as a zero-sum game. This assumption stands in contrast to the school of international relations known as *liberalism*, which assumes that states recognize that they are interdependent in a multitude of ways and, as a result, generally seek institutions and relationships that foster the development of jointly beneficial outcomes. In liberalism, states are assumed to be more concerned with absolute gains than with their standing relative to other states.[7]

With the foregoing in mind, we now proceed to our first level of analysis, *individuals*. This category typically encompasses state and military leaders but could presumably include non-state individuals such as the secretary general of the United Nations or the heads of large terrorist groups, among others. Similar to bouts of international conflict, individual leaders can also pose unique risks to investors. For example, assume that a given country has an economic and market system that possesses features that are deemed desirable by certain investors. It may nevertheless be the case that a particular leader exhibits behaviors and views that override, at least for the period that they are in office, the otherwise attractive features of that country's investment climate. For a specific example, consider the case of Turkey. The country has several significant and deep-rooted structural problems, which have been compounded since 2003 when Recep Tayyip Erdoğan began to rule that country. Erdoğan has arguably served to undermine much of the (admittedly modest) institutional progress Turkey had made over the preceding two decades. The institutional

[3] Waltz also refers to these levels of analysis as *images*.

[4] Waltz uses the term *international system* for the third level of analysis. Our labeling reflects its somewhat different characterization in our framework compared to Waltz's.

[5] Here we are directly inspired by the German concept of *Weltanschauung*.

[6] Waltz (1979) is widely considered the canonical statement of defensive realism. Mearsheimer (2001) provided the original outline and argument for offensive realism.

[7] The classic statement of the neoliberal view is provided by Keohane (1984).

erosion precipitated by Erdoğan's rule extends from the judiciary to monetary policy.[8] For emerging market (EM) investors, it could be convincingly argued that as long as Turkey is governed by the precepts of Erdoğanism, exposure to the Turkish market should be given a strategic underweight relative to a given benchmark or zeroed out altogether.

States, our second level of analysis, are defined as the aggregation of institutions that regulate the domestic workings of a given country. There is an important interaction between the individual and state levels: An effective (ineffective) national leader may lessen (increase) the geopolitical risk associated with the structure of a state's underlying institutions. State leaders have varying skills and abilities. However, as capable as individual leaders may be, their ultimate effectiveness will almost necessarily be constrained by the institutions governing their country's political, fiscal, and monetary order.[9]

State-level risks are often the primary type of risk associated with EM countries. This is understandable given that the judicial systems of many EMs are not yet fully formed and often dispense justice in an unreliable and arbitrary manner. Moreover, the mechanisms of democracy, such as elections and separation of powers, are also often ill-formed in EM countries. As a result, the organizational structure of EM countries is generally more fragile and prone to failure when compared to their developed market (DM) counterparts. Nevertheless, although institutional fragility is an important part of assessing the risk associated with EM markets, it is notoriously difficult to quantify. A common approach to quantifying state-level risk is the production of scores for individual countries. Scores are generally aggregations of values assigned to a country in various categories (e.g., corruption, legal system, regulatory regime). The individual scores for each category can be thought of as roughly analogous to the ratings that are assigned to corporate and sovereign bonds.

The third and final level of analysis, *interstate relations*, encompasses the political, military, and economic relations between states. This level of analysis is perhaps most prominent in the minds of investors when they think of geopolitical risk, because political, economic, and military confrontations between states often have readily observable market consequences. Indeed, even when countries are blessed with skilled leadership and an effective domestic institutional structure, they may be plagued by interstate conflicts that hamper economic performance. To appreciate the importance of interstate relations for markets, one need only look to the market gyrations caused by the trade war with China during the Trump administration. Another stark example is the damage caused to the Russian market in the aftermath of the sanctions regime initiated against that country by the United States and the EU beginning in March 2014 as retaliation for the annexation of Crimea and the invasion of Eastern Ukraine. Indeed, the Russian market did not recover its July 2013 level until January 2018. It goes without saying that any assessment of interstate risk must be multifaceted. Consider again the relations between the United States and China. They involve trade relations, intellectual property, the status of Taiwan, and human rights in Hong Kong and within China (e.g., in Xinjiang province). All of the latter points of conflict have held and will continue to hold the potential to negatively affect the global economy and, by extension, global markets.

We highlight two further points with regard to the relationship between interstate relations and financial markets. First, we should remember that different points of

[8] See, for example, Atabay (2021).

[9] A somewhat analogous relationship exists between states and superstate structures such as the European Union (EU), in which leaders need to operate within the institutional structure of the EU as well as the institutions specific to their home countries. For most if not all member countries, the institutional makeup of the EU serves as a constraint on their ability to effect change in their home countries.

conflict can be more or less global in their impact, both in their geographic impact and potential to move various markets. For example, United States/China interactions almost always have global implications, whereas other interstate interactions often have more localized impact. For example, political–military flare-ups in the Middle East, although usually headline grabbing, do not generally put pressure on global markets, save for the oil markets. Of course, the latter conflicts have the potential (and have come close) to devolving into 'World War III' scenarios, but that is a lower probability outcome. A second point that needs to be kept in mind by any investment professional doing geopolitical analysis is that it is important to have an understanding of not only the hot sources of potential tension around the globe but also the frozen conflicts that may reignite at any moment. The Kashmir conflict between India and Pakistan is a case in point, as well as the border tension between China and India. We note that the latter conflict, although occasionally flaring up into violence, is generally underappreciated as a source of genuine geopolitical risk, at least by investors. The need to keep track of geopolitical risks of varying levels of intensity requires investment firms to maintain both a thorough process for geopolitical analysis and personnel with the requisite competence in the multitude of political–economic systems, cultures, and national histories that drive geopolitics. This is not easy and is arguably the reason why high-quality geopolitical analysis is usually not produced by investment firms.

Determining the relevant unit of analysis is but one dimension of analyzing international relations. A second fundamental aspect of understanding the behavior of global actors is determining whether the primary drivers of their actions are internal or external. This distinction is seen most clearly in states. As an example, consider trade policy, which plainly affects the economic relations between states. In the event of competitive pressures, a government may enact tariffs or other trade barriers to protect domestic industries. In this case, the driver of the state's trade policy is external to the country. In another instance, we may imagine a situation in which there is no exogenous driver of a change in trade policy, but a state's internal actors nevertheless seek to induce a particular change in a state's trade relations. For example, it could be companies belonging to a certain sector that are lobbying the government to reduce tariffs or other trade barriers to make the inputs to their industries cheaper, or free trade groups that believe in the benefits of maximally liberalized markets.[10]

The interplay between internal and external drivers of international relations is constant and extends to virtually every policy area. In the zone of security policy, for example, there is the familiar case of a nation's security policy being influenced by the struggle between military hawks, who advocate for a harder military line against a nation's adversaries, and doves, who believe in a softer, more conciliatory approach when dealing with a nation's security challenges. The latter dynamic is an internal driver of security policy. In contrast, an increase in either aggressive or pacific behavior on the part of a state's adversaries is a potential external driver of a change in security policy. Finally, we note that the jockeying for influence among internal actors primarily occurs in states with some semblance of a democratic system, however minimal. In totalitarian systems (e.g., Azerbaijan, North Korea, Turkmenistan), domestic interest groups, aside from small groups of elites, generally have little to no influence on policy-making.

[10] For an extended discussion of the tug-of-war between domestic actors in the realm of exchange-rate policy, see Frieden (2015).

INTERMEZZO: THE SPECIAL CASE OF MONETARY POLICY

Monetary policy occupies a special place in the analysis of geopolitical risk. On one hand, the object of monetary policy, the level of interest rates, has a direct connection to financial markets and therefore represents a direct source of financial risk. On the other hand, monetary policy is also an arena for political–economic conflict in which exchange rates are often the preferred weapon of choice. One prominent historical example of monetary conflict is the US decision to suspend gold convertibility in 1971 as a response to the failure of the participating countries of the Bretton Woods system to rectify global imbalances, which resulted in an excessive strengthening of the US dollar in the late 1960s and early 1970s. Another episode occurred in the late 1970s when the US government became dissatisfied with the pace of global growth. To "encourage" Japan and Germany to enact fiscal stimulus, the United States informed these countries that in the absence of adequate growth-enhancing measures, it would be content to allow the US dollar to depreciate against their respective currencies. As the yen and deutschemark appreciated, Japan and Germany experienced slowing growth and, in the face of domestic pressure, ultimately yielded to US pressure to embark on fiscal expansion.

When analyzing the interaction of global actors, especially states, we generally categorize their actions into two broad categories: actions that initiate or further the potential for military/political/economic conflict and those that eliminate or lessen that potential. No less important in monetary relations, however, are two other types of action: *delay* and *deflection*, which come into play during the process of adjustment which states engage in to bring their balance of payments into equilibrium.[11] This adjustment takes the form of countries with current account deficits reducing their imports and those with current account surpluses reducing their exports. When this happens, there is an asymmetric cost burden, with current account deficit countries bearing more adjustment costs relative to current account surplus countries. To see why, just consider a two-country example, with one current account deficit country and one current account surplus country. As adjustment occurs and the current account deficit country reduces imports, it will end up worse off than the current account surplus country because it will end up consuming less of the total output of both countries, all things being equal. Thus, current account deficit countries are incentivized to either delay their adjustment or deflect it. Delay is made possible through sufficient liquidity, which is maintained through reserves or borrowing capacity. The latter channel is enjoyed more by developed countries, which generally have better standing to borrow in international markets. The United States is perhaps unique in that its power to delay is seemingly unlimited owing to its role as the provider of the world's reserve currency. Deflection is made possible through a reduction in the sensitivity of a state to adjustment or through the adaptability of its economy. Reduced sensitivity to adjustment is generally enjoyed by countries that are or can make themselves relatively less open and hence less dependent on international trade. Adaptability is a characteristic of states that can repurpose productive capacity, whether labor or capital, to alternative purposes that will allow a lessening of the pain of adjustment in the form of reductions in the income and overall well-being of their citizenry.

[11] For an extended discussion of delaying and deflecting in monetary policy, see Cohen (2006).

ALGORITHMS

The framework discussed in the previous section was decidedly qualitative in its approach. This is understandable because statistical methods are arguably less suited to political analysis than to economic or financial analysis. Compared to the natural sciences, the social sciences are data poor. However, in the case of economics and finance, the existence of periodically released economic and financial data (e.g., macroeconomic data, security prices) gives them an advantage over other social sciences such as international relations, which have even less access to robust statistical data. As such, conceptual analysis is arguably a more fundamental component of assessing geopolitical risk than is the analysis of (sparse) data.[12] This is perhaps the reason why qualitative methods are predominant in geopolitical analysis, especially in the investment industry. The qualitative nature of geopolitical analysis is not limited to the inputs used but also extends to the conclusions derived from geopolitical analysis, which are also generally in qualitative form. That said, although it may not be possible to apply quantitative methods to geopolitics in the same way they are applied in finance, it is nevertheless possible to refine our understanding of geopolitical risk using a variety of analytical tools.

Because the data that are relevant to geopolitical analysis are generally found in a form that precludes straightforward statistical analysis, the assessments and forecasts that are produced through geopolitical analysis are also often imprecise. As such, judgments of geopolitical risk must play a different role in the portfolio selection process relative to traditional investment signals derived from time series. Given this fact, we begin this section by describing a way to transform qualitative, or soft, probability assessments into a mathematical form so they can be used as inputs into quantitative models. Having a mechanism to convert qualitative judgments into numerical form is useful because the probability estimates of individuals are generally imprecise or vaguely directional and hence unusable in their raw form. One way to transform qualitative probability assessments into quantitative form is known as the *Bayes factor* (Jeffreys 1998). The Bayes factor K, shown in Equation 1, is used to compare the strength of competing hypotheses, or models H_1 and H_2, on the basis of observed data D. For our purposes, hypotheses H_1 and H_2 are simply a proposition (e.g., the trade agreement will be signed) and its negation (it is not the case that the trade agreement will be signed).

$$\mathrm{K} = \frac{\Pr\left(D \middle| H_1\right)}{\Pr\left(D \middle| H_2\right)} = \frac{\Pr\left(H_1 | D\right)\Pr\left(H_2\right)}{\Pr\left(H_2 | D\right)\Pr\left(H_1\right)} \tag{1}$$

In those instances in which only a qualitative probability assessment can be made, K is assigned a numerical value according to Exhibit 1.

Although there is no single correct way to incorporate assessments of geopolitical risk into the management of investment portfolios, perhaps the most natural way is to use them as countervailing factors to investment-based views of current or proposed portfolio positions. Such factors are known as *defeaters* in epistemology, the branch of philosophy that studies knowledge acquisition and belief formation in individuals and groups.[13] Defeaters are beliefs that undermine an agent's other currently held beliefs.

[12] A somewhat related point is raised in a paper by Mearsheimer and Walt (2013), who argued that an overemphasis on statistical methodology (especially what they call "simplistic hypothesis testing") at the expense of (empirically informed) theory building is detrimental to knowledge creation in and the practical applicability of international relations research.

[13] This section draws on the work of Kotzen (2019), who provided an extensive formal account of defeaters.

EXHIBIT 1

Bayes Factor Probability Translation Table

K	Strength of Evidence
10^{1}–$10^{1/2}$	Minimal
$10^{1/2}$–10^{1}	Substantial
10^{1}–$10^{3/2}$	Strong
$10^{3/2}$–10^{2}	Very Strong

There are two basic types of defeaters. The first, what is known as an *opposing defeater*, is a proposition D that, if learned, lowers the probability P of a previously held hypothesis H. It may be formally defined in the following manner:

$$P(H|E \wedge D) < P(H) < P(H|E) \tag{2}$$

For an illustration of this type of defeater, let us consider a simple example. We assume that our hypothesis H is "it will likely be profitable to invest in Russian securities" based on recent positive economic news (E). This hypothesis can be expressed through maintaining a current position in Russian securities or establishing new positions in them. Let us further assume that a proposition relating to Vladimir Putin is the defeater in this case (e.g., "Putin's military adventures will scare off investors"). We would then assume that acceptance of the latter proposition overrides the strength that E provides to H, to the extent that the probability of H falls below some benchmark belief that Russia is investable, perhaps expressed in a portfolio through an underweight in Russian securities relative to a neutral benchmark position.

The second type of defeater is known as an *undercutting defeater*, which is a proposition D that undermines the positive evidential impact of evidence E on hypothesis H. Its formal definition is as follows:

$$P(H) \leq P(H|E \wedge D) < P(H|E) \tag{3}$$

To illustrate this type of defeater, let's use the example of Putin again. Similar to the previous example, we assume that our hypothesis H is that "Russia should be invested in" based on recent positive economic news (E). In this case, our defeater is the lack of a clear successor to Putin, injecting a degree of uncertainty into the base case positive view on the Russian market H. As such, the potential power vacuum serves to degrade our confidence in H provided by E, but not to the extent that H is undermined below some base rate. The defeater-modified probability could be expressed through maintaining a benchmark position rather than adding to it or reducing the amount of a proposed overweight.

Although there are a variety of approaches to building formal models of geopolitical risk, some are more likely than others to provide investors with actionable output. Game theory is perhaps the most commonly used in geopolitical analysis. Indeed, the mathematical framework provided by contemporary game theory provides a practical paradigm with which strategic interaction among geopolitical actors can be analyzed.[14] Any analysis of the strategic interaction among agents invariably begins with a characterization of agent preferences. However, the characterization of preferences in geopolitical analyses typically differs from instances of strategic analysis of a more purely economic nature.[15]

In economics and finance, assuming that individuals uniformly seek to maximize wealth and that firms universally seek to maximize profit is relatively uncontroversial. In geopolitical analysis, however, we are effectively blocked from assuming uniform preferences across agents, whether they be individuals, states, or other types of non-state actors. States, for example, will have preferences regarding economic and trade issues, military strategy, human rights, environmental issues, and cultural

[14] See Osborne and Rubinstein (1994) for a formal introduction to game theory.

[15] Frieden (1999) provided an extensive discussion of preferences in the context of international relations.

questions, among others. The multiplicity of preferences in international relations is an especially important factor for investors to take into account when considering the impact of geopolitical developments on financial markets. This is so because non-economic preferences may very well dominate economic preferences among political decision-makers, even though their ultimate decisions will almost certainly affect financial markets. Over the years, the characterization of *Homo economicus* has been refined to be more in line with the actual attributes of human rationality and decision-making. We assume that actors in the geopolitical realm are rational in a way that is consistent with this refined picture of human rationality, which emphasizes three important features of human deliberation: (1) that it is *bounded*, which constrains individuals' ability to maximally realize their goals; (2) that it possesses both *synchronic* (short-term) and *diachronic* (long-term) perspectives, the latter of which motivates actors to at times eschew present gains for future ones; and (3) that it is sometimes *non-instrumental*, in the sense that individuals' values, as opposed to their interests, can serve as the prime motivators of action.

Given the foregoing assumptions, it is possible to apply game theory to realistically model both cooperative and noncooperative interaction in a variety of contexts.[16] In game theory a *game* is considered any situation in which the outcome for each person depends not only on his or her own action but also on the actions of the people with whom they interact, the other players. Two important game-theoretic concepts are *Pareto optimal* and *Nash equilibrium*. An outcome is Pareto optimal relative to another state of affairs if and only if at least one person prefers the first state of affairs to the second and no one prefers the second to the first. A state of affairs is in Nash equilibrium when each player's action is the best response to the actions of the other players. We further note that a *dominant* strategy is the best strategy no matter how a player's opponent plays. Any dominant strategy is always a Nash equilibrium. However, not all Nash equilibria are dominant strategies.

In game theory, a game consists of sets of players, rules, and actions. Moves may be determined by choices that players deliberately make or by random occurrences, such as the roll of a die. A game can be represented by a matrix with $m \times n$ cells where m and n are the number of moves that each player has. Cells of the matrix contain values, one for each player, which represent the payoffs that the players would receive from their moves given the moves of the other players. The values of the payoffs are decided by the rules of the game, and each player tries to choose in a way that leads to the highest possible payoff. Game theory is useful precisely because it explicitly lays out the choices of the players as well as the payoffs that result from the combination of choices made. An important result is that for a number of games it is always possible to find an equilibrium from which no player should deviate; that is, there is no move they can make that will lead to a higher payoff. These equilibria exist for every two-player game that (1) has a finite number of moves after which the game ends; (2) has one player's losses equal their opponent's gain (i.e., a zero-sum game); and (3) is a game in which the players know their own moves and preferences and those of the other player.

One of the most frequently studied games in game theory is the Prisoner's Dilemma (PD). A common version of the PD tells the tale of two criminals who have been apprehended after committing a serious crime together. The police do not

[16] This includes financial models. Bell and Cover (1988) recast portfolio selection as a noncooperative game. Mussard and Terraza (2008) applied the cooperative game concept known as the Shapley value to the decomposition of portfolio risk. Simonian (2012) applied the Shapley value to the aggregation of multiple investment views. Simonian (2014) built on the latter work and used the Shapley value to solve the problem of aggregating sets of interconnected probability estimates in a logically coherent manner. Simonian (2019) applies the Shapley value to portfolio selection.

EXHIBIT 2
Prisoner's Dilemma

		Player 2	
		Cooperate	Defect
Player 1	Cooperate	1, 1	0, 10
	Defect	10, 0	5, 5

EXHIBIT 3
Maximizing Difference

		Player 2	
		Column 1	Column 2
Player 1	Row 1	10, 10	3, 2
	Row 2	9, 3	2, 1

have evidence to prove that the two committed this crime, but they do have evidence to prove that the criminals are guilty of a lesser infraction. The police offer each of the criminals a deal in which, if they confess to the crime and implicate their partner, they will be exonerated and have the minor charges dropped. In turn, the other prisoner will be incarcerated for a long time. However, the police will only honor the deal if the other prisoner does not confess to the crime. If both prisoners confess, they will both receive a moderate jail term. If neither prisoner confesses, then both will be charged with the minor infraction and will be given lighter sentences. The acts of confessing or not confessing are known, respectively, as *defection* and *cooperation*.

In any given instance of the PD, one of the following outcomes will materialize: (1) both prisoners defect and each spends a moderate amount of time in jail, (2) both prisoners cooperate and each spends a small amount of time in jail, or (3) one prisoner defects and the other tries to cooperate, leading to the defector being freed and the cooperator spending a long time in jail. Two rational prisoners would presumably both choose to defect, leading to a situation in which they do not obtain the best possible payoff. This is the main point of the PD: If both players choose the option with the highest payoff for them individually, they end up with a moderate term in jail, which is an undesirable outcome for both of them. On the other hand, if both prisoners cooperate and do not confess, they each receive the second-highest payoff, a short jail term. This strategy contains some risk, however, because if one prisoner cooperates while his partner defects, then he will receive the worst payoff, a long prison term, while his partner will be released.

The PD is useful because it formally presents a major paradox of rationality: how a thoroughly rational action may not always be the best action to take from the standpoint of self-interest. Indeed, single-stage PDs possess two distinct characteristics that can be easily observed in Exhibit 2. The two characteristics are (1) defection as the dominating strategy for each player and (2) cooperation as the Pareto optimal outcome. Recall that an outcome X is Pareto optimal relative to another outcome Y just in the case that at least one member of a group prefers X to Y. From this, it follows that in the case of a one-stage PD, rational agents will defect because defection is the dominating strategy. Regardless of the other player's strategy, defection maximizes an individual's expected utility. Thus, the game leads to a collectively unsatisfactory conclusion. In other words, the individually dominant option and the cooperative option conflict.

Although the standard assumptions of game theory often facilitate informative analyses of real-life strategic situations, they sometimes fail to do so in important ways. For example, one of the problematic assumptions from game theory is that players are only concerned with absolute payoffs. This assumption is at odds with the realities of many types of geopolitical interaction. For example, consider the game shown in Exhibit 3. Under the standard assumptions of game theory, the equilibrium solution is Row 1/Column 1 with a payoff of (10,10). However, a well-known study by Marvell and Schmitt (1968) found that experimental results generally deviate

EXHIBIT 4
Run-Pass Game 1

		Defense	
		Defend Pass	**Defend Run**
Offense	Pass	0, 0	10, –10
	Run	5, –5	0, 0

from that proscribed by game theory. Specifically, they found that the most common result is Row 2/Column 1, indicating that players are often willing to sacrifice their absolute gains to a certain extent to ensure a significant deterioration in their opponent's position, an objective that is called *maximizing difference*. It is possible to think of the sacrificed payoff as a cost that one player is willing to pay to secure a stronger position relative to another player.[17]

Aside from the PD, there are a host of games that are used to represent different types of human interaction. One type of game is what is known as an *attack-defense* game, in which one player wishes to change the status quo and another player wants to preserve it. For example, let us consider the game called the *Run-Pass* game.[18] The game is usually articulated as one being played by two (American) football teams. One team, *offense*, is contemplating its next play. It has two options, either run or pass; the second team, *defense*, can choose either to defend against a run or to defend against a pass. If offense runs while defense defends against a pass, the offense gains a payoff of 5 yards. If defense correctly predicts offense's play, then offense gains a payoff of 0 yards. If offense passes and defense defends against a run, then offense gains a payoff of 10 yards. The payoffs associated with each outcome are shown in Exhibit 4.

There are many types of geopolitical interaction that are analogous to the Run-Pass game. Perhaps the most obvious example is political–military conflict, in which warring sides try to deduce and predict each other's respective points of weakness. However, the game may also be applied to non-military engagements such as trade negotiations. For example, one side of a negotiation may be considering which one of two possible concessions to ask for in the current round of negotiations. They may surmise that the other party will be more amenable to giving one concession rather than another. This could be the case for a variety of reasons, such as one party's belief that their negotiating partner is under pressure from domestic interest groups (e.g., trade groups, labor unions) to bring negotiations on a specific item to a close.[19]

Payoff matrixes show the *expected payoffs*, which are the product of a gain (loss) amount and the probability that the gain (loss) is obtained. Differences in gain (loss) amounts need not be precisely calibrated but can simply reflect relative differences in the value of perceived action combinations. It is also possible to assign different payoffs given different probability and/or gain (loss) assignments to each combination of actions depending on the state of the world in which agents find themselves. We can thus set up what is known as a *game of incomplete information* and investigate the efficacy of different decisions over time. Our particular measure of strategy effectiveness is the average payoff accruing to a strategy over a given period.[20]

[17] The findings of this study can also be interpreted as providing evidence that supports the foundational tenets of political realism versus those of political liberalism. See Ullmann-Margalit (1977) for a more detailed discussion of the concept of maximizing difference.

[18] The Run-Pass game is a slightly more sophisticated variant of a well-known game called Matching Pennies. For an extensive discussion of Matching Pennies, see Weirich (1998).

[19] It might be remarked that the results of a negotiation are typically not zero-sum as in the Run-Pass game. However, it is possible to assume that the payoffs denote the amount of relative benefit transferred to one party from another as a result of negotiations, analogous to the territory gained or lost in military engagements.

[20] Our approach is thus in the spirit of the tournaments involving the iterated PD described by Axelrod (1981) and the idea of an evolutionarily stable strategy as described by Maynard Smith and Price (1973).

EXHIBIT 5

Run-Pass Game 2

		Defense	
		Defend Pass	Defend Run
Offense	Pass	0, 0	3, –3
	Run	2, –2	0, 0

We model the evolution of payoffs for different actions by building an iterated version of the Run-Pass game by means of a simulation.

We begin by recasting the basic Run-Pass game within a reinforcement learning framework called a *contextual multi-armed bandit* (CMAB).[21] In reinforcement learning, an algorithm learns the optimal solution to a problem through the rewards and punishments it receives when taking specific actions. In bandit problems, the goal is to maximize the accumulative payoff or minimize the expected regret over a set of repeated actions.[22] A multi-armed bandit is like a slot machine with more than one arm, with each arm representing an action that an agent can take. We can adapt the CMAB framework to model a game of incomplete information. We do this by formalizing the notion of a context within the model. A context is simply a vector of features (probabilities, payoffs) that are assigned to each arm. It is assumed that at each time step t, agents are presented with contextual information. Agents then choose an action a from K possible actions and are presented with a reward r for the action. Thus, in addition to modeling the possible evolution of outcomes for the Run-Pass game in Exhibit 4 as a single given state, we can also model variants of it as additional states—for example, the game shown in Exhibit 5.

The game in Exhibit 5 has the same structure as the game in Exhibit 4. However, the differences between the payoffs resulting from different action combinations in Exhibit 5 are narrower than those found in Exhibit 4.

Various algorithms can be used to drive a CMAB. We implement our CMAB using what is known as the upper confidence bound (UCB) algorithm,[23] which is described formally in Exhibit 6. An important aspect of the UCB algorithm is that it attempts to balance *exploitation* versus *exploration*. With exploitation, we select the optimal choices that we are already familiar with. With exploration, we take some risk and choose an option whose benefits are unknown to us. The difference between the two is akin to choosing to eat at one of your favorite restaurants versus trying a new establishment.

In Exhibit 7, we show the evolution of payoffs for the games shown in Exhibits 4 and 5, with each game respectively representing a state. To run the simulations in each exhibit, one additional piece of information is required to build a CMAB: the probabilities associated with achieving a positive payoff for each action combination in each state.[24] Starting from the top left in each matrix and moving clockwise, we posit the following probabilities for each action combination: [[(0,0),0.25], [(10, –10),0.55], [(0,0),0.20], [(5, –5),0.45]] for the game shown in Exhibit 4 and [[(0,0),0.10], [(3, –3),0.35], [(0,0),0.20], [(2, –2),0.60]] for the game shown in Exhibit 5. In Exhibit 7, Panel A, we see that Action Combination 2, (10, –10), results in the highest average payoff over 105 games. In contrast, we see that in Exhibit 7, Panel B, Action Combination 4, (2, –2), is visibly superior to all of the other action combinations. This result

[21] Technically, contextual bandits sit between standard multi-armed bandits and genuine reinforcement learning frameworks. This is due to the fact that, although contextual bandits incorporate states, agents' actions do not influence the state as in standard reinforcement learning algorithms.

[22] The multi-armed bandit problem was first studied in mathematical detail by Robbins (1952) and Gittins (1979). For further discussion of the multi-armed bandit problem, see Katehakis and Veinott (1987). Contextual bandit problems are also analyzed by Dudik et al. (2011). An overview of reinforcement learning applications to game theory is provided by Crandall and Goodrich (2011).

[23] We use the UCB algorithm because it provides a balance between effectiveness and simplicity. It is one of several popular algorithms available for application to multi-armed bandit problems.

[24] In a given model, it is also possible to incorporate probabilities relating to the likelihood of a specific context materializing. This would be akin to imbuing the CMAB with a regime-switching type feature.

EXHIBIT 6
UCB Algorithm

For K possible actions, at any time $t > k$

Parameter: c

Initialize, for all actions a:

$$N_a(t) \leftarrow 0$$
$$Q_t(a) \leftarrow 0$$

Repeat for $t = 1, 2, \ldots$

$$a \leftarrow \underset{a}{\text{argmax}}\left(Q_t(a) + c\sqrt{\frac{\log t}{N_a(t)}}\right)$$

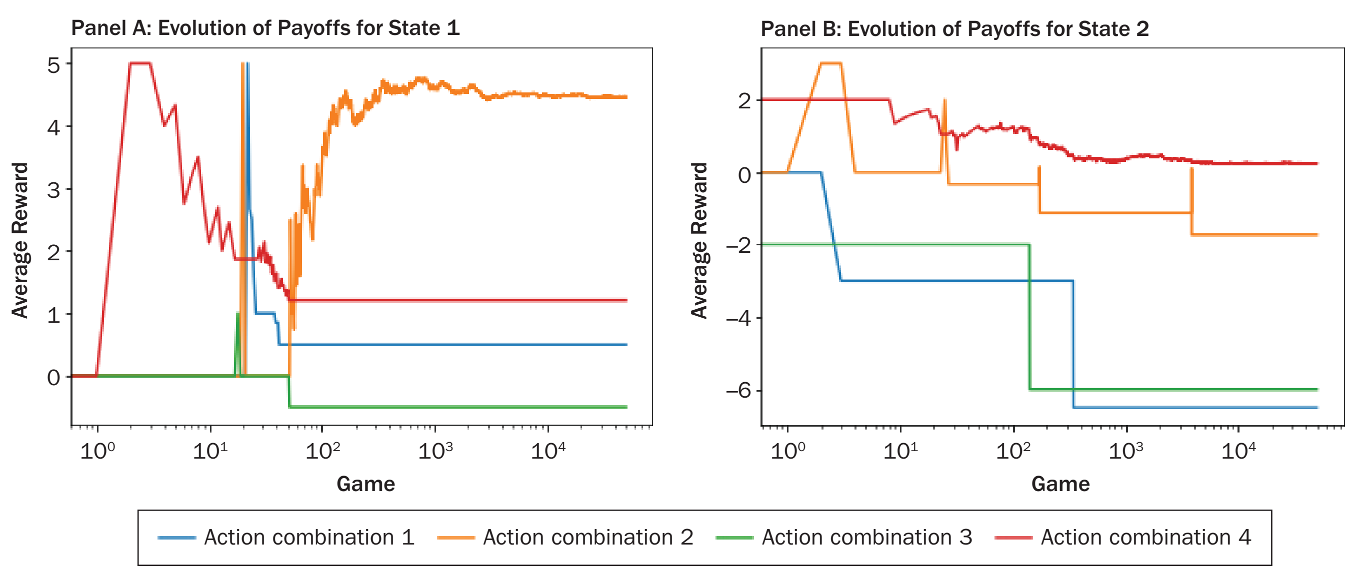
$$r \leftarrow \text{reward}(a)$$

$$N_a(t) \leftarrow N_a(t) + 1$$

$$Q_t(a) \leftarrow Q_t(a) + \frac{1}{N_a(t)}\left(r - Q_t(a)\right)$$

where $Q_t(a)$ is the average real-valued payoff to taking action a and $N_a(t)$ is the number of times an action has been taken. The term $\sqrt{\frac{\log t}{N_a(t)}}$ represents the confidence interval for the average reward. The parameter c is a constant that controls the degree of exploration.

EXHIBIT 7
Evolution of Payoffs for Run-Pass Game



indicates that even though the payoff to Action Combination 2 is higher than that of Action Combination 4, the higher probability of receiving a payoff is enough to provide the latter with a material advantage relative to the other action combinations over the longer term. Finally, we highlight that a notable feature of the results in both panels in Exhibit 7 is that the action combinations with payoff values of (0, 0) do not

EXHIBIT 8
Alliance Formation Algorithm

We consider two distinct sets, L and G, which represent what we call lesser powers and greater powers. Each greater power $g \in G$ has the capacity $c_g \in \mathbb{N}$ to accommodate a finite number of allies.

1. Each lesser power $l \in L$ must rank a non-empty subset of G. We denote this preference by $p(l)$.
2. Each greater power $g \in G$ must rank all lesser powers under consideration for alliance formation. Thus, the preference list of l, denoted be $p(g)$, is a permutation of the set given by $\{l \in L \mid g \in p(l)\}$.

A matching M is any mapping between L and G. If a pair $(l, g) \in L \times G$ are matched in M, we say that $M(l) = g$ and $l \in M^{-1}(g)$.

A match is considered valid if all of the following are satisfied:

3. For all $l \in L$ with a match we have $M(r) \in p(l)$.
4. For all $g \in G$ with matches we have $M^{-1}(g) \subseteq p(g)$.
5. For all $g \in G$ we have $|M^{-1}(g) \leq c_g|$.

A valid match M is considered stable if it does not contain a *blocking pair* (r, h), which is defined thus:

6. There is mutual preference: $l \in p(g) \wedge g \in p(l)$.
7. Either l is unmatched or prefers g to $M(l) = g'$.
8. Either $|M^{-1}(g) < c_g|$ or g prefers l to at least one $l' \in M^{-1}(g)$

produce average payoffs of zero. This is due to the exploration feature of the UCB algorithm, which allows for the occasional choice of actions that deviate from an established pattern.

In addition to game-theoretic approaches, various types of algorithmic frameworks can be used to analyze geopolitical questions of a more structural nature, such as the stability of relationships among various actors in the international system. For example, it is possible to apply what is known as the hospital-resident problem to the analysis of alliance formation among states. The hospital-resident problem is a variant of the stable marriage problem solved by the Gale–Shapley (1962) algorithm, which is used to determine what configuration of pairings from two equal size sets of individuals will exhibit the most stability given their preferences for being matched with members of the opposing set. Formally, a match is a bijection from the elements of one set to the elements of another set. A match is in turn considered stable when there does not exist any match that the members prefer over an existing match. The hospital-resident problem is a more general version of the stable marriage problem, allowing one set (hospitals) to be matched with more than one element from the opposing set (residents). The formal solution to solving the alliance formation variant of the hospital-resident problem is described in Exhibit 8.

The hospital-resident problem is similar to alliance formation among states. What we will call *greater powers* are somewhat analogous to hospitals and have the capacity to ally with several countries that we call *lesser powers*. Although any kind of alliance formation is presumably of interest to investors, economic alliances are particularly important to the consideration of countries' future economic prospects. The act of alliance formation in an economic context could be implemented by greater powers offering economic aid, trade preferences, or direct investment to lesser powers in exchange for economic and/or political concessions on the part of the lesser power. Their choice of lesser powers to ally with could also be based on a number of political considerations, such as geography or security alignment.

As an example, consider a situation in which we have three greater powers (GP) and five lesser powers (LP). Let us assume that the respective rankings of each of the greater and lesser powers is as follows: GP1: {LP2, LP5, LP1}; GP2: {LP3, LP5, LP4}; GP3: {LP2, LP4}; LP1: {GP2}; LP2: {GP2, GP1}; LP3: {GP3, GP1, GP2}; LP4: {GP1, GP2}; LP5: {GP3, GP1}. We further assume that each greater power only has the resources to undertake alliances with two lesser powers. Using the algorithm in Exhibit 8, we come to the following set of matches: GP1: {LP2, LP3}; GP2: {LP4}; GP3: {None}. As we see by the results, LP1 and LP5 are not matched with any greater power, whereas GP1 is matched with two lesser powers.

How would we use this type of analysis in an investment context? Well, the preferences attributed to each respective greater or less power presumably derive from research on the economic strengths and challenges of each of the countries under consideration. The alliance preferences of countries are also often revealed by their behavior. For example, countries will often pass legislation to harmonize the relevant parts of their economies with potential partners. Based on the foregoing, if we assume confidence in the assigned preferences, then the application of the Gale–Shapely algorithm can be further assumed to give us an accurate characterization of the equilibrium alliance structure. With this information in hand, it is possible to track the countries' economic relations over time and, as events play out, determine whether they are unfolding in a manner that is likely to bode well or ill for the stability of the global economic system and for each individual country. These observations can then be used to fill out a more comprehensive assessment of a country's economic prospects over a specified investment horizon.

PUTTING IT ALL TOGETHER

How do we incorporate geopolitical considerations at the portfolio level? There is, of course, no shortage of portfolio construction methodologies available. That said, it is also beyond the scope of this article to provide a comprehensive overview of frameworks such as the Black–Litterman model that provide various ways of formally incorporating manager views (including geopolitical views) into portfolio construction.[25] We can, however, present a relatively straightforward portfolio optimization framework that aligns with the general methodological approach presented in the previous sections of this article.

To begin, let us assume that we have a portfolio of five assets, two of which are vehicles that track the market indexes in two distinct countries. The precise nature of each of the other three assets is not important. Let us further assume that we have developed a bearish view of the two country-specific assets based on geopolitical considerations. In the simplest case, we would exclude them from our portfolio altogether. However, even in this case we would still be left with the challenge of reducing the correlation of our portfolio with these countries while simultaneously pursuing other portfolio goals related to risk and return.

In Equation 4, we show one way of approaching the foregoing challenge within a basic linear programming framework. As we see in the formulation of the problem, the optimization is a constrained maximization problem, with maximizing portfolio return being the objective of the optimization. In terms of constraints, the first two listed require that the weighted sum of asset Pearson correlations to each of the two excluded assets be less than 0.2 and 0.3, respectively. The third listed constraint requires that the weighted sum of the asset betas to a stated benchmark be less

[25] For a detailed discussion of the Black-Litterman model, see Kolm, Ritter, and Simonian (2021).

than 0.8. The fourth constraint is that the portfolio weights sum to 1. The final two constraints set the lower and upper bounds of the portfolio assets, respectively.

$$\text{Maximize} \quad 0.04x_1 + 0.03x_2 + 0.07x_3 \tag{4}$$

$$\text{s.t.} \quad 0.2x_1 + 0.1x_2 + 0.4x_3 \le 0.2$$

$$0.1x_1 + 0.3x_2 + 0.3x_3 \le 0.3$$

$$0.60x_1 + 1.0x_2 + 0.85x_3 \le 0.8$$

$$x_1 + x_2 + x_3 = 1$$

$$x_1, x_2, x_3 \ge 0.05$$

$$x_1, x_2, x_3 \le 0.50$$

Running the optimization produces the following set of assets weights: {x_1:43%,x_2:38%,x_3:19%}, with an expected return of 4.19% We make two final notes relating to this framework. First, it was not necessary to exclude the two unfavorably viewed country indexes from the optimization. It is possible to include negatively viewed assets and retain the same optimization. The assets that a manager is bearish on may nevertheless be given zero weights as a result of the optimization. Second, we can readily observe that including favorably viewed countries in the optimization only requires that the ≤ relating to country-specific correlations be changed to ≥.

CONCLUSION

Geopolitical risk is perhaps the primary non-financial risk to which investment portfolios are exposed. In this article, the main contours of a theoretically grounded approach to analyzing geopolitical risk were outlined. In the first half of the article, a qualitative framework for analyzing geopolitical risk in an investment-relevant manner was presented. The framework draws on well-established concepts from international relations theory. In the second half of the article, various quantitative approaches to the analysis of geopolitical risk were considered, with a special emphasis on the analysis of structural relationships among international actors. A method for converting qualitative probability judgments into numeric form was first described. The article then provided an overview of the rational choice paradigm and its applicability to the analysis of geopolitical risk. A special focus of the discussion was how game-theoretic methods can be combined with machine learning to build detailed simulations of strategic interaction. The latter discussion was followed by a demonstration of how a well-known matching algorithm can be used to analyze international alliances. In the last section of the article, the incorporation of geopolitical views in portfolio construction was considered. To that end, a concise and simple optimization approach was presented.

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Disclaimer

Firm-Level Cybersecurity Risk and Idiosyncratic Volatility

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KEY FINDINGS

- The authors propose a new measure of firm-level cybersecurity risk that applies textual analysis to earnings conference call transcripts; they use that measure to investigate the effect of cybersecurity risk on firm-level return volatility.
- They find that discussion of issues related to cybersecurity risk during earnings calls is associated with an increase in the component of volatility that responds only to firm-specific news.
- The authors show that the impact of cybersecurity risk on firm-level volatility is robust to alternative measurements of the language in earnings call discussions and to different industry classifications.

ABSTRACT

The authors propose a measure of firm-level cybersecurity risk developed by employing pattern-based sequence-classification method from computational linguistics to determine the proportion of time devoted to issues related to cybersecurity risk during earnings conference calls. Using their measure, they investigate the effect of cybersecurity risk on firm-level return volatility; they examine both idiosyncratic volatility and implied volatility and find that firm-level cybersecurity risk is positively correlated to idiosyncratic volatility on the days on which earnings calls are held. This suggests that the discussion of issues related to cybersecurity risk during earnings calls is related to an increase in the component of the volatility that responds only to firm-specific news. That positive relationship is robust to alternative measurements of the language in earnings call discussions and to industry classifications.

TOPICS

Security analysis and valuation, risk management, big data/machine learning*

Risks associated with data breaches and cyberattacks have been identified as one of the most important factors on which regulators, investors, and company executives should focus. In February 2018, the US Securities and Exchange Commission (SEC) issued its "Statement and Guidance on Public Company Cybersecurity Disclosures," which that that "given the frequency, magnitude and cost of cybersecurity incidents, the Commission believes that it is critical that public companies take all required actions to inform investors about material cybersecurity risks and incidents in a timely fashion, *including those companies*

*All articles are now categorized by topics and subtopics. **View at PM-Research.com**.

that are subject to material cybersecurity risks but may not yet have been the target of a cyberattacks."[1,2]

Historically, cyberattacks on businesses mainly compromised customer records and other operational data of the target, and the decrease in the targeted firm's (equity) value following such incidents usually was due to reputation damage for failing to protect those data. However, daily operations of targeted firms usually were not significantly interrupted. For example, Equifax reported on September 7, 2017 that unauthorized access occurred from mid-May through July 2017 and stole 145.5 million consumer records from the company. Although the stock price of Equifax declined by 35.5% within a week of the reporting of this incident, daily operations of Equifax were not heavily interrupted.[3]

In contrast, a noticeable trend is that ransomware cyberattacks are now more frequent. These directly affect the targeted firm's daily operations by blocking access to computer systems and/or shutting down facilities until a ransom is paid by a deadline. Consequently, the recent prevalence of ransomware attacks has a more direct impact on the targeted firms' operating cash flows, and attacks affect the financial situation of targeted firms more directly than reputational damage. For example, Colonial Pipeline, the largest US pipeline system for refined oil products, suffered a ransomware attack on May 7, 2021, which led to fuel shortages in the next few days across several states. The company paid $4.4 million in bitcoin as ransom within a few hours of the attack (Eaton and Volz 2021). Similarly, another ransomware attack targeted JBS, the world's largest meatpacker, on May 30, 2021, which rendered all JBS-owned beef facilities in the United States temporarily inoperative. JBS had to pay an $11 million ransom in bitcoin (Bunge 2021). Such cybersecurity incidents highlight the vulnerability of the cybersecurity system and the necessity of managing and controlling cybersecurity risk at the firm level.

The academic literature on cybersecurity risk primarily focuses on changes in the market value of targeted firms following the reporting of cybersecurity incidents and finds that such reports appear to have a negative impact on the firm's value. Although these studies are informative, a very important question remains to be answered: How should we measure cybersecurity risk when there are no uniform regulatory disclosure requirements (which would have provided some guidance)?

In this article, we propose a new measure of firm-level cybersecurity risk by adopting the methodology of Hassan et al. (2019), who used it to calculate political risk. Specifically, we analyze the transcripts of (quarterly) earnings conference calls of public companies using textual analysis and employ pattern-based sequence-classification methodology from computational linguistics to determine the proportion of time devoted to issues related to cybersecurity risk during these calls. Existing academic research mostly focuses on cybersecurity incidents that are publicly reported by companies and compiled by organizations such as Privacy Rights Clearinghouse (PRC). This list of incidents is likely not exhaustive because it relies on voluntary reporting. In addition, some of these cybersecurity incidents are not immediately detected by companies and are reported to the public with a delay.[4] Our measure of cybersecurity risk circumvents these issues by using the earnings call transcripts of all companies over the whole sample period, regardless of whether they had a cybersecurity attack.

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[1] See https://www.sec.gov/rules/interp/2018/33-10459.pdf.

[2] A cybersecurity incident is "[a]n occurrence that actually or potentially results in adverse consequences to … an information system or the information that the system processes, stores, or transmits and that may require a response action to mitigate the consequences." See the US Computer Emergency Readiness Team website, available at https://niccs.us-cert.gov/glossary#I.

[3] The stock price decreased from $142.72 to $92.98 from September 8 to September 15, 2017.

[4] For example, an Equifax data breach was reported on September 7, 2017, although the cyberattack had taken place a few months earlier, from mid-May to July of 2017.

Using our firm-specific cybersecurity risk measure, we investigate the relationship between firm-level return volatility and cybersecurity risk. We use a new measure of intraday return based idiosyncratic volatility proposed by Engle et al. (2021). With this measure, we focus on the portion of stock volatility that is specific to each firm and not affected by marketwide events. As an alternative measure, we use implied volatility from end-of-day option prices to analyze the changes in a firm's overall stock volatility on the days of the earnings conference calls.

Controlling for market cap, leverage, return on assets (ROA), five-year beta, short interest, and earnings surprise, we find that firm-level cybersecurity risk is positively correlated with idiosyncratic volatility on the days that earnings call conferences are held, suggesting that the discussion of issues related to cybersecurity risk by executives and other earnings conference call participants tends to increase the component of volatility that responds only to firm-specific news. Using implied volatility as a secondary measure of stock volatility, we also find a positive relationship, although the coefficient is smaller in magnitude between cybersecurity risk and volatility. This smaller magnitude can be explained by the fact that idiosyncratic volatility is computed using intraday returns, whereas implied volatility is computed from option prices at the end of a trading day. Therefore, idiosyncratic volatility can capture in a timely manner the arrival of new firm-specific information contained in earnings calls throughout a trading day; however, implied volatility only captures part of that information at the end of the trading day—after some of that information has already been absorbed by prices.

We also find that the coefficients of various cybersecurity risk indexes (CRIs) computed from different cybersecurity training libraries (i.e., cybersecurity-related texts) are close in magnitude (as are their corresponding *t*-statistics). This suggests that the overall impact of cybersecurity risk on idiosyncratic volatility is robust to alternative measurements of the language in earnings call discussions. The positive relationship is also robust to various industry classifications. Therefore, relying on our results from an analysis of a panel dataset of 54,154 earnings call transcripts of 2,761 US firms over a 10-year period, we believe that our proposed measure of firm-level cybersecurity risk is a viable measure to investigate firm-level cybersecurity risk and volatility.

The organization of this article is as follows. In the second section, we review the current literature on cybersecurity risk and cybersecurity incidents. In the third section, we explain the methodology we use to construct our measures of firm-level volatility and cybersecurity risk. Our data sources and the summary statistics of all variables used in our empirical analysis are discussed in the fourth section. We present our empirical results in the fifth section. The sixth section concludes.

LITERATURE REVIEW

The largest strand of literature on firm-level cybersecurity risk focuses on the changes in the market value of targeted firms before and after the reporting of various types of cybersecurity incidents, relying on event study methodology. Although a few studies find that there is no statistically significant association between cybersecurity incidents and the targeted firms' market value (e.g., Hovav and D'Arcy 2003; Kannan, Rees, and Sridhar 2007; Bolster, Pantalone, and Trahan 2010; Kvochko and Pant 2015), most studies find a decline in market value following the reporting of a cybersecurity incidents (e.g., Campbell et al. 2003; Cavusoglu, Mishra, and Raghunathan 2004; Acqusisti et al. 2006; Goel and Shawky 2009; Bose and Leung 2014; Spanos and Angelis 2016).[5] In particular, Akey, Lewellen, and Liskovich (2018) studied the impact of cybersecurity incidents on the reputation of the target and documented that the occurrence of a cybersecurity incident decreases the firm's market value by 10%–20%, a decrease that lasts for several years. Tosun (2021) found that, following the first-time reporting of a cybersecurity incident, the daily excess returns of the targeted firm drop, trading volume increases, and liquidity deteriorates, which indicates that the reporting of cybersecurity incidents represents unexpected negative shocks to firms' reputation. Kamiya et al. (2021) showed that with rational, fully informed agents and with no hysteresis, the reporting of cybersecurity incidents has no impact on the reputation of the target and post-attack policies when the firm is financially unconstrained. However, among incidents that involve the loss of personal financial information, targeted firms tend to suffer a significant loss in shareholder wealth. In contrast, Michel, Oded, and Shaked (2020) found mixed results, which they called the "shareholder puzzle," around the reporting of cybersecurity incidents. They found that during the period of 2005–2017, the mean abnormal return was negative in the period prior to the announcement date of the incident, likely reflecting a leakage of information, whereas the mean abnormal return was positive following the announcement, with the subsequent positive abnormal return often being larger than the previous negative one.

The second strand of literature extends the event study analysis to other firms that are related to those targeted in business operations (e.g., competitors and IT consulting firms). This strand analyzes the intra-industry information transfer, or externalities, of the targeted firm. For example, Garg (2020) found that the effect of cybersecurity incidents is not limited to the targeted firm only: It spills over to peer firms, which take precautionary measures following the reporting of the incident. Kamiya et al. (2021) showed similar results using a theoretical model. Jeong, Lee, and Lim (2019) documented that competitors of the targeted company have opportunities to absorb market power following the cybersecurity incident, especially competitors that have invested in cybersecurity. The impact of a cybersecurity incident is not limited to the industry of the targeted firm: It spills over to other vertically related industries as well. For example, Chen et al. (2012) found that the market value of IT consulting firms increases following the reporting of a cybersecurity incident—with an average abnormal return of 4.01% during the two-day period after incidents were reported.

The third strand of literature, although sparse, focuses on targeted firms' reactions to cybersecurity incidents. For example, Akey, Lewellen, and Liskovich (2018) found that targeted firms invest significantly more in corporate social responsibility during the years after a cybersecurity incident, partially as insurance against reputational damage. Other studies suggest that firms should respond in a more passive manner. For example, Amir, Levi, and Livne (2018) analyzed the extent to which firms withhold information on cybersecurity incidents and showed a cost for being less transparent: Withholding this information is associated with a decline of 3.6% in the firm's equity value in the month following the incident, compared with an average 2.6% loss in equity value among firms that act positively by disclosing the incident. Boasiako and Keefe (2019) and Laube and Böhme (2016) studied the relationship between state-level data breach disclosure laws and corporate policies and showed that disclosure laws influence firms' liquidity risk management and compel firms to account for the cost of their data insecurity.

To the best of our knowledge, the only paper in the literature that proposes a measure for firm-level cybersecurity risk is by Jiang, Khanna, and Yang (2020). In that

[5] One reason for the lack of significance is that the type of information accessed in a cyberattack attempt may vary across companies. Furthermore, stock prices may not fully absorb the risk inherent in a successful cyberattack within a short time window. See Makridis and Dean (2018).

paper, the authors used firm characteristics to estimate a firm's ex ante likelihood of experiencing a cyberattack using logistic LASSO regressions combined with cross validation and hence constructed a cybersecurity risk measure.[6] They found that institutional investors tend to sell stocks of high cybersecurity risk and buy those of low cybersecurity risk, and that tendency is stronger during a period when there are higher data breach concerns. They also showed that a one-standard-deviation increase in their cybersecurity risk measure is associated with a premium of 3.41% per annum.

Our firm-level cybersecurity risk measure differs from the one proposed by Jiang, Khanna, and Yang (2020) in two ways. First, although both use textual analysis to measure firm-level cybersecurity risk, different texts are used: Our article uses the texts of earnings call transcripts, whereas Jiang, Khanna, and Yang (2020) used 10-K documents. Using earnings call transcripts enables us to capture the attention paid by executives and other earnings call participants (especially analysts covering the specific firms and industries) to matters related to cybersecurity risk in a timely fashion, because an earnings call transcript usually incorporates the text of the question-and-answer (Q&A) session between managers and other conference call participants. Second, Jiang, Khanna, and Yang (2020) constructed a measure by combining firm characteristics and words/phrases related to cybersecurity chosen a priori (e.g., "data breach" and "cyberattack"). In contrast, we distinguish between cybersecurity-related and non-cybersecurity topics using a pattern-based sequence-classification method developed by computational linguistics (e.g., Manning, Raghavan, and Schutze 2008; Song and Wu 2008), which is adopted by Hassan et al. (2019).

METHODOLOGY

Measuring Cybersecurity Risk at the Firm Level

In this article, we propose a measure of firm-level cybersecurity risk established by analyzing the text of earnings call transcripts based on the methodology by Hassan et al. (2019), who constructed an index to measure firm-level political risk. In essence, we measure the proportion of time during an earnings call conference (and, hence, the proportion of the transcript text) devoted to matters related to the risk associated with cybersecurity. By identifying the text surrounding synonyms of words such as "risk"/"risky" and "uncertain"/"uncertainty", we are able to extract the portion of earnings call transcript text devoted to the discussion of cybersecurity risk, instead of more general matters related to cybersecurity (e.g., technical issues related to improving a firm's cybersecurity).[7]

Specifically, we begin by defining a training library of cybersecurity text (hereafter, cybersecurity library), C, and a training library of non-cybersecurity text (hereafter, non-cybersecurity library), N. Each training library is a set of all adjacent two-word combinations, or *bigrams*, contained in the cybersecurity- and non-cybersecurity-related texts, respectively.[8] Although our construction of the training library is similar to that by Hassan et al. (2019), they differ in two aspects. First, Hassan et al. (2019)

[6] Firm characteristics range from firm size, asset intangibility, and financial constraints to the inclusion of a risk committee.

[7] The list of synonyms for "risk," "risky," "uncertain," and "uncertainty" is obtained from the Oxford English Dictionary: "ambiguous," "arguable," "chancy," "changeable," "conjectural," "danger," "dangerous," "erratic," "fitful," "gamble," "hazard," "hazardous," "imprecise," "incalculable," "inclusive," "inconstant," "indefinite," "indeterminate," "irregular," "peril," "perilous," "precarious," "speculation," "speculative," "unclear," "unconvincing," "undecided," "undetermined," "unforeseeable," "unknown," "unpredictable," "unreliable," "unresolved," "unsafe," "variable," and "venture." If the word is a noun, we also include its plural form in our list.

[8] We remove all punctuations and stop-words before extracting bigrams from both libraries.

constructed the training library of the political text (because they focus on measuring firm-level political risk) from one undergraduate textbook on US politics and articles from the political section of US newspapers. We construct our cybersecurity library (C) from a pool of books and articles on topics related to cybersecurity issues because there are no well-recognized textbooks in the area of cybersecurity management.

We report in Exhibit 1 the detailed information for the pool of 17 texts we use to construct the cybersecurity library, including 13 books on cybersecurity or cybersecurity risk management published between 2015 and 2019, three transcripts of US congressional hearings on cybersecurity-related issues, and one guidance on public company cybersecurity disclosures from the SEC. Second, because those books and texts cover a wide range of issues discussed by academics, business practitioners, regulators, and so on, we classify our cybersecurity-related books into three topics: finance, law and regulation, and technology.[9] Accordingly, we also use different combinations of books and texts under these three categories to construct various training libraries and calculate several versions of our cybersecurity risk index. In comparison, Hassan et al. (2019) constructed different training libraries based on the sources of the text (i.e., textbook versus newspaper articles) instead of the topic/content of the text. As it turns out later in our analysis, the choice of texts based on their content in constructing the training library (i.e., the set of cybersecurity-related bigrams) has a salient impact on the magnitude of cybersecurity risk index across industries and over time.

We use all bigrams extracted from an undergraduate textbook on financial accounting (Libby, Libby, and Short 2010), to construct the non-cybersecurity library (N) following Hassan et al. (2019).[10] In addition, we include all bigrams obtained from the text of the *Santa Barbara Corpus of Spoken American English* (Du Bois et al. 2000) to capture bigrams specific to spoken language.[11]

With the cybersecurity library (C) and non-cybersecurity library (N), we then build our measure of firm-level cybersecurity risk by introducing the text of earnings call transcripts. First, we decompose the earnings call transcript text of firm i in quarter t into a list of bigrams contained in the transcript, $b = 1, \ldots, B_{it}$, where B_{it} is the total number of bigrams in the transcript. We then define our measure of cybersecurity risk by counting the occurrences of bigrams contained in C but not in N (i.e., the difference between sets C and N, or C\N) within a range of 10 words surrounding a synonym for "risk" or "uncertainty" on either side and divide it by the total number of bigrams in the transcript.[12] Hence, our measure of the firm-level cybersecurity risk, CRI, can be represented as follows:

[9] We keep the bigrams extracted from each cybersecurity-related book/article with a frequency of ≥10.

[10] We choose a textbook on financial accounting to construct the non-cybersecurity library because, in general, discussions during earnings calls tend to focus more on financial and accounting information.

[11] https://www.linguistics.ucsb.edu/research/santa-barbara-corpus.

[12] We take bigrams of the following forms out of C\N using a part-of-speech tagger based on the online appendix from Hassan et al. (2019): (1)"pronoun-pronoun," in which the pronoun is, for example, [hers, herself, him, himself, it, itself, me, myself]; (2) "preposition-preposition," in which the preposition is, for example, [among, upon, whether, out, inside, pro, despite, on, by, throughout, below]; (3) "adverb-adverb," in which the adverb is, for example, [occasionally, unabatingly, maddeningly, adventurously, professedly, stirringly]; (4) "wh-adverb," in which the wh-adverb is, for example, [how, however, whence, wherever, where, whereby, wherever, wherein, whereof]; (5) "preposition-adverb" or "adverb-preposition"; (6) "preposition-wh-adverb" or "wh-adverb-preposition"; (7) "preposition-determiner" or "determiner-preposition," in which the determiner is, for example, [all, an, another, any, both, del, each, either, every, half, many]; (8) "adverb-wh-adverb" or "wh-adverb-adverb"; (9) "adverb-determiner" or "determiner-adverb"; (10) "wh-adverb-determiner" or "determiner-wh-adverb"; (11) bigrams that contain "i," "ive," "youve," "weve," "im," "youre," "were," "id," "youd," "wed," and "thats." (See https://www.bu.edu/econ/files/2019/05/Firm-levelPoliticalRisk.pdf.)

EXHIBIT 1

Texts Used to Construct the Cybersecurity Training Library

Category		Year	Title	Text Type	Authors	Total Cyber-Bigrams	Total Bigrams
Finance	1	2019	Financial Cybersecurity Risk Management	Book	Rohmeyer and Bayuk	645	29,333
	2	2019	Digital Asset Valuation and Cyber Risk Measurement	Book	Ruan	2,067	47,645
	3	2016	Managing Cyber Risk in the Financial Sector	Book	Taplin	1,123	35,102
Law and Regulation	1	2018	Cyber Criminology	Book	Jahankhani	1,509	64,686
	2	2018	Cyber Security: Law and Guidance	Book	Wong	5,319	144,397
	3	2018	Commission Statement and Guidance on Public Company Cybersecurity Disclosures	Hearing, Guidance	Securities and Exchange Commission	124	3,115
	4	2010	Cyber Security 2010	Hearing, Guidance	US Congress	1,375	37,774
	5	2016	Oversight of the Cybersecurity Act of 2015	Hearing, Guidance	US Congress	714	21,113
	6	2015	Cybersecurity	Hearing, Guidance	US Government Accountability Office	25	2,428
Technology	1	2017	The Cyber Risk Handbook	Book	Antonucci	3,808	60,507
	2	2016	Cybersecurity Investments	Book	Beissel	1,400	53,402
	3	2018	Cyber Threat Intelligence	Book	Dehghantanha, Conti, and Dargahi	3,266	52,163
	4	2019	Cybersecurity and Secure Information Systems	Book	Hassanien and Elhoseny	4,048	48,308
	5	2016	How to Measure Anything in Cybersecurity Risk	Book	Hubbard and Seiersen	686	40,193
	6	2015	Cyber-Risk Management	Book	Refsdal, Solhaug, and Stølen	1,791	22,738
	7	2016	Cyber-Risk Informatics	Book	Sahinoglu	2,107	56,517
	8	2019	Cyberdanger	Book	Willems	412	40,933

NOTES: We use the text of books and articles on issues related to cybersecurity to construct our cybersecurity training library, following the method of Hassan et al. (2019). Because there are no well-recognized textbooks in the area of cybersecurity risk management, we use a pool of 17 books and texts, which includes 13 books on cybersecurity or cybersecurity risk management published between 2015 and 2019, three transcripts of US congressional hearings on cybersecurity-related issues, and one guidance on public company cybersecurity disclosures from the SEC. Because texts cover a wide range of issues discussed by academics, business practitioners, regulators, and so on, we further classify them into three categories: finance (three books), law and regulation (two books and four guidance from SEC and the US Congress), and technology (eight books).

$$CRI_{it} = \frac{\sum_{b}^{B_{it}} 1[b \in C \setminus N] \times 1[|b-r| < 10] \times \frac{f_{b,C}}{B_C}}{B_{it}} \tag{1}$$

where $1[\cdot]$ is the indicator function and r is the position of the nearest synonym of "risk" or "uncertainty." The first two terms in the numerator count the number of bigrams related to cybersecurity topics that occur within a 10-word range of a synonym of "risk" or "uncertainty." Because different cybersecurity-related bigrams might be used with different frequencies in the cybersecurity library, instead of using a straight sum of the occurrence of cybersecurity-related bigrams within a 10-word range as the numerator, we use the weighted average of the occurrences, using the ratio of the frequency of a particular bigram in the cybersecurity library C ($f_{b,C}$) to the total number of bigrams in it (B_C) as weights. Therefore, our firm-level cybersecurity risk index represents the share of the earnings call transcript text devoted to the discussion of cybersecurity-related risks.

In addition, we use seven alternative cybersecurity libraries as training libraries to compute CRI. The seven cybersecurity libraries are constructed based on the categories of (1) finance only; (2) law and regulation only; (3) technology only; (4) finance and law and regulation; (5) finance and technology; (6) law and regulation and technology; and (7) finance, law and regulation, and technology. We label the cybersecurity risk index calculated from those seven training libraries as *CRI-Fin*, *CRI-Law*, *CRI-Tech*, *CRI-Fin&Law, CRI-Fin&Tech, CRI-Law&Tech,* and *CRI-Fin&Law&Tech*, respectively.

Measures of Volatility

Using our cybersecurity risk index, we investigate the relationship between firm-level volatility and cybersecurity risk. We use two different measures of volatility in our empirical tests: the intraday return-based idiosyncratic volatility proposed by Engle et al. (2021) and implied volatility from end-of-day option prices.

Idiosyncratic volatility. Because our measure of cybersecurity risk is constructed using transcripts of firm-specific events (i.e., earnings conference calls), it would be more informative to look at the relationship between firm-level cybersecurity risk and the volatility component associated only with firm-specific factors. As such, we adopt the measure of *idiosyncratic volatility* developed by Engle et al. (2021). In that paper, the authors decomposed the total variance of a stock's return into two parts, one that is firm-specific and another common to all firms in the market; this distinguishes news associated only with revisions in a firm's expected future cash flows from news with marketwide influence. After the arrival of new information, stock market participants adjust their expectations of a firm's future cash flows and, consequently, revise their expectations of its stock return.

Engle et al. (2021) modeled the expected stock return as a contemporaneous relationship with the marketwide return, $r_{m,t}$, and defined the residual to be the unexpected stock return responding to firm-specific shocks. Letting $r_{i,t}$ denote the return of stock i on trading day t and $\varepsilon_{i,t}$ the unexpected return, we can write the return-generating process as follows:

$$r_{i,t} - E_{t-1}(r_{i,t}) = r_{i,t} - \mu - \beta r_{m,t} = \varepsilon_{i,t} \tag{2}$$

where $E_{t-1}(r_{i,t})$ denotes the expected return of stock i on trading day t based on available information on trading day $t-1$. The coefficient β (computed as $\frac{Cov(r_{i,t}, r_{m,t})}{Var(r_{m,t})}$) measures the linear response of $r_{i,t}$ to $r_{m,t}$, and μ is a constant.

Moreover, following French and Roll (1986), Engle et al. (2021) distinguished between private and public information to construct a component of returns due to public information and one due to the private processing of public information. They demonstrated that the conditional variance of $\varepsilon_{i,t}$ can be written as

$$Var\left(\varepsilon_{i,t}|_{i,t-1}, n_{i,t}, x_{i,t}\right) = \sigma_{i,t}^2 + \delta n_{i,t} \tag{3}$$

where $\varepsilon_{i,t-1}$ contains the history of firm i's stock return, and $x_{i,t}$ is a vector of exogenous information captured by $r_{m,t}$ (e.g., news related to the macroeconomy or the performance of the firm's industry). The vector $n_{i,t}$ indicates the arrival of various public information at t. $\sigma_{i,t}^2$ denotes the return variance component due to the private processing component of public information and is assumed to follow a GARCH (1,1) process:

$$\sigma_{i,t}^2 = \omega + \alpha\varepsilon_{i,t-1}^2 + \theta\sigma_{i,t-1}^2 \tag{4}$$

The realized counterpart of $Var\left(\varepsilon_{i,t}|\Omega_{i,t-1}, n_{i,t}, x_{i,t}\right)$ in Equation 3 is defined as the firm-specific realized variance $FV_{i,t}$, which is the idiosyncratic volatility measure that we use in this article. To be specific, we estimate it by

$$FV_{i,t} = RV_t^i - \beta_t^2 RV_t^{SPY} \text{ using } \beta_t = \frac{RCov_t^{i,SPY}}{RV_t^{SPY}} \tag{5}$$

where $RCov_t^{i,SPY}$ represent the covariance matrix between returns of stock i and the S&P 500 index (as represented by the SPY exchange-traded fund) within trading day t. RV_t^i and RV_t^{SPY} denote the realized variance of stock returns and the S&P 500 index, which are estimated by aggregating squared five-minute returns within trading day t.[13] β_t in Equation 5 can be interpreted as a realized beta.

Implied volatility. We start our calculation with implied volatilities of 30-day, at-the-money call and put options contained in the standardized option price files (*stdopd*) of the OptionMetrics database and denote them as $iVol^c$ and $iVol^p$, respectively. We then construct the daily implied volatility for each firm as the weighted average of call and put implied volatilities, (i.e., $iVol^c$ and $iVol^p$), where the weights are the daily trading volume of corresponding call and put options:

$$iVol_{i,t} = \left(\frac{N_{i,t}^c}{N_{i,t}^c + N_{i,t}^p} iVol_{i,t}^c + \frac{N_{i,t}^p}{N_{i,t}^c + N_{i,t}^p} iVol_{i,t}^p\right) \times 100 \tag{6}$$

where $iVol_{i,t}$ denotes the implied volatility of firm i on day t, and $iVol_{i,t}^c$ and $iVol_{i,t}^p$ denote the (annualized) implied volatilities from 30-day, at-the-money call and put options, respectively. $N_{i,t}^c$ and $N_{i,t}^c$ represent the trading volume of the 30-day, at-the-money call and put options of firm i on day t.[14]

[13] It can be shown that $FV_{i,t}$ is always positive.

[14] In contrast, Hassan et al. (2019) used firm-quarter-level implied volatility measured using 90-day, at-the-money options from the same data source, without identifying whether implied volatility value is volume-weighted averaged.

DATA

We extract from Standard and Poor's Global Intelligence (SPGI) database transcripts of earnings calls held in conjunction with an earnings release of firms listed in the United States from 2010 to 2019.[15] At the beginning of the earnings call, executives usually share the information they wish to emphasize regarding their firm's quarterly performance. Following that, typically there is a Q&A session with market participants (e.g., financial analysts). We also extract from transcript files other specific information, such as the Key Development ID (the unique SPGI identifier for the key development with which the transcript is associated), company name, company ticker, event time, and event type (including, e.g., earnings calls, M&A calls, and company conference presentations). In total, we processed transcripts from 844,028 events held by 12,657 firms listed in the United States from 2010 to 2019.

We extract the intraday data for each company's common stock from the NYSE Trade and Quote (TAQ) database during 2010–2019 to construct the measure of the idiosyncratic volatility, following Engle et al. (2021).[16] Because we use intraday data to compute the daily idiosyncratic volatility and certain earnings conference calls are held after stock market closes (4 p.m. Eastern standard time [EST]), following Alan, Engle, and Karagozoglu (2021), we include in our dataset only the earnings calls that are held before and during market hours (i.e., between 12:00 a.m. and 4:00 p.m. EST on trading days) to capture the immediate impact of the discussion of cybersecurity risk in earnings conference calls. Implied volatility data used to calculate our second volatility measure are downloaded from the OptionMetrics database.

We obtain the firm's fundamental information from the S&P Capital IQ database, including the market capitalization, leverage ratio, return on assets, beta (based on historical prices within a five-year range), short interest, and earnings surprise. In particular, our measure of earnings surprise is constructed as

$$Earnings\ Surprise = \left| \frac{Actual}{Estimate} - 1 \right| \tag{7}$$

where *Actual* refers to the earnings per share (EPS) reported in the earnings release corresponding to the conference call, and *Estimate* is the consensus estimate of EPS compiled by Capital IQ for the corresponding earnings call date. We combine the various datasets mentioned earlier based on company ID and the fiscal year-quarter time dimension to construct the panel dataset that we use in our empirical analysis, which includes 54,154 earnings call transcripts from 2,761 firms during the period of 2010–2019. We winsorize all variables at 1% and report the summary statistics in Exhibit 2, Panel A.

Exhibit 2, Panel A also presents the summary statistics of CRI constructed using seven training libraries, respectively.[17] We make two observations from the summary statistics. First, whichever library we use as the cybersecurity training library, there is large variation among firms in discussing cybersecurity risk during earnings conference calls, as can be seen from the large standard deviation (relative to mean) and the wide range (maximum minus minimum) of each index. For example, some firms never discuss risk related to cybersecurity issues (indicated by a zero CRI), whereas others spend relatively substantial time on it. Second, compared with *CRI-Law*, both

[15] We do not include the year 2020 in our analysis because the COVID-19 pandemic might greatly shift the focus of companies' discussions during earnings call conferences.

[16] Although the NYSE TAQ data are collected and disseminated by the NYSE, they include intraday trading information for all stocks listed on the NYSE, NASDAQ, and AMEX.

[17] Following Hassan et al. (2019), the CRI measures reported in Exhibit 2 are scaled by $\times 10^8$.

EXHIBIT 2
Summary Statistics

Panel A: Summary Statistics of Variables

Variables	Count	Mean	Std	Min	Max
Cybersecurity Risk Index					
CRI-Fin	51,632	6.640	38.322	0.000	1,451
CRI-Law	51,632	1.547	9.267	0.000	366
CRI-Tech	51,632	6.672	39.241	0.000	1,504
CRI-Fin&Law&Tech	51,632	4.824	28.205	0.000	1,075
CRI-Fin&Law	51,632	3.027	17.603	0.000	659
CRI-Fin&Tech	51,632	6.664	38.980	0.000	1,491
CRI-Law&Tech	51,632	4.510	26.488	0.000	1,011
Volatility					
Idiosyncratic Volatility (ln)	53,477	2.481	1.234	–0.630	5.471
Implied Volatility (ln)	47,005	3.501	0.464	2.644	4.831
Control Variables					
Market Cap	53,547	7.548	1.881	2.626	11.917
Leverage	54,031	0.291	0.225	0.000	0.960
ROA	53,404	3.506	9.354	–53.362	26.798
5-Yr Beta	51,607	1.212	0.649	–0.123	3.441
Short Interest	53,336	4.510	5.061	0.041	27.407
Earnings Surprise: |Act/Est-1|	50,747	0.814	0.907	0.020	7.850

Panel B: Summary Statistics of Cybersecurity Risk Indexes (*CRI-Fin* and *CRI-Fin&Law&Tech*) by Industry Sector

Industry Sector	Count	Mean	Std	Min	Max
Cyber Risk Index (*CRI-Fin*)					
Communication Services	1,995	1.006	13.053	0.000	458
Consumer Discretionary	7,204	1.047	10.328	0.000	515
Consumer Staples	1,997	6.241	44.434	0.000	1,059
Energy	4,931	2.228	16.488	0.000	570
Financials	8,242	30.135	83.534	0.000	1,451
Health Care	5,121	1.927	12.274	0.000	467
Industrials	9,173	2.59	18.332	0.000	527
Information Technology	4,498	2.946	18.821	0.000	380
Materials	3,380	0.832	6.734	0.000	133
Real Estate	3,679	1.477	9.784	0.000	226
Utilities	1,412	4.476	18.839	0.000	219
Cyber Risk Index (*CRI-Fin&Law&Tech*)					
Communication Services	1,995	0.684	9.548	0.000	335
Consumer Discretionary	7,204	0.773	7.738	0.000	385
Consumer Staples	1,997	4.683	33.32	0.000	796
Energy	4,931	1.6	12.366	0.000	432
Financials	8,242	21.84	61.35	0.000	1,075
Health Care	5,121	1.323	9	0.000	351
Industrials	9,173	1.898	13.78	0.000	397
Information Technology	4,498	2.212	13.907	0.000	285
Materials	3,380	0.589	5.018	0.000	100
Real Estate	3,679	1.09	7.348	0.000	170
Utilities	1,412	3.349	14.226	0.000	187

(continued)

EXHIBIT 2 *(continued)*

Summary Statistics

Panel C: Number of Earnings Call Transcripts and Firms by SPGI Industry Sector and Groups (2010–2019)

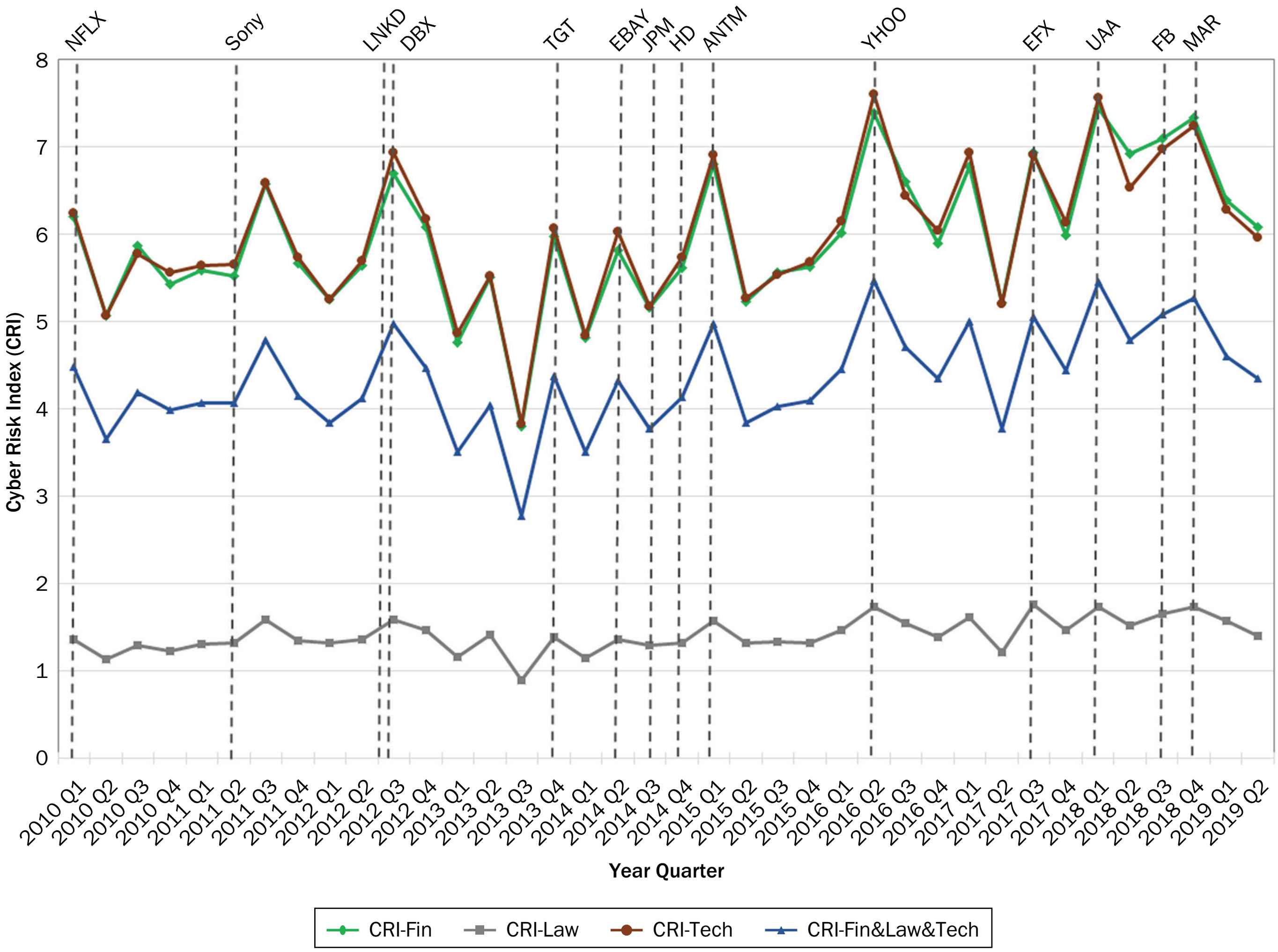
Industry Sectors (11), Industry Groups (24)	Number of Earnings Call Transcripts	Number of Firms
1. Communication Services	**2,130**	**127**
Media and Entertainment	1,522	97
Telecommunication Services	608	30
2. Consumer Discretionary	**7,729**	**372**
Automobiles and Components	906	40
Consumer Durables and Apparel	2,092	98
Consumer Services	1,861	107
Retailing	2,870	127
3. Consumer Staples	**2,069**	**96**
Food and Staples Retailing	361	17
Food, Beverage, and Tobacco	1,232	56
Household and Personal Products	476	23
4. Energy	**5,318**	**258**
Energy	5,318	258
5. Financials	**8,414**	**426**
Banks	3,307	164
Diversified Financials	3,360	186
Insurance	1,747	76
6. Health Care	**5,342**	**404**
Health Care Equipment and Services	2,699	151
Pharmaceuticals, Biotechnology, and Life Sciences	2,643	253
7. Industrials	**9,541**	**399**
Capital Goods	6,413	255
Commercial and Professional Services	1,814	83
Transportation	1,314	61
8. Information Technology	**4,712**	**297**
Semiconductors and Semiconductor Equipment	714	53
Software and Services	1,915	126
Technology Hardware and Equipment	2,083	118
9. Materials	**3,594**	**147**
Materials	3,594	147
10. Real Estate	**3,801**	**173**
Real Estate	3,801	173
11. Utilities	**1,504**	62
Utilities	1,504	62
Total	54,154	**2,761**

CRI-Fin and *CRI-Tech* have much greater means and standard deviations (more than four times as large as *CRI-Law*). This indicates that in discussing cybersecurity risk–related issues, firm executives and other earnings call participants tend to use words and phrases contained in finance- and technology-related texts more frequently than those in law-related texts. However, the difference between *CRI-Fin* and *CRI-Tech* is small: Their summary statistics reported in Exhibit 2 are very close in magnitude.

Exhibit 3 presents the quarterly averages of the cybersecurity risk indexes across all firms computed using different training libraries (*CRI-Fin*, *CRI-Law*, *CRI-Tech*, and *CRI-Fin&Law&Tech*), further illustrating that average levels of *CRI-Fin* and *CRI-Tech* are much higher than *CRI-Law* in each quarter, and their changes are more volatile over

EXHIBIT 3

Quarterly Average CRI across Firms (2010–2019)



time than *CRI-Law*. That said, changes among the three CRIs appear to be strongly correlated: When the quarterly average of one index increases (decreases), the other two tend to increase (decrease) as well. Although quarterly averages of *CRI-Fin* and *CRI-Tech* are close in magnitude in each quarter, their differences are noticeable. In certain quarters (e.g., 2012Q3 and 2012Q4), the value of *CRI-Fin* is larger than that of *CRI-Tech*, which indicates that firms tend to use words and phrases contained in finance-related texts more frequently, whereas in other quarters (e.g., 2010Q4 and 2011Q1) *CRI-Tech* is higher. The comparison among CRIs computed from different training libraries suggests that the choice of cybersecurity training library matters in measuring firm-level cybersecurity risk. In later analysis, we investigate whether the choice of training library affects the relationship between firm-level cybersecurity risk and volatility and find qualitatively similar results.

In addition to these data, we obtain records of disclosed corporate cybersecurity incidents from the website of the PRC, which has published 9,015 records of disclosed cybersecurity incidents in the United States during the period of 2005–2019, including names of targeted firms, dates of the incidents reported, the total number of records compromised, the ascribed cause of the incident, and the organization type of targeted firm.[18,19,20] In Exhibit 3, we highlight 14 cybersecurity incidents with 40 million or more records compromised during the period of 2010–2019, which includes incidents reported for Anthem (February 5, 2015), Dropbox (July 17, 2012), eBay (May 21, 2014), Equifax (September 7, 2017), Facebook (September 28, 2018), Home Depot (September 2, 2014), J.P. Morgan Chase (August 28, 2014), LinkedIn (June 6, 2012), Marriott International (November 30, 2018), Netflix (January 1, 2010), Sony PlayStation Network (April 27, 2011), Target (December 13, 2013), Under Armour (March 30, 2018), and Yahoo (September 22, 2016).[21] Exhibit 3 provides further support for our cybersecurity risk index measurement: For 12 out of 14 incidents, the quarterly average CRI across firms increases compared to the earlier quarter (regardless of which training libraries are used to measure cybersecurity risk), which indicates that our CRI is able to capture the increased attention paid to issues related to cybersecurity risk by corporate executives and other earnings call participants when a major cybersecurity incident is reported.

Exhibit 4 shows the total number of data breaches listed by PRC in each quarter over our sample period, grouped into three categories based on the total number of records compromised: incidents with less than 100,000 records compromised, 100,000 to 1 million, and more than 1 million. During the period of 2010Q1–2013Q3, the total number of incidents with less than 100,000 records exposed tends to be relatively stable, whereas the other two groups fluctuate more from quarter to quarter. During the period of 2013Q4–2016Q2, the total number of incidents with less than 100,000 records compromised shows a clear V shape, dropping rapidly before 2015Q3 and bouncing back quickly afterward, but total incidents in the other two categories show no clear pattern. In the remaining period of 2016Q3–2019Q3, the total number of incidents in all three groups increases significantly from 2016Q3 to around 2018Q2 and quickly drops to a relatively low level after 2018Q3.[22]

Exhibit 5 presents quarterly averages of *CRI-Fin* and *CRI-Fin&Law&Tech* during the period of 2010–2019 across all industries as well as 11 industry sectors classified by SPGI.[23] We make the following observations from Exhibit 5. First, CRI appears to be strongly correlated with the firm's industry. For example, financials firms have the highest level of cybersecurity risk–related discussion during their earnings call conferences among firms in all 11 SPGI industry sectors. Furthermore, CRI also finds that the financial industry has the largest fluctuation. CRIs in other industries, such as consumer staples, energy, and utilities, although lower than those in financials, are also relatively high. However, industries such as consumer discretionary, materials, and real estate tend to have the smallest cybersecurity risk discussions in earnings conference calls. In particular, although both financials and the health care industry are heavily regulated to protect customer data, there is a sharp contrast between their CRIs. Those differences across industries reflect that the amount of attention

[18] See https://privacyrights.org/data-breaches.

[19] PRC categorizes cyberattack causes into eight groups: unintended disclosure, hacking or malware, payment card fraud, insider, physical loss, portable device, stationary device, and unknown or other.

[20] Seven industry groups are used by PRC: nonprofit, health care, and medical providers, government and military, educational institutions, businesses—retail/merchant, businesses—financial and insurance services, and businesses—other.

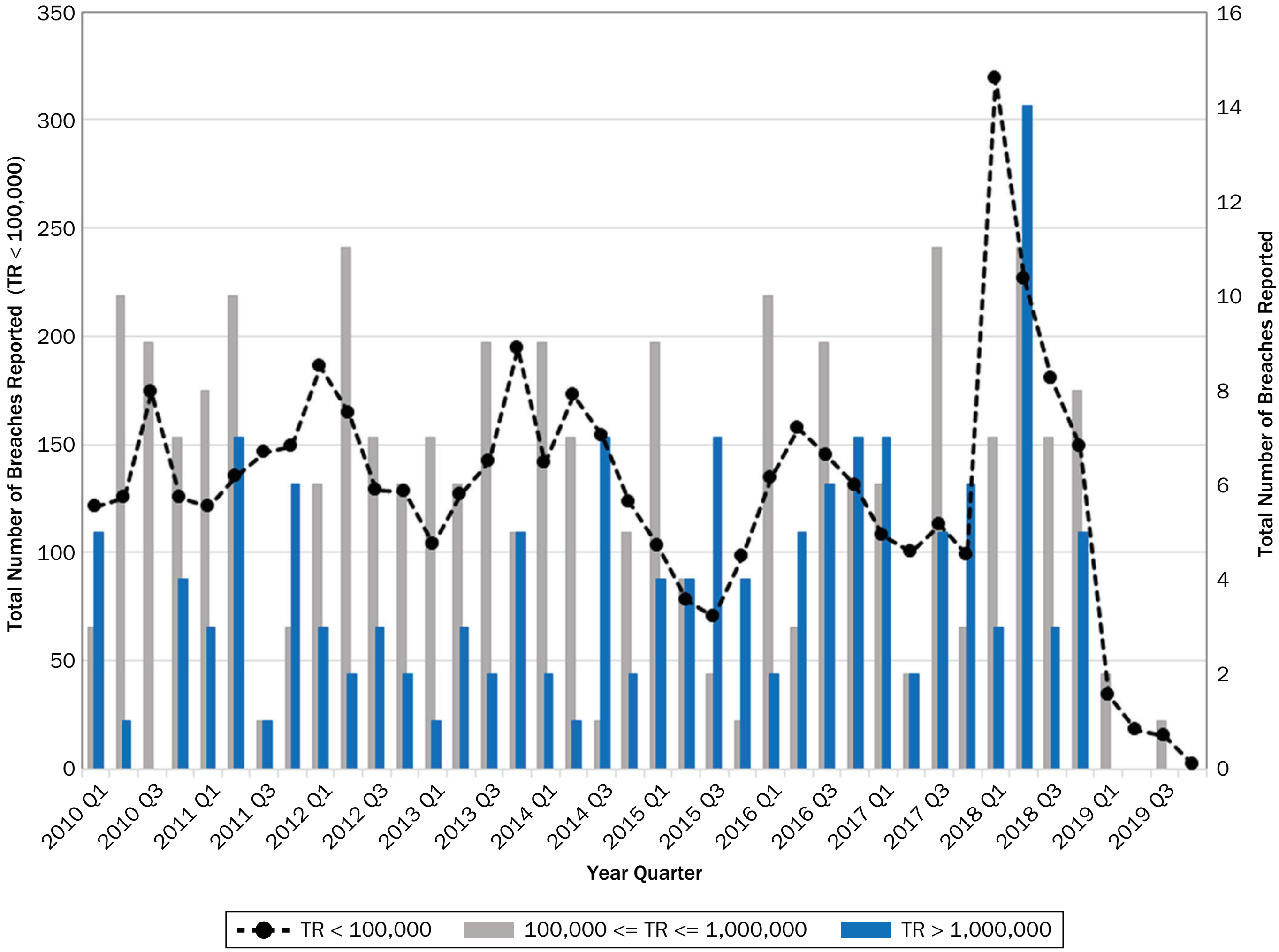
[21] A full list of 33 cybersecurity incidents with more than 40 million records compromised is shown in Exhibit A1, sorted by total number of records.

[22] The abrupt decrease in the number of reported cybersecurity incidents after 2018 is due to PRC no longer publishing on their website cybersecurity incidents after October 2019 and only reporting cybersecurity incidents targeting health care and medical providers in 2019.

[23] Although we only report the summary statistics of *CRI-Fin& Law&Tech* for 11 SPGI industry sectors in Panel B of Exhibit 1, summary statistics of all the other variables by industry sector are available upon request. Exhibit A2 identifies the different SPGI industry classifications (i.e., 11 industry sectors, 24 industry groups, and 69 industries).

EXHIBIT 4

Cybersecurity Incidents Reported by PRC (2010–2019)



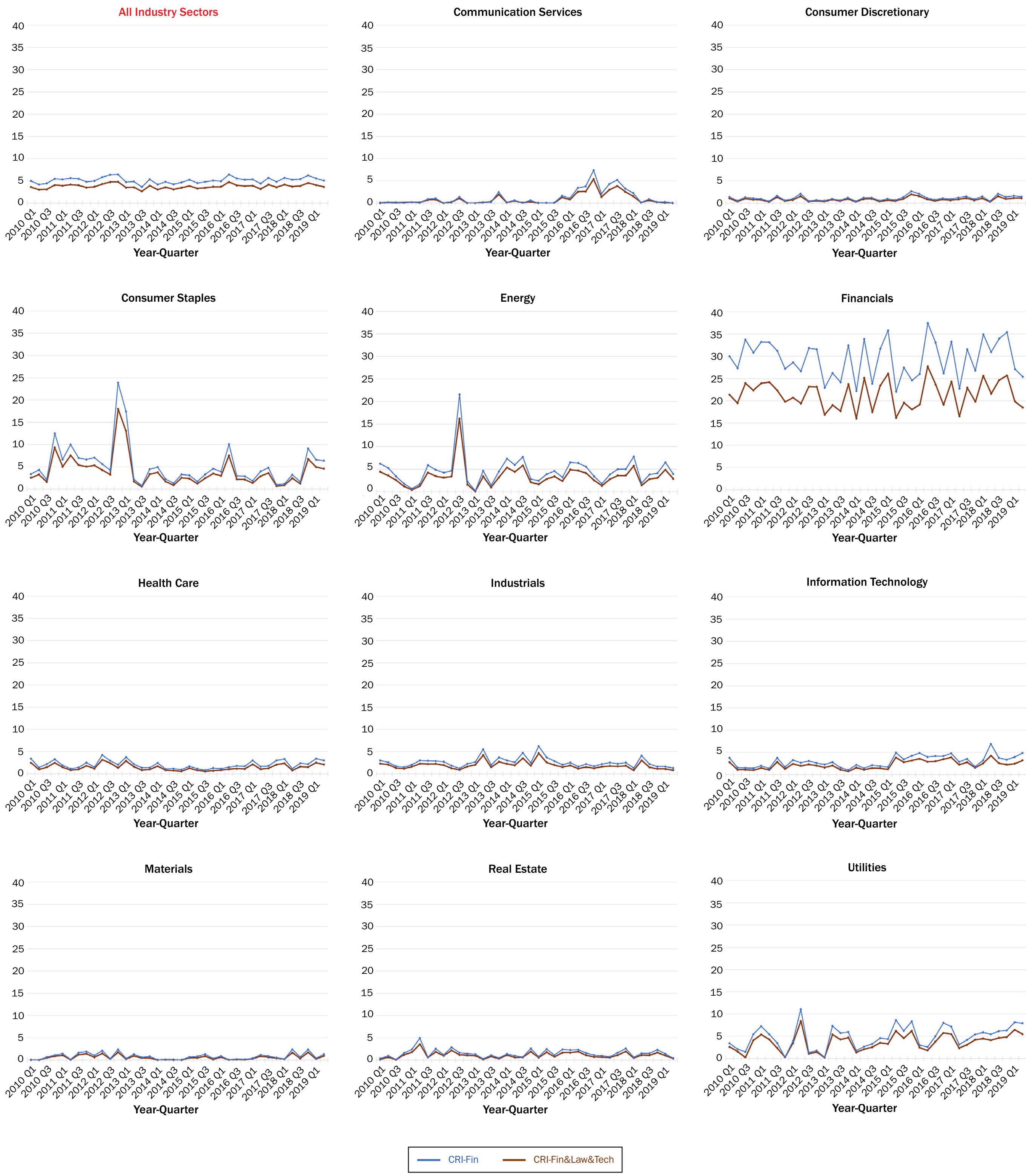
NOTE: This exhibit presents the total number of cybersecurity incidents reported under three categories based on the total records (TR) compromised: Incidents with fewer than 100,000 records compromised, 100,000 to 1 million, and more than 1 million.

paid to issues related to cybersecurity risk by corporate executives and other earnings call participants is dependent on industry characteristics. Similar results are reported in Exhibit 2, Panel B. More detailed information on the number of earnings conference calls transcripts and firms in our dataset by SPGI industry sector and group is presented in Exhibit 2, Panel C.

Second, there are important differences among the three industries with the highest CRI levels. The CRI in the financials industry is consistently higher than that in consumer staples and energy, and it fluctuates persistently in a relatively wider range over the sample period. However, the average CRIs of firms in consumer staples and energy have smaller fluctuations most of the time, except for one or two abrupt spikes in the first half of our sample period. This observation suggests that financial firms discuss cybersecurity risk more often during earnings conferences with varying depth over time, whereas firms in the other two industries discuss these issues in a less consistent manner.

EXHIBIT 5

CRI by SPGI Industry Sectors from 2010–2019



Third, in Exhibit 5, comparing *CRI-Fin* to *CRI-Fin&Law&Tech* over time, we notice that although the two measures move very similarly on average across all industries, we observe differences in sectors such as consumer staples and energy. For these two sectors, when there is an increased use of cybersecurity risk terms during earnings conferences, the spike is more pronounced for *CRI-Fin*, suggesting that at times of higher cybersecurity risk, executives are more likely to use finance-based cybersecurity risk terms rather than terms from law and technology topics. These differences show that the choice of training library matters in estimating cybersecurity risk from the language used in earnings calls. Therefore, our extensive collection of texts on three categories related to cybersecurity ensures our risk measures are more robust.

An advantage of our cybersecurity risk index is that, instead of focusing on ex post cybersecurity incidents only, our CRI captures the risks of potential cybersecurity incidents that may not have occurred yet. That is because firm managers and other earnings call participants may have more information regarding the potential cybersecurity risks their firms and industries may be encountering, regardless of whether an actual incident occurs. As a result, if they find that their firms are faced with high likelihood of potential cyberattacks, they are likely to discuss this issue during earnings calls and to invest in improving their firms' cybersecurity defenses, which in turn may reduce the actual occurrence of cybersecurity incidents.

Exhibit 6 exemplifies that advantage in comparison to PRC data by plotting the CRI (*CRI-Fin*, *CRI-Law,* and *CRI-Tech*) on each of the quarterly earnings call dates (from 2010 to 2019) for a sample of four firms and dates of notable cybersecurity incidents reported for these firms: eBay (May 21, 2014), Equifax (September 7, 2017), J.P. Morgan Chase (August 28, 2014), and Target (December 13, 2013). Although the data breach of eBay occurred on May 21, 2014, a sharp increase in CRI is observed almost a year before it was reported (2013Q2, 2013Q3, and 2013Q4). However, there are no discussions related to cybersecurity risk during earnings calls held in the three immediate quarters after it. In comparison, for Equifax, changes in CRI occurred after a cybersecurity incident was reported on September 7, 2017. In the case of J.P. Morgan Chase, the company discusses cybersecurity risk during almost all quarterly earnings calls over an extended period before and after August 28, 2014, when a notable incident was reported. Lastly, for Target, our CRIs do not detect discussions of cybersecurity risk–related matters during earnings calls within a window of five quarters around the incident.

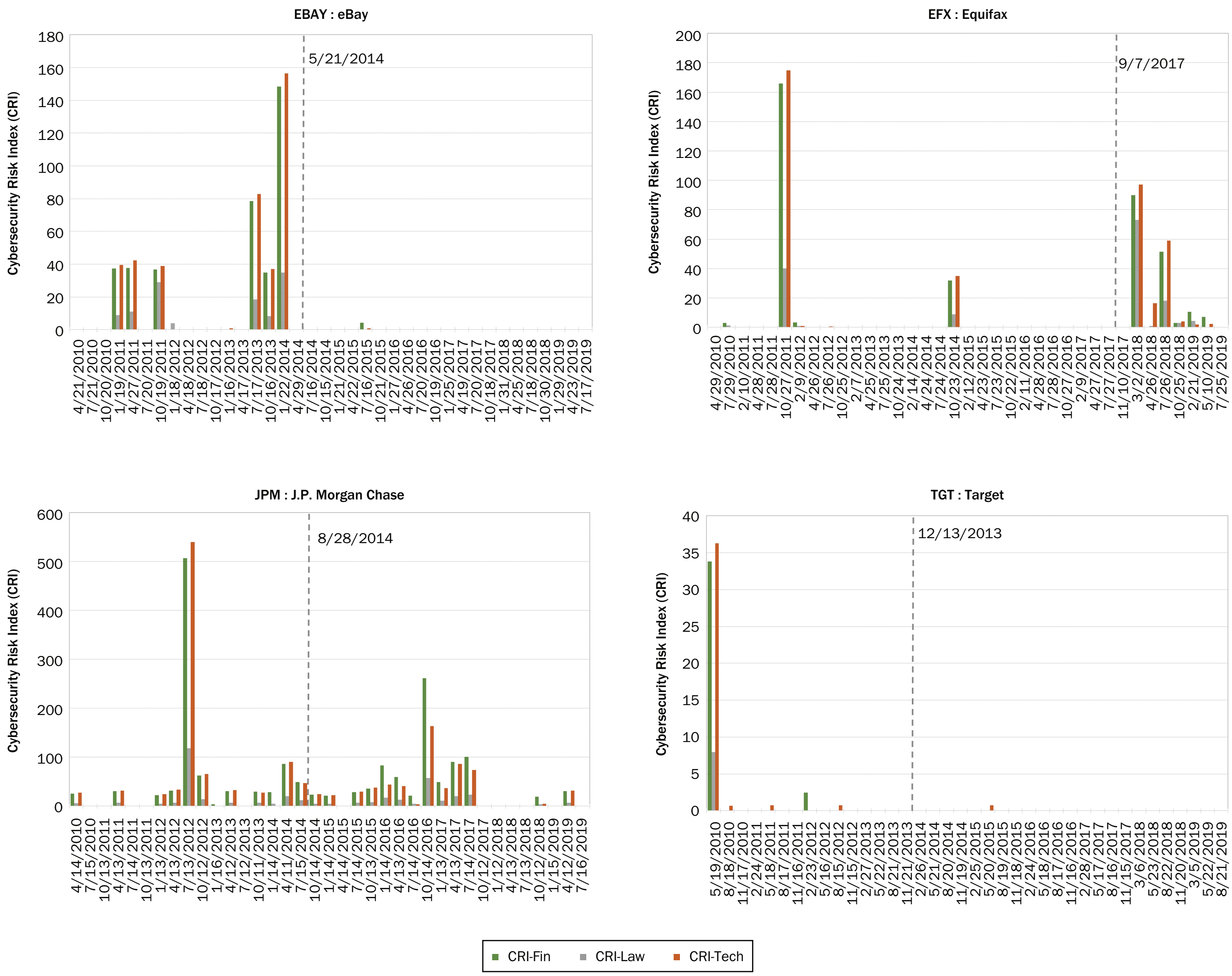
Exhibit 6 suggests that the information contained in the PRC data breach database is mixed, and the reporting dates may not reflect accurately the firm-level cybersecurity risk across time and industries. That might be because firm executives want to delay reporting of such negative news, or it might be because targeted firms are unable to detect non-ransomware attacks when they happen.

EMPIRICAL RESULTS

In this section, we investigate the relationship between firm-level volatility and our cybersecurity risk measure, CRI. As discussed in "Empirical Methodology," we use two measures of firm-level volatility: idiosyncratic volatility and implied volatility. We expect the coefficient of the idiosyncratic volatility to be larger than that of the implied volatility. Because idiosyncratic volatility is computed using intraday returns, it captures in a timely manner the arrival of new firm-specific information throughout a trading day, while that information (in our investigation, the discussion of cybersecurity risk in earnings calls) is being absorbed by the market. In contrast, implied volatility, which is computed from option prices at the end of a trading day, may only be able to partially capture the impact of firm-specific news; that is, some of the

EXHIBIT 6

CRI and Cybersecurity Incident Reporting Dates for Selected Firms



new information may have already been absorbed by prices during the trading day. Therefore, we expect CRI to be more highly correlated with idiosyncratic volatility than with implied volatility because it reflects changes in the language used to discuss cybersecurity-related matters during earnings conference calls.

To analyze the relationship between firm-level volatility and CRI, we estimate the following linear regression model:

$$y_{i,t} = \alpha_0 + \alpha_1 CRI_{i,t} + Controls_{i,t} + Industry_j + \lambda_t + u_{i,t} \quad (8)$$

where the dependent variable $y_{i,t}$ denotes the stock volatility of firm i at time t, and $y_{i,t}$ measures the volatility of the company's stock on the days that earnings calls are held. In our analysis, $y_{i,t}$ represents either (the natural log of) the idiosyncratic volatility, ln $(FV_{i,t})$, or (the natural log of) the implied volatility, ln$(iVol_{i,t})$. $CRI_{i,t}$ denotes the standardized cybersecurity risk index, and $Controls_{i,t}$ represents a linear combination of all relevant control variables that we include in our analysis. $u_{i,t}$ denotes the regression error term.

From our analysis of CRI in the earlier section, we observe that a firm's choice of language in discussing cybersecurity risk both matters—reflected in differences in CRIs—and is dependent on industry characteristics. Therefore, to control for the unobserved industry-specific characteristics that affect both stock volatility and CRI, we include industry fixed effects in our regression equation, denoted $Industry_j$ in Equation 8, where j represents the industry that firm i is in. We choose not to include firm fixed effects in our analysis because, as Exhibit 6 suggests, the discussion of cybersecurity-related issues is not consistent for the majority of firms, which results in discontinuity in CRI over time at the firm level. Therefore, including firm fixed effects does not truly reflect the relevant unobserved firm-specific factors that affect both CRI and volatilities. In our analysis later, we use various industry classifications by SPGI to capture industry fixed effects at different levels. Similarly, the time fixed effect, denoted λ_t in Equation 8, is included to capture the time-dependent unobserved variation that might affect the realization of both daily volatility and CRI.

We use the Stata package *reghdfe* developed by Correia (2016) to estimate the parameters in our regression equation.[24] The package *reghdfe*, which is a generalization of *areg* and *xtreg* Stata packages, enables us to estimate linear and instrumental-variable regressions with multiple levels of fixed effects absorbed. We use heteroskedasticity-consistent standard errors (the White standard errors) to test the statistical significance of our coefficient estimates.

Among the control variables ($Controls_{i,t}$), we first control for the size of the firm by including the market capitalization (*Market Cap*) of firm i at time t. Large and well-known firms appear to be more likely to be attacked (Exhibit 4); therefore, they might pay more attention to cybersecurity risk. Furthermore, cybersecurity incidents reported by large firms tend to have a more significant impact on the market than those reported by small firms; consequently, investors in larger firms respond more promptly to the reporting, which leads to larger changes in volatility. We also include leverage ratios (*Leverage*) and return on assets (*ROA*) to capture the effects of the firm's capital structure and its profitability.

To control for possible marketwide impact of risk factors that may be incorporated in firm-level volatilities, we include in our regression the five-year beta to proxy for systematic shocks. Studies such as those by Garg (2020), Kamiya et al. (2021), Jeong, Lee, and Lim (2019), and Chen et al. (2012) suggest that the impact of cybersecurity incidents is not limited to targeted firms but also spills over to competitors and related industries. Jiang, Khanna, and Yang (2020) found that firm-level cybersecurity risk influences investors' portfolio choices, and institutional investors tend to sell stocks with high cybersecurity risk and buy those with low risk.

We also include the short interest and earnings surprise as additional controls to capture other possible information contained in earnings conference calls that might affect the firm-level volatility, which may not be related to cybersecurity risk issues per se. For example, Bao et al. (2019) found that managers tend to withhold bad news in general by detecting a negative relationship between bad-news disclosure and residual short interest. In addition, because institutional investors tend to sell stocks with high cybersecurity risk and buy stocks with low risk (Jiang, Khanna, and Yang 2020), we are also able to control for this effect by incorporating short interest as another control variable for institutions that are major players in short-selling.

If firm executives devote more time to reviewing the firm's financial performance, less time may be spent on discussing cybersecurity-related issues. To control for the impact of non–cybersecurity-related new information from earnings calls on volatility, we include earnings surprise (Equation 7) as another control variable (Lei, Wang, and

[24] See http://scorreia.com/software/reghdfe/.

EXHIBIT 7

Cybersecurity Risk Index and Firm-Level Volatility

	Panel A: Idiosyncratic Volatility (FV)				Panel B: Implied Volatility (iVol)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CRI-Fin	1.313***				0.352**			
	[3.03]				[2.20]			
CRI-Law		1.239***				0.351**		
		[2.84]				[2.20]		
CRI-Tech			1.206***				0.375**	
			[2.80]				[2.35]	
CRI-Fin&Law&Tech				1.210***				0.370**
				[2.80]				[2.32]
Market Cap	–0.255***	–0.255***	–0.255***	–0.255***	–0.145***	–0.145***	–0.145***	–0.145***
	[–87.44]	[–87.43]	[–87.43]	[–87.43]	[–145.59]	[–145.59]	[–145.60]	[–145.60]
Leverage	–0.330***	–0.330***	–0.330***	–0.330***	–0.013*	–0.013*	–0.013*	–0.013*
	[–15.01]	[–15.00]	[–15.00]	[–15.00]	[–1.72]	[–1.71]	[–1.72]	[–1.72]
ROA	–0.003***	–0.003***	–0.003***	–0.003***	–0.007***	–0.007***	–0.007***	–0.007***
	[–5.99]	[–6.00]	[–6.00]	[–6.00]	[–33.39]	[–33.38]	[–33.38]	[–33.38]
5-Yr Beta	0.305***	0.305***	0.305***	0.305***	0.142***	0.142***	0.142***	0.142***
	[40.61]	[40.61]	[40.61]	[40.61]	[53.91]	[53.92]	[53.92]	[53.92]
Short Interest	0.036***	0.036***	0.036***	0.036***	0.008***	0.008***	0.008***	0.008***
	[43.01]	[43.00]	[43.00]	[43.00]	[25.52]	[25.51]	[25.52]	[25.52]
Earnings Surprise: |Act/Est-1|	0.028***	0.028***	0.028***	0.028***	0.036***	0.036***	0.036***	0.036***
	[5.09]	[5.09]	[5.10]	[5.10]	[17.63]	[17.63]	[17.64]	[17.64]
Intercept	3.957***	3.957***	3.956***	3.956***	4.428***	4.428***	4.428***	4.428***
	[136.98]	[136.97]	[136.98]	[136.98]	[445.65]	[445.71]	[445.70]	[445.69]
SPGI-Industry Sector-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.457	0.457	0.457	0.457	0.598	0.598	0.598	0.598
Adj-within R^2	0.303	0.303	0.303	0.303	0.519	0.519	0.519	0.519
N	45,944	45,944	45,944	45,944	41,771	41,771	41,771	41,771

NOTE: *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Yan 2020). All control variables are winsorized at the 1% level and standardized in our empirical analysis.

Exhibit 7, Panel A reports the estimation results of regression Equation 8, in which we use the idiosyncratic volatility, $\ln(FV_{i,t})$, as the dependent variable. Columns 1 to 4 present results for models using four cybersecurity risk indexes based on training library categories: *CRI-Fin*, *CRI-Law*, *CRI-Tech*, and *CRI-Fin&Law&Tech*. To control for industry fixed effects, we use the industry sector classification by SPGI, which classifies firms into 11 sectors. Time fixed effects are controlled for at the quarter level.

The coefficients of CRI in all four columns of Exhibit 7, Panel A are positive and statistically significant at the 1% level.[25] Estimated coefficients of all our control variables are statistically significant at the 1% level and have the expected

[25] To show the differences in results more clearly, coefficient estimates of CRI are scaled by ×102 in Exhibits 7–9.

signs (e.g., larger earnings surprises and short interest are associated with higher volatility).[26] After controlling for other factors, we find that firm-level cybersecurity risk is positively correlated with the idiosyncratic volatility on the days that earnings call conferences are held. In other words, the discussion of issues related to cybersecurity risk by executives and other earnings conference call participants tends to increase the component of the volatility that responds only to firm-specific news. In addition, although the CRI coefficients vary both numerically and statistically in all four columns, they are close in magnitude (as are their corresponding *t*-statistics). Therefore, although the choice of training library affects the estimated coefficient of CRI on volatility (and is largest for *CRI-Fin*), the overall impact of cybersecurity risk on idiosyncratic volatility is robust in its measurement using language of earnings call discussions.

In comparison, we report in Exhibit 7, Panel B the estimation results of Equation 8 using implied volatility, $\ln(iVol_{i,t})$, as the dependent variable instead of the idiosyncratic volatility. Compared with Panel A, coefficient estimates of CRI are smaller in magnitude, which is consistent with our expectations. All control variables except *Leverage* retain the same sign and statistical significance in Panel B as in Panel A.

We focus on four cybersecurity risk indexes in Exhibit 7, *CRI-Fin*, *CRI-Law*, *CRI-Tech*, and *CRI-Fin&Law&Tech*, which are constructed using training libraries containing texts in the subject categories of finance, law, technology, and the combination of all three categories, respectively. As a further robustness check, Exhibit 8 presents results from estimations using CRIs computed from three alternative cybersecurity training libraries: the combinations of finance and law, finance and technology, and law and technology subject categories. Consistent with findings presented in Exhibit 7, we find in Exhibit 8 that cybersecurity risk remains positively and statistically significantly related to the idiosyncratic volatility as well as the implied volatility on the days that earnings conference calls are held. Results in Exhibit 8 provide further evidence that the positive relationship between firm-level cybersecurity risk and volatility is robust to the choice of training libraries in constructing our proposed cybersecurity risk measure.

We use the SPGI industry sector categories to capture industry fixed effects in Exhibits 7 and 8, which assigns firms into 11 relatively broad industry sectors: communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate, and utilities. To exclude the possibility that results in Exhibits 7 and 8 are mainly driven by the choice of the particular industry classification to control for industry fixed effects, we use two alternative industry classifications provided by the SPGI: SPGI industry group and SPGI industry categories, which group firms into finer industry classes. In Exhibit A2, we present detailed information on the nesting relationship between SPGI industry sector, industry group, and industry categories. The SPGI industry group classification assigns firms into 24 groups, whereas the SPGI industry classification has 69 categories; for example, industry sector "Communication Services" contains the "Media and Entertainment" group that nests "Entertainment," "Interactive Media and Services," and "Media" categories, and the "Telecommunication Services" group nests "Diversified Telecommunication Services" and "Wireless Telecommunication Services" categories.

We report in Exhibit 9 estimation results of Equation 8 using SPGI industry group (Part 1) and SPGI industry (Part 2) classifications to control the industry fixed effects. We find that with finer industry classifications, coefficient estimates of CRI remain

[26] We find in Exhibit 7 that the estimated coefficient of the leverage ratio is negative and statistically significant at the 1% level, suggesting higher leverage is negatively correlated to firm-level idiosyncratic risk. The negative leverage effect on stock volatility has been documented in the literature (e.g., Brandt et al. 2010; Chun et al. 2008; and Wei and Zhang 2006).

EXHIBIT 8

Robustness Check for Training Libraries

	Panel A: Idiosyncratic Volatility (FV)			Panel B: Implied Volatility (iVol)		
	(1)	(2)	(3)	(1)	(2)	(3)
CRI-Fin&Law	1.265***			0.351**		
	[2.91]			[2.20]		
CRI-Fin&Tech		1.223***			0.372**	
		[2.84]			[2.33]	
CRI-Law&Tech			1.192***			0.372**
			[2.76]			[2.33]
Market Cap	–0.255***	–0.255***	–0.255***	–0.145***	–0.145***	–0.145***
	[–87.43]	[–87.43]	[–87.43]	[–145.59]	[–145.60]	[–145.60]
Leverage	–0.330***	–0.330***	–0.330***	–0.013*	–0.013*	–0.013*
	[–15.01]	[–15.00]	[–15.00]	[–1.72]	[–1.72]	[–1.72]
ROA	–0.003***	–0.003***	–0.003***	–0.007***	–0.007***	–0.007***
	[–5.99]	[–6.00]	[–6.00]	[–33.38]	[–33.38]	[–33.38]
5-Yr Beta	0.305***	0.305***	0.305***	0.142***	0.142***	0.142***
	[40.61]	[40.61]	[40.61]	[53.92]	[53.92]	[53.92]
Short Interest	0.036***	0.036***	0.036***	0.008***	0.008***	0.008***
	[43.00]	[43.00]	[43.00]	[25.52]	[25.52]	[25.52]
Earnings Surprise: |Act/Est-1|	0.028***	0.028***	0.028***	0.036***	0.036***	0.036***
	[5.09]	[5.10]	[5.10]	[17.63]	[17.64]	[17.64]
Intercept	3.957***	3.956***	3.956***	4.428***	4.428***	4.428***
	[136.97]	[136.98]	[136.98]	[445.68]	[445.69]	[445.71]
SPGI-Industry Sector-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter-FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.457	0.457	0.457	0.598	0.598	0.598
Adj-within R^2	0.303	0.303	0.303	0.519	0.519	0.519
N	45,944	45,944	45,944	41,771	41,771	41,771

NOTES: This exhibit reports estimation results of regression Equation 8 using three additional proxies for cybersecurity risk, *CRI-Fin&Law*, *CRI-Fin&Tech*, and *CRI-Law&Tech*, which are constructed using the combinations of finance and law training libraries, finance and technology libraries, and law and technology libraries. The dependent variable in Panel A is (the natural log of) the idiosyncratic volatility (measured by firm-specific realized variance, or FV) on the days that earnings conference calls are held, and that in Panel B is the (the natural log of) the implied volatility (iVol). All explanatory variables, including CRI, are standardized after being winsorized at 1%. We include market size (market capitalization, or Market Cap), leverage ratio (Leverage), profitability (ROA), five-year beta, short interest, and earnings surprise to control for other variables that might be correlated with firm-level volatilities. Industry and time (year-quarter) fixed effects are also controlled for in all columns. We use heteroskedasticity-consistent standard errors to compute the *t*-values (reported in brackets under coefficient estimates). *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

positively correlated to both idiosyncratic volatility (Panels A and C) and implied volatility (Panels B and D). In addition, all coefficient estimates of CRI are statistically significant at the 5% level.[27,28]

[27] When using idiosyncratic volatility as the dependent variable, we notice a slight drop in the magnitude and statistical significance of CRI coefficients as industry classification gets finer. That is because a finer industry classification is able to capture more firm-specific factors on idiosyncratic volatilities, which in turn partials out a larger fraction of the firm-specific impact of CRI on idiosyncratic volatility.

[28] Although not reported in the article, we also estimate Equation 8 with firm fixed effects (in place of industry fixed effects) while still controlling for year-quarter time fixed effects. However, the relationship between CRI and FV does not appear to be significant at the firm level. The possible reason may be, as Exhibit 6 suggests, the lack of uniform cybersecurity risk disclosure requirements mandated by regulators; discussion of cybersecurity-related issues is largely voluntary and not consistent over time for most firms, making the CRI at the firm level discontinuous over time. Therefore, estimations using firm fixed effects may not truly capture the relevant unobserved firm-specific factors that affect both CRI and volatilities.

EXHIBIT 9

Robustness Check for Industry Classifications

Part 1: Industry Classification—SPGI Industry Group (24 Categories)

	Panel A: Idiosyncratic Volatility (FV)				Panel B: Implied Volatility (iVol)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CRI-Fin	1.174***				0.397**			
	[2.70]				[2.51]			
CRI-Law		1.148***				0.408***		
		[2.62]				[2.59]		
CRI-Tech			1.078**				0.407**	
			[2.49]				[2.57]	
CRI-Fin&Law&Tech				1.082**				0.407***
				[2.49]				[2.58]
Market Cap	–0.259***	–0.259***	–0.259***	–0.259***	–0.147***	–0.147***	–0.147***	–0.147***
	[–88.22]	[–88.21]	[–88.21]	[–88.21]	[–148.56]	[–148.58]	[–148.58]	[–148.57]
Leverage	–0.252***	–0.251***	–0.251***	–0.251***	–0.001	–0.001	–0.001	–0.001
	[–11.09]	[–11.07]	[–11.08]	[–11.08]	[–0.10]	[–0.09]	[–0.10]	[–0.10]
ROA	–0.003***	–0.003***	–0.003***	–0.003***	–0.006***	–0.006***	–0.006***	–0.006***
	[–4.25]	[–4.25]	[–4.26]	[–4.26]	[–26.49]	[–26.49]	[–26.49]	[–26.49]
5-Yr Beta	0.308***	0.308***	0.308***	0.308***	0.139***	0.139***	0.139***	0.139***
	[40.27]	[40.28]	[40.28]	[40.28]	[51.86]	[51.86]	[51.86]	[51.86]
Short Interest	0.035***	0.035***	0.035***	0.035***	0.007***	0.007***	0.007***	0.007***
	[41.55]	[41.55]	[41.55]	[41.55]	[22.27]	[22.27]	[22.27]	[22.27]
Earnings Surprise:								
|Act/Est-1|	0.027***	0.027***	0.027***	0.027***	0.035***	0.035***	0.035***	0.035***
	[4.92]	[4.92]	[4.93]	[4.93]	[17.29]	[17.29]	[17.30]	[17.30]
Intercept	3.963***	3.963***	3.962***	3.962***	4.443***	4.443***	4.443***	4.443***
	[136.69]	[136.68]	[136.69]	[136.68]	[447.43]	[447.51]	[447.50]	[447.49]
SPGI-Industry Group-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.460	0.460	0.460	0.460	0.607	0.607	0.607	0.607
Adj-within R^2	0.301	0.301	0.301	0.301	0.512	0.512	0.512	0.512
N	45,944	45,944	45,944	45,944	41,771	41,771	41,771	41,771

Part 2: Industry Classification—SPGI Industry (69 Categories)

	Panel C: Idiosyncratic Volatility (FV)				Panel D: Implied Volatility (iVol)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CRI-Fin	1.001**				0.346**			
	[2.33]				[2.22]			
CRI-Law		0.995**				0.357**		
		[2.30]				[2.30]		
CRI-Tech			0.912**				0.355**	
			[2.14]				[2.28]	
CRI-Fin&Law&Tech				0.915**				0.356**
				[2.14]				[2.28]

(continued)

EXHIBIT 9 *(continued)*

Robustness Check for Industry Classifications

	Panel C: Idiosyncratic Volatility (FV)				Panel D: Implied Volatility (iVol)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Market Cap	–0.255***	–0.255***	–0.255***	–0.255***	–0.148***	–0.148***	–0.148***	–0.148***
	[–84.59]	[–84.59]	[–84.60]	[–84.59]	[–144.59]	[–144.61]	[–144.61]	[–144.60]
Leverage	–0.094***	–0.093***	–0.094***	–0.094***	0.047***	0.047***	0.047***	0.047***
	[–3.88]	[–3.86]	[–3.87]	[–3.87]	[5.77]	[5.78]	[5.77]	[5.77]
ROA	–0.004***	–0.004***	–0.004***	–0.004***	–0.006***	–0.006***	–0.006***	–0.006***
	[–6.11]	[–6.11]	[–6.12]	[–6.11]	[–24.72]	[–24.72]	[–24.72]	[–24.72]
5-Yr Beta	0.276***	0.276***	0.276***	0.276***	0.134***	0.134***	0.134***	0.134***
	[35.32]	[35.32]	[35.33]	[35.32]	[49.43]	[49.43]	[49.43]	[49.43]
Short Interest	0.034***	0.034***	0.034***	0.034***	0.006***	0.006***	0.006***	0.006***
	[39.88]	[39.87]	[39.87]	[39.87]	[19.04]	[19.04]	[19.04]	[19.04]
Earnings Surprise:								
|Act/Est-1|	0.019***	0.019***	0.019***	0.019***	0.029***	0.029***	0.029***	0.029***
	[3.32]	[3.33]	[3.34]	[3.33]	[14.42]	[14.42]	[14.42]	[14.42]
Intercept	3.942***	3.942***	3.941***	3.941***	4.451***	4.451***	4.451***	4.451***
	[132.99]	[132.98]	[133.00]	[132.99]	[438.56]	[438.67]	[438.64]	[438.63]
SPGI-Industry-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.474	0.474	0.474	0.474	0.620	0.620	0.620	0.620
Adj-within R^2	0.274	0.274	0.274	0.274	0.488	0.488	0.488	0.488
N	45,944	45,944	45,944	45,944	41,771	41,771	41,771	41,771

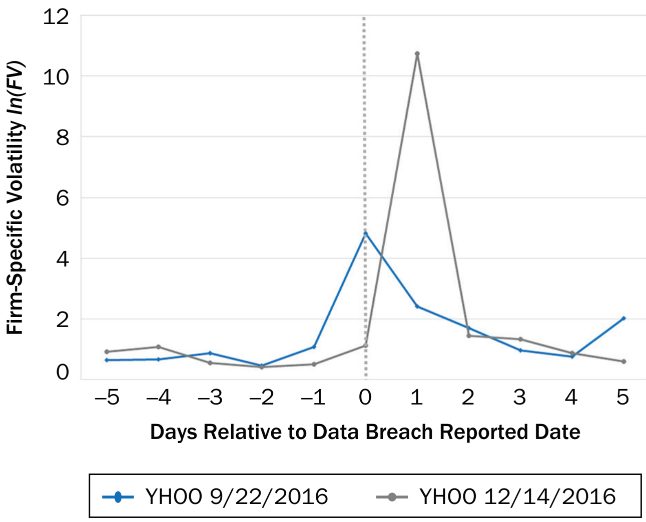
NOTES: This exhibit reports estimation results of Equation 8 using two alternative industry classifications, SPGI industry groups (24 categories, Part 1) and SPGI industry classification (69 categories, Part 2). Variables *CRI-Fin*, *CRI-Law*, *CRI-Tech*, and *CRI-Fin&Law&Tech* represent the cybersecurity risk indexes calculated using four training libraries, respectively: finance, law, technology, and the combination of the three. The dependent variable in Panels A and C is (the natural log of) the idiosyncratic volatility (measured by firm-specific realized variance, or FV) on the days that earnings conference calls are held, and that in Panels B and D is the (the natural log of) the implied volatility (iVol). All explanatory variables, including CRI, are standardized after being winsorized at 1%. We include market size (market capitalization, or Market Cap), leverage ratio (Leverage), profitability (ROA), 5-year beta, short interest, and earnings surprise to control for other variables that might be correlated with firm-level volatilities. Industry and time (year-quarter) fixed effects are also controlled for in all columns. We use heteroskedasticity-consistent standard errors to compute the *t*-values (reported in brackets under coefficient estimates). *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

To investigate the change in idiosyncratic volatility on the days that a cybersecurity incident was reported in the PRC data breaches list, we select 10 incidents that caught much media attention: eBay (May 21, 2014), Equifax (September 7, 2017), Home Depot (September 2, 2014), J.P. Morgan Chase (August 28, 2014), LinkedIn (June 6, 2012 and May 17, 2016), Netflix (January 1, 2010), Target (December 13, 2013), and Yahoo (September 22, 2016 and December 14, 2016), which are indicated to have had 40 million or more records compromised. Using Yahoo, which was breached twice over our sample period, as an example, we plot in Exhibit 10 idiosyncratic volatility within a five-day event window around the reporting of the incident. Exhibit 10 shows the jump in idiosyncratic volatility on day(0) (i.e., September 22, 2016, when the cybersecurity incident was reported in the media before the opening of the stock market).[29] Because the cybersecurity incident dated December 14, 2016 was reported in the media after the

[29] "Yahoo is expected to confirm a massive data breach, impacting hundreds of millions of users," reported at 2:18 a.m. on September 22, 2016 on tech news site Recode (https://www.vox.com/2016/9/22/13012836/yahoo-is-expected-to-confirm-massive-data-breach-impacting-hundreds-of-millions-of-users) and referenced in *The New York Times* on the next day (https://www.nytimes.com/2016/09/23/technology/yahoo-hackers.html).

EXHIBIT 10

Changes in Idiosyncratic Volatility of Yahoo, Inc., within a Five-Day Event Window around Its Reported Cybersecurity Incidents in 2016



market closed on that date, in Exhibit 10 we observe the jump in Yahoo's idiosyncratic volatility on day(1) (i.e., December 15, 2016), which is the next trading day following reporting.[30]

Exhibit 11 presents the daily idiosyncratic volatilities within a five-day event window for all 10 cybersecurity incidents, with day(0) being the reported date of the breach contained in the PRC database. The numbers reported in brackets represent *p*-values of the difference between the idiosyncratic volatility on each day from day(0) to day(5) and the five-day average of idiosyncratic volatilities before the event was reported. First, Exhibit 11 shows that there is a statistically significant increase in idiosyncratic volatility for most cybersecurity incidents (7 out of 10). Second, we observe that increases in idiosyncratic volatility tend to last for at least a few days following the reported incidents. For example, the increase in idiosyncratic volatility for Equifax and Home Depot stay strong and significant even after five days following their reported data breaches. The increase in idiosyncratic volatility for Netflix persisted for four days after the incident was reported, and that of Yahoo persisted for three days.

However, we may need to be cautious when interpreting the results of the univariate analysis presented in Exhibit 11. Although an increase in idiosyncratic volatilities suggests that market participants react to the reporting of cybersecurity incidents, it does not fully and accurately reveal the relationship between firm-level volatility and cybersecurity risk a priori. Therefore, relying on our results from an analysis of a panel dataset of 54,154 earnings call transcripts of 2,761 US firms over a 10-year period, we believe that our proposed CRI, which is based on language used during earnings conference calls, is a viable measure to investigate firm-level cybersecurity risk and volatility.

CONCLUSION

Cybersecurity has been identified to be among significant risk factors that are of concern to financial market participants, including regulators, investors, and managers of public firms. Although many firms have taken various measures to protect themselves from being breached, recent events indicate that cybersecurity vulnerabilities persist. Different from the current literature, we do not focus on disclosed cyberattack incidents only. Instead, we propose a new measure of firm-level cybersecurity risk by adopting the methodology of Hassan et al. (2019), who used it to calculate political risk. Specifically, we analyze the transcripts of (quarterly) earnings conference calls of public companies using textual analysis and employ a pattern-based sequence-classification method from computational linguistics to determine the proportion of time devoted to issues related to cybersecurity risk during these calls.

[30] A quotation from a Reuters article (Roumeliotis and Toonkel 2016) published at 10:38 a.m. on Thursday, December 15, 2016: "Shares of the Sunnyvale, California-based internet pioneer fell more than 6 percent after it announced the breach of data belonging to more than 1 billion users late on Wednesday." This was reported at 6:27 p.m. on Wednesday, December 14, 2016 on information technology site Wired (Newman 2016).

EXHIBIT 11

Idiosyncratic Volatility around the Reported Breaches for Selected Firms

Ticker	Breach Report Date Day(0)	Daily FV before Breach Reported					Reported	Daily FV after Breach Reported				
		Day(−5)	Day(−4)	Day(−3)	Day(−2)	Day(−1)	Day(0)	Day(1)	Day(2)	Day(3)	Day(4)	Day(5)
EBAY	May 21 2014	0.528	0.723	2.037	0.432	0.478	1.33*	0.795	0.399	0.4	1.557***	0.974
							[0.053]	[0.558]	[0.927]	[0.926]	[0.009]	[0.329]
EFX	September 7, 2017	0.337	0.647	0.479	0.486	0.215	0.685***	27.085***	8.813***	7.624***	26.564***	54.098***
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
HD	September 2, 2014	0.399	0.283	0.134	0.459	0.201	4.083***	1.339***	0.764***	0.495***	0.41**	0.583***
							[0.000]	[0.000]	[0.000]	[0.000]	[0.028]	[0.000]
JPM	August 28, 2014	0.431	0.374	0.587	0.261	0.204	0.306	0.174	0.252	0.474*	0.445	0.3
							[0.834]	[0.998]	[0.963]	[0.064]	[0.137]	[0.857]
LNKD	June 6, 2012	5.831	10.524	2.932	8.617	4.819	6.228	3.29	4.077	3.24	3.917	3.533
							[0.593]	[0.992]	[0.966]	[0.993]	[0.974]	[0.987]
LNKD	May 17, 2016	3.124	3.888	3.761	2.193	2.151	6.979***	2.392	2.538	2.776	1.738	1.11
							[0.000]	[0.956]	[0.905]	[0.748]	[0.999]	[0.999]
NFLX	January 1, 2010	1.299	1.567	0.752	1.964	1.814	4.852***	12.956***	12.456***	3.59***	3.676***	1.521
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.423]
TGT	December 13, 2013	1.368	0.774	0.628	0.445	0.600	0.769	0.407	0.616	0.953	1.018*	0.44
							[0.484]	[0.987]	[0.821]	[0.117]	[0.055]	[0.978]
YHOO	September 22, 2016	0.646	0.677	0.878	0.452	1.079	4.817***	2.415***	1.703***	0.963**	0.768	2.012***
							[0.000]	[0.000]	[0.000]	[0.022]	[0.418]	[0.000]
YHOO	December 14, 2016	0.918	1.085	0.541	0.409	0.499	1.133***	10.741***	1.452***	1.338***	0.872*	0.596
							[0.000]	[0.000]	[0.000]	[0.000]	[0.084]	[0.764]

NOTES: This exhibit presents daily idiosyncratic volatilities within a five-day event window for 10 cybersecurity incidents that caught much media attention: eBay, Equifax, Home Depot, J.P. Morgan Chase, LinkedIn, Netflix, Target, and Yahoo. The numbers reported in brackets represent *p*-values of the difference between the idiosyncratic volatility on that day and the five-day average of idiosyncratic volatility before the incidents were disclosed. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

SOURCE: Privacy Rights Clearinghouse Cybersecurity Database.

Using our firm-specific cybersecurity risk measure, we investigate the relationship between firm-level return volatility and cybersecurity risk. Our main volatility measure is intraday return-based idiosyncratic volatility that measures changes in return volatility responding only to the arrival of firm-specific news (in contrast to news that has marketwide effects). We adopt a new measure of idiosyncratic volatility proposed by Engle et al. (2021). As a secondary measure, we compute implied volatility from end-of-day option prices to analyze the changes in the overall stock volatility of a firm on the days of earnings conference calls.

Controlling for market cap, leverage, ROA, five-year beta, short interest, and earnings surprise, we find that firm-level cybersecurity risk is positively correlated with idiosyncratic volatility on the days that earnings call conferences are held, suggesting that the discussion of issues related to cybersecurity risk by executives and other earnings conference call participants tends to increase the component of the volatility that responds only to firm-specific news. Using implied volatility as a secondary measure of stock volatility, we also find a positive relationship, although the coefficient is smaller in magnitude, between cybersecurity risk and volatility. The smaller magnitude can be explained by the fact that idiosyncratic volatility is computed using intraday returns, whereas implied volatility is computed from option prices at the end of a trading day. Therefore, idiosyncratic volatility can capture in a timely manner the arrival of new firm-specific information contained in earnings calls throughout a trading day;

however, implied volatility only captures part of that information at the end of the trading day—after some of that information has already been absorbed by prices.

We also find that coefficients of various CRIs computed from different cybersecurity training libraries (i.e., cybersecurity-related texts) are close in magnitude (as are their corresponding *t*-statistics). This suggests that the overall impact of cybersecurity risk on idiosyncratic volatility is robust to alternative measurements of the language in the earnings call discussions. The positive relationship is also robust to various industry classifications. Therefore, relying on our results from analyzing a panel dataset of 54,154 earnings call transcripts of 2,761 US firms over a 10-year period, we believe that our proposed measure of firm-level cybersecurity risk is a viable measure to investigate firm-level cybersecurity risk and volatility. Although Lopez-Lira (2021) presented an economic model that justifies using novel textual analytics methods similar to our approach to measure firms' different risk exposures, financial markets would benefit from more structured cybersecurity regulatory disclosure requirements.

APPENDIX

EXHIBIT A1

Privacy Rights Clearinghouse Cybersecurity Breaches

Date Made Public	Year of Breach	Company	Type of Breach	Type of Organization	Total Records (in Millions)	Information Source	Ticker*	Earnings Call Transcripts
December 14, 2016	2016	Yahoo	HACK	BSO	3,000.0	Media	YHOO*	n/a
March 8, 2017	2017	River City Media	DISC	BSO	1,370.0	Media	n/p	n/a
September 22, 2016	2016	Yahoo	HACK	BSO	500.0	Media	YHOO*	n/a
November 16, 2016	2016	FriendFinder	HACK	BSO	412.0	Media	n/p	n/a
May 31, 2016	2016	MySpace	HACK	BSO	360.0	Media	n/p	n/a
July 3, 2018	2018	Exactis	DISC	BSO	340.0	Media	MAR	n/a
11/30/2018	2018	Marriott International	HACK	BSR	327.0	Media	n/p	n/a
4/2/2011	2011	Epsilon	HACK	BSO	250.0	Databreaches.net	n/p	n/a
6/19/2017	2017	Deep Root Analytics	DISC	BSO	198.0	Media	n/p	n/a
6/6/2012	2012	LinkedIn.com	HACK	BSO	167.0	Media	LNKD*	n/a
3/30/2018	2018	Under Armour	HACK	BSR	150.0	Media	UAA	YES
9/7/2017	2017	Equifax Corporation	HACK	BSF	145.5	Media	EFX	YES
5/21/2014	2014	eBay	HACK	BSO	145.0	Media	EBAY	YES
6/27/2018	2017	NameTests	DISC	BSR	120.0	Media	n/p	n/a
5/17/2016	2016	LinkedIn	HACK	BSO	117.0	Media	LNKD*	n/a
10/11/2018	2018	MindBody–FitMetrix	DISC	BSR	113.5	Media	n/p	n/a
4/27/2011	2011	Sony, PlayStation Network (PSN)	HACK	BSR	101.6	Media	SONY	n/a
1/1/2010	2010	Netflix	UNKN	BSO	100.0	Media	NFLX	YES
6/4/2018	2018	MyHeritage	DISC	BSO	92.3	Media	n/p	n/a
2/13/2015	2015	Anthem Inc.	HACK	MED, BSF	80.0	US DHHS	yes	n/a
8/28/2014	2014	J.P Morgan Chase	HACK	BSF	76.0	Media	JPM	YES

(continued)

EXHIBIT A1 *(continued)*
Privacy Rights Clearinghouse Cybersecurity Breaches

Date Made Public	Year of Breach	Company	Type of Breach	Type of Organization	Total Records (in Millions)	Information Source	Ticker*	Earnings Call Transcripts
5/24/2018	2018	T-Mobile	DISC	BSR	74.0	Media	TMUS	YES
10/12/2017	2017	T-Mobile	HACK	BSO	69.6	Media	TMUS	YES
7/17/2012	2012	Dropbox	UNKN	BSR	68.0	Media	DBX	YES
5/13/2016	2016	Tumblr	HACK	BSO	65.5	Media	n/p	n/a
11/21/2017	2017	Uber	HACK	BSO	57.0	Media	UBER	YES
9/2/2014	2014	The Home Depot	HACK	BSR	56.0	Media	HD	YES
3/3/2013	2013	Evernote	HACK	BSO	50.0	Media	n/p	n/a
9/28/2018	2018	Facebook, Inc.	HACK	BSO	50.0	Media	FB	YES
4/18/2018	2018	Localblox	DISC	BSO	47.0	Media	n/p	n/a
10/20/2016	2016	Weebly	HACK	BSO	43.4	Media	n/p	n/a
12/13/2013	2013	Target Corp.	HACK	BSR	40.0	Media	TGT	YES
10/1/2018	2018	Chegg	HACK	EDU	40.0	SEC filing	CHGG	YES

NOTES: This exhibit presents information on cybersecurity incidents with 40,000,000 or more records during 2010 to 2019, published by PRC. The asterisk after the ticker symbol indicates that the company is no longer an independently traded firm. n/p indicates that the firm is not publicly traded. YES indicates that our database contains the earnings call transcripts for the firm to calculate CRI.

EXHIBIT A2
SPGI Classifications

1. Communication Services
Media and Entertainment
Entertainment
Interactive Mediaand Services
Media
Telecommunication Services
Diversified Telecommunication Services
Wireless Telecommunication Services

2. Consumer Discretionary
Automobiles and Components
Auto Components
Automobiles
Consumer Durables and Apparel
Household Durables
Leisure Products
Textiles, Apparel, and Luxury Goods
Consumer Services
Diversified Consumer Services
Hotels, Restaurants and Leisure
Retailing
Distributors
Internet and Direct Marketing Retail
Multiline Retail; Specialty Retail

3. Consumer Staples
Food and Staples Retailing
Food and Staples Retailing
Food, Beverages, and Tobacco
Beverages
Food Products
Tobacco
Household and Personal Products
Household Products; Personal Products

4. Energy
Energy
Energy Equipment and Services
Oil, Gas, and Consumable Fuels

5. Financials
Banks
Banks
Thrifts and Mortgage Finance
Diversified Financials
Capital Markets
Consumer Finance
Diversified Financial Services
Mortgage Real Estate Investment Trusts
Insurance
Insurance

6. Health Care
Health Care Equipment and Services
Health Care Equipment and Supplies
Health Care Providers and Services
Health Care Technology
Pharmaceuticals, Biotechnology, and Life Science
Biotechnology
Life Sciences Tools and Services
Pharmaceuticals

7. Industrials
Capital Goods
Aerospace and Defense
Building Products
Construction and Engineering
Electrical Equipment
Industrial Conglomerates
Machinery
Trading Companies and Distributors
Commercial and Professional Services
Commercial Services and Supplies
Professional Services
Transportation
Air Freight and Logistics
Airlines; Marine
Road and Rail

(continued)

EXHIBIT A2 *(continued)*

SPGI Classifications

Transportation Infrastructure **8. Information Technology** ***Semiconductors and Semiconductor Equipment*** Semiconductors and Semiconductor Equipment ***Software and Services*** IT Services Software ***Technology Hardware and Equipment*** Communications Equipment Electronic Equipment, Instruments, andComponents Technology Hardware, Storage, and Peripherals	**9. Materials** ***Materials*** Chemicals Construction Materials Containers and Packaging Metals and Mining Paper and Forest Products **10. Real Estate** ***Real Estate*** Equity Real Estate Investment Trusts Real Estate Management and Development	**11. Utilities** ***Utilities*** Electric Utilities Gas Utilities Independent Power and Renewable Electricity Production Multi-Utilities; Water Utilities

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Investment Management Post Pandemic, Post Global Warming, Post Resource Depletion

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KEY FINDINGS

- Government plans for sustainable growth will require more than a change in technology; they will also require a shift to qualitative growth.
- An economic theory to understand and eventually model qualitative growth is needed.
- Investors will have to cope with new types of risk and need to understand the cultural changes implied by sustainable growth.

ABSTRACT

Environmental issues including mitigating climate change, reducing pollution, and halting exhaustion of natural resources are no longer marginal cultural issues but have become parts of serious government plans with substantial funding in both the United States and Europe. Government plans explicitly call for sustainable growth with no (or minimal) use of resources. In this article, the authors argue that sustainable growth requires shifting to qualitative growth. This is more than a change in technology because it implies changes in products and services and therefore a change in demand. It also implies developing an economic theory able to understand and eventually model qualitative growth. Practical and theoretical changes will affect asset management. Investors will have to cope with new types of risk, both exogenous and endogenous, and will need to understand the cultural changes implied by sustainable growth. Although environmental issues, per se, will not affect returns, financial sustainability might imply a reduction of inequalities and therefore affect returns.

TOPICS

*ESG investing, developed markets, tail risks, performance measurement**

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For many decades the business community was hostile to environmental movements and ignored the warning of scientists that human activity is severely damaging the natural environment. The belief that environmental issues are inimical to free-market activity has been reinforced by the many publications claiming that the current economic growth path is unsustainable (Bardi 2011; Kallis, Kerschner, and Martinez-Alier 2012). Early warnings that current economic growth is not sustainable include the landmark book by Georgescu-Roegen (1971) and an MIT report (Meadows et al. 1974).

On the basis of the law of entropy, Georgescu-Roegen claimed that economic processes are irreversible, causing unsustainable depletion of resources. Many economists, sociologists, and philosophers subsequently developed theories of de-growth and de-industrialization. In Europe, perhaps the best-known exponent of the de-growth movement is Serge Latouche (see Latouche 2009). The recent movement started by Greta Thunberg, a young Swedish environmental activist, calls for taking immediate actions to stop climate change and tackle other environmental issues but does not propose an economic agenda (Johnson 2019).

In the last decades, it has become clear that environmental issues cannot be ignored. In particular, the magnitude of climate change and its catastrophic effects have captured the public's attention. In the 2015 Paris conference, almost all nations agreed to protocols to reduce carbon emissions. It is widely believed that carbon emissions are the main culprit of climate change through the *greenhouse effect.* Thus far, the transition to green sources of energy has been considered a major technology change because sources of energy based on fossil fuels have to be replaced by clean sources of energy such as wind turbines and solar panels.

The business community has changed its attitude from hostility to cautious optimism about the opportunities of the green transition. For example, the car industry has been quick to understand that electric cars offer great potential for growth. The construction industry has also understood the potential for creating a new generation of energy-saving buildings. Even aeronautics is beginning to consider a transition to hydrogen-powered planes.

Although climate change is the major environmental issue, it is not the only one. Industrial and biological pollution, exhaustion of natural resources, and inordinate population growth are all major environmental threats. In addition, both economies and the ecosystem are complex systems with many interacting parts and emerging properties. Mitigating climate change is not only a technological issue but also a political one. The COVID-19 pandemic has possibly changed the perception of the economic consequences of environmental issues. The need to distance people has changed the basic structure of work organization. It is conceivable that many of the current job reorganizations will go much further and will become permanent.

Coping with all environmental issues—from climate change to pandemics—will require a major reorganization of economic activity, but it will not imply de-growth. It will instead imply a sustainable growth path. This belief is now embodied in the European Green Deal, approved by the European Parliament on January 15, 2020,[1] that clearly identifies sustainable development with three criteria: (1) no net emissions of greenhouse gases (GHGs) by 2050, (2) decoupling economic growth from resource use, and (3) the notion of leaving no person or no place behind. But how can sustainability be achieved? The January 2021 report by the European Environmental Agency (EEA), *Growth without Economic Growth,* discusses how sustainable growth can be achieved. The conclusion of the report is that "societies need to rethink what is meant by growth and progress and their meaning for global sustainability."

In this article, we argue that moving from the current notion of quantitative growth to a new notion of growth that is both quantitative and qualitative requires changes in economic activity and theoretical changes in economics. Theoretical changes are needed to allow policymakers to gain a correct understanding of qualitative growth. Consequently, the fields of economics and finance must adapt. Given that the green transition is now driven by governments and is increasingly perceived as a profit opportunity, these aforementioned changes will have a lasting impact on investment management. We primarily contend that sustainable growth must be supported by

[1] Available at https://www.eea.europa.eu/publications/growth-without-economic-growth/growth-without-economic-growth.

a new economic theory that is able to recognize and measure qualitative growth. However, with current economic theory, plans such as the European Green Deal could be perceived as de-growth and may have a negative impact on investors and investment decision-making.

Consequently, investors must recognize that the green transition has two different aspects: (1) Progressive reduction of emission of greenhouse gases, which is a major change of technology, will offer several profit opportunities, and (2) sustainable growth without use of natural resources will require profound social changes. Therefore, it is possible that in aggregate the green transition might not reduce the amount of profit available to investors; however, through a redistribution of profit opportunities from conventional to more complex and environmentally friendly goods and services, we could see a substantial overhaul to investment management that will change as exogenous risks due to environmental conditions become increasingly important and unpredictable.

In the following sections, we will first outline how economic theory needs to change; we will then outline the changes that will be needed in practice and, finally, the impact on investment management.

ECONOMICS NEEDS A MAJOR OVERHAUL: IT MUST UNDERSTAND QUALITATIVE CHANGES

To illustrate the thesis of this section, that economics needs a major overhaul, let's first consider some economic data from Federal Reserve Economic Data.

In the 1950–2020 period, the US real per capita GDP grew by approximately four times. Exhibit 1 shows that, in 1950–2020, the nominal per capita GDP grew by 36 times, whereas inflation, according to its usual measurement, pushed up prices nine times. Although this ninefold difference between nominal and real per capita GDP is attributed to inflation, it is likely due to innovation. Economic intuition would suggest that these data are misleading. In 1950–2020, the US economy (as well as many other developed economies) experienced major technological revolutions that brought jet planes, a vast array of sophisticated home appliances, high-definition color TV, and the digital and communication revolution. Intuition would further suggest that at least a fraction of the ninefold inflation increase is in reality product and service innovation (Dervis and Quereshi 2016; Aghion et al. 2019). Aghion et al. (2019) discussed the issues of overstating inflation due to product innovation. As we move into a situation of increasing constraints on energy and usage of natural resources, it is critical that qualitative growth be measured accurately and appreciated. Therefore, our first step is to discuss how we measure the output of an economy.

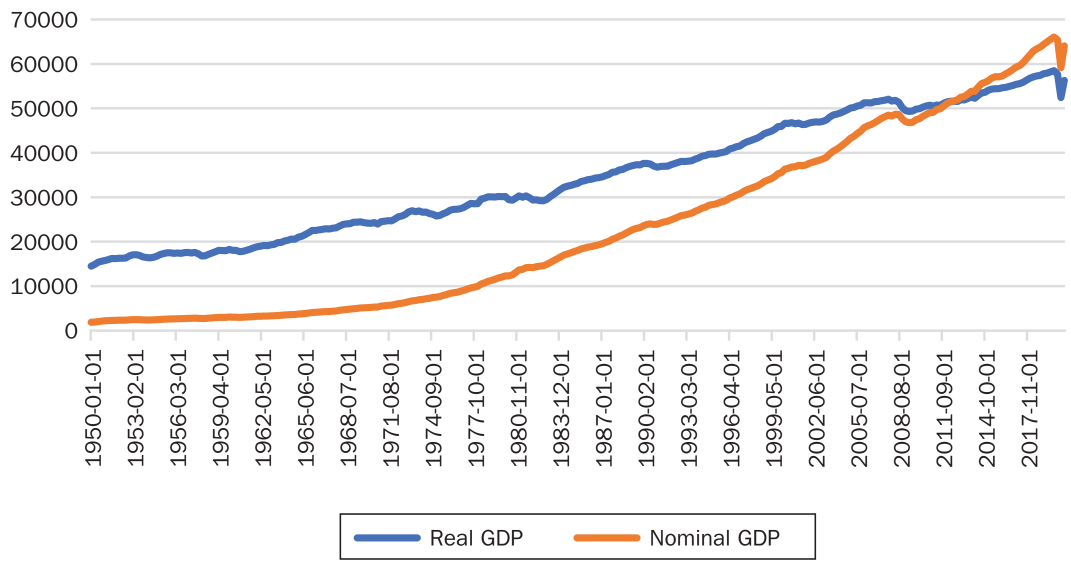
How Do We Measure Economic Output?

There is a fundamental ambiguity in political and economic discourse on how to measure economic growth. In general, today, political and economic discourses consider a growing economy to be an economy that produces an increasing amount of goods and services, thus employing more people, whereas a declining economy produces a decreasing amount of goods and services, thus yielding unemployment. However, official political and economic discourses identify growth in terms of percentage changes in real GDP (i.e., changes in the value of the output after inflation). Can the two measures be reconciled?

Modern economies produce a huge number of goods and services. The six-digit classification of product categories according to the Harmonized System of the Standard International Trade Classification includes more than 5,000 product

EXHIBIT 1

Comparison of US Nominal and Real GDP in the 1950–2020 Period



NOTE: US real per capita gross domestic product (GDP), chained 2012 dollars so that in 2012 real and nominal per capita GDP coincide.

types. However, if we look at individual products and services, it can be estimated that a modern economy produces hundreds of thousands of different products and services. In his book *The Origin of Wealth*, Beinhocker (2006) estimated that the New York economy includes hundreds of thousands of stock keeping units (SKUs). SKUs are the product identifiers used in logistics. In addition, many of these goods and services are subject to a process of rapid innovation and change, both for technological and symbolic reasons.

These products and services are heterogeneous, and there is no physical measure applicable to all. It is therefore impossible to aggregate them directly: We cannot add together the number of cars, mobile phones, and cruises produced in a year. It is therefore impossible to arrive at an aggregate physical measurement of the amount produced, and it becomes problematic to measure growth.

From a mathematical point of view, the problem of measuring economic growth is the problem of finding a summary representation of the variation of a set of heterogeneous variables (i.e., variables expressed in different units of measurement). This mathematical problem has long been debated since the late 19th century. The proposed solution is indexes. Although we cannot aggregate heterogeneous variables, we can calculate the percentage of change in each variable. Rates of change are pure numbers that do not have units of measurement and, therefore, can be aggregated. An index of the change in heterogeneous variables is a weighted average of the rates of change of each variable. Superficially, indexing may seem to solve the problem of quantitatively representing economic growth. Actually, it is not like that for two reasons. The first is that the determination of weights is not defined. What weight do we attribute to the percentage change in each variable? To give a proper weight to each variable, we should be able to compare heterogeneous variables, but that would lead to a circular reasoning. The construction of indexes was widely debated, and it was concluded that not only can we not define a single optimal index, we cannot even define criteria that all indexes must meet. The second reason is that in the presence of innovation, indexes cannot be defined—it is not possible to define the rate of change of constantly changing quantities. Therefore, it seems to be impossible to measure the output of a nation as a sum of the quantities produced, and it seems impossible to build a unique index that represents the average change of these quantities.

In practice, following the ideas of Simon Kuznets, economic output is aggregated by value to compute GDP, which is the key quantity on which economic decisions are assessed. GDP is determined by aggregating by value (i.e., by adding the market value of all the final goods and services produced in a nation). Apart from the enormous practical difficulties in obtaining these numbers, theoretically, the process of aggregation by value is correct because prices are homogeneous quantities that can be added up. Even when aggregating by value, however, there are problems. Prices are only relative prices. If all prices are multiplied by the same factor, there are no economic consequences. For example, in 1960, the French franc was replaced by a new franc worth a hundred old francs (Blancheton 2004). In 2005, six zeros were dropped from the Turkish lira. These operations had no economic consequences

How is the multiplication factor defined at two different times? Inflation is, in principle, the price change of a unit of output. Because it is not possible to aggregate the output, all advanced countries adopt some form of the Consumer Price Index (CPI), which can be computed in the following way. Periodically, the government selects a basket of goods that it considers representative of the consumption of average households and calculates their change in value over a period, such as a year. Several ways of performing this calculation have been proposed. The most widely used indexes today are the Laspeyres, Paasche, and Fisher indexes. Fisher's index is the geometric mean of the two Laspeyres and Paasche indexes.[2] The percentage change in the price of the basket from a certain date, calculated according to one of these methods, is the CPI.

The calculation of consumer price indexes is subject to all of the problems associated with the construction of indexes. There is no single way to weight the various prices because prices and quantities change over time. The index cannot be calculated in the event of a product change. In fact, certain goods and services with strong innovation are excluded from the CPI calculation and therefore from the calculation of inflation. Periodically, the basket of goods is updated by inserting new products and excluding old products. This update, however, does not affect the calculation of inflation. Inflation should represent the change of the price level, but it is a theoretical index that must be interpreted exactly as a function of how it is constructed.

The orthodox view argues that real GDP is proportional to the amount produced, in which the proportionality factor is the weighted average of prices. If an economy really produced a single commodity or a composite commodity, then this interpretation would be correct. But this interpretation of GDP does not stand up to the empirical analysis of complex economies. Real GDP is an abstract amount, which, by consensus alone, is considered proportional to the real amount of economic activity.

Measuring Inflation: A Well-Known Problem

The problems in the measurement of inflation created by qualitative changes are well known. In 1995, the US Senate appointed a committee to investigate possible CPI anomalies. This committee is referred to as the Boskin Commission, named after its president, Michael Boskin, professor of economics at Stanford. The report (Boskin et al. 1996) concluded that inflation was overestimated by 1.1% in 1996 and 1.3% before 1996 because it did not consider qualitative changes of the output.

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[2] Milana (2009) gives an historical perspective on the problem of forming indexes.

Several studies discuss the problem of overstating inflation.[3] Feldstein (2017) argued that "I have concluded that, despite the various improvements to statistical methods that have been made through the years, the official data understate the changes of real output and productivity."

Note that it would have been more correct to say that the concept of inflation had to be revised. Inflation, in itself, is the change in the price of the same thing. In the static economies of the past, the interpretation of the CPI as a percentage change in price levels could be somewhat acceptable. However, today, with the highly innovative economies in which we live, this interpretation is not sustainable. Not only that, but it is not sustainable to use macroeconomic models that want to describe the quantitative output of an economy.

Let's try to reinterpret the previous data. The fourfold increase in real growth cannot be understood as an increase in production because, in the meantime, all of the products have changed. We can interpret it as nominal growth discounted with the CPI. However, the CPI does not really represent inflation because it actually represents price increases that correspond to significant qualitative changes. Although the Boskin Committee concluded that inflation is overestimated, and academics such as Feldstein agree, we do not really have a measure of qualitative changes, so we cannot even say that inflation is overestimated.

These considerations become increasingly fundamental at a time when climate change and exhaustion of natural resources suggest dividing the economy into a quantitative part, whose growth is not sustainable and must be blocked, and a qualitative part that should be environmentally sustainable. This division is already in place, but it is not recognized by theory or economic practice. Already today an important part of economic growth is linked to innovation and qualitative changes in output, but this growth is not recognized. To manage the transition to an environmentally sustainable economy, it is important that these considerations can be made explicit and included in a theory so that policymakers can recognize qualitative growth.

If qualitative changes are not recognized and measured as true growth, it is likely that future economic evolution will be labeled a recession. Policymakers must be able to appreciate, and communicate, that qualitative growth is genuine growth. This is why theory is important.

Qualitative and Quantitative Growth

Real GDP fails to consider qualitative changes and innovation in products and services. If we want to move to measures of economic output that consider innovation and qualitative changes, we need a measure of innovation and qualitative changes.

First, let's emphasize that any solution to this problem (i.e., any measure of innovation) is a theoretical term that cannot be justified in itself but only through its relationships with other quantities that are observable. This reasoning is obvious in the physical sciences, in which many terms are purely theoretical and acquire meaning within the entire theory. Perhaps the most obvious illustration of this principle is information theory, in which *information* does not correspond to the term as used in daily life but proved to be very useful in the theory of communication and encoding.

Given that we cannot reasonably quantify the output of an economy in physical terms, we cannot define inflation as the price change of a unit of output. To do this, the composition of a unit of output should remain constant. A simple approximate solution would be to divide economic output into two sectors, one formed by goods and services that change slowly and the other by goods and services that innovate rapidly.

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[3] See, for example, Boskin et al. (1998), Boskin (2005), D'Amico et al. (2018), and Israel and Schnabel (2020).

For the slowly changing goods and services, we can compute inflation as usual, whereas for the other sector, we can assume that inflation is zero. This procedure can be extended to more than two sectors. We anchor the computation of inflation to the most traditional sector, and then we move toward the most innovative sector following a curve that can be simply a linear curve.

A more theoretically oriented approach involves using some measure of complexity to estimate qualitative changes. Measures of economic complexity have been proposed by Hidalgo and Hausman (2009), Hausman et al. (2013), Hidalgo (2016), and Tacchella et al. (2012). It is important to point out that, whatever method we use, it does not yield the true real GDP or the true inflation. These quantities do not exist. Real GDP is something that must agree with observable quantities and must have predictive power.

Implications of the Mismeasuring Economic Outputs for Climate Change

Within the context of the mismeasurement of GDP, inflation, or other economic outputs, researchers have examined the issue of productivity slowdown and have largely focused on the magnitude of information and communication technologies. However, even after accounting for all accurate measurements, data seem to suggest that the implied change in real revenues in these industries would be five times larger. That being said, the disconnect between GDP and welfare as conceived by Stiglitz, Sen, and Fitoussi (2018) is still a problem. Even though mismeasurement of GDP does not explain the productivity slowdown, it is still problematic because it has other important consequences. Particularly, mismeasurement leads to misallocation of resources. For example, within the context of the high-tech sector, the mismeasurement of tech prices has implications for labor productivity and multifactor productivity growth. The multifactor productivity growth rates inform macroeconomists about the pace of innovation (see Syverson, 2017 and Bryne et al. 2016, 2017).

At present, stabilizing concentrations of carbon dioxide and other greenhouse gas emissions require a technological revolution. Researchers suggest that the current pace of technology can achieve only modest targets; to attend to the climate change problem on a dramatic scale, a breakthrough revolution is necessary. For such a change to occur, investment is required both at public and private sector levels. Environmental economists have long researched the role of regulation in creating incentives for the private sector to invest in research and development and to innovate. Consequently, to bring about the change that is necessary, resolve among institutions to engineer a technological revolution may be the long-term and first line of defense against anthropogenic climate change. Regulators cannot redirect resources and policy based on unreliable data. For there to be a reliable response to the threat posed by climate change, there needs to be an appropriate measurement of the multifactor productivity growth. Moreover, recent data on the magnitude of environmental deterioration suggest that it has been vastly underestimated. Without a full appreciation of the extent of mismeasurement, any policy to address the implication of climate change is doomed to fail or underdeliver.

HOW WILL ECONOMIES CHANGE TO BECOME SUSTAINABLE?

The current approach to environmental issues consists primarily of mitigating climate change by curbing carbon emissions. Governments have approved rules that impose limits and prohibitions. For example, Germany set emission-related targets to be achieved between 2030 and 2050, including the complete decommissioning of coal-fired power stations by 2050 (Climate Action Plan 2016).[4] Other rules limit the emission of carbon monoxide.

As noted earlier, adopting clean energy sources is considered essentially a technology change. At the same time, new generations of products are being developed, such as electric cars and eco-buildings. Clearly there will be opportunities and failures, but essentially the transition to clean energy is perceived to offer many opportunities.

Clean energy is not the only element of sustainability. Pollution and depletion of natural resources are also critical aspects. Globally, the attention to these issues has been quite marginal. Although many rules to curb pollution have been imposed, a very high level of environmental pollution has been tolerated, and little attention has been paid to the exhaustion of natural resources. For example, destruction of the green masses that contribute to the production of oxygen has reached alarming levels. The use of pesticides is a serious threat to the environment. Biological pollution is the first case of pollution that is forcing governments to act. The COVID-19 pandemic is the deadliest and most widespread example of biological pollution. How governments and businesses will react in the medium and long term is still to be seen.

It is difficult to believe that sustainability issues can be treated only as a technology change. Resources are finite and must not be exhausted; pollution must be stopped. In the next few sections, we will discuss the possible scenarios associated with finite exhaustible resources.

De-Growth or Qualitative Growth?

There are essentially two economic strategies to mitigate climate change and address other sustainability issues. The first is to reduce consumption and goes by the name of *de-growth*. The second is to change consumption from a quantitative view to a qualitative view of economic growth.

The need to reduce consumption and return to a simpler way of life has been supported by many. From the point of view of companies and, in general, industrial capitalism, de-growth is anathema. De-growth means that production activities and profits are reduced. The fear of de-growth is perhaps the main reason why large companies (but also many governments) have tried to deny the reality of man-made climate change and have provided research support to scientists who argue that climate change does not have a human cause.

What is the attitude of the general public toward de-growth? In Western culture, attitudes toward a return to a simple life have always been ambivalent. On one hand, bucolic simplicity has its own charm; on the other hand, no one wants to give up the comforts of modern life. This ambivalence is not recent. In describing the farmer's return from the fields, the 14th century Italian poet Petrarca wrote: "and then sets out the meal of an impoverished life, like those acorns in the Golden Age that all the world rejects but honours" (Petrarch, Rhymes, Song IX translated by A.S. Kline). The Western world has always honored frugality, the meal of simple acorns, while building a life of luxurious consumption. Most people are fundamentally hostile to embracing a simpler lifestyle. No one wants to give up cars, travels, or all the comforts of modern life.

Social De-Growth and Inequality

De-growth has a profound social implication: A society that plans de-growth, provided that it can exist, must be extremely egalitarian or face devastating social conflicts. Western culture is not egalitarian; rather, it has theorized social inequalities.

[4] See: https://www.bmu.de/en/topics/climate-energy/climate/national-climate-policy/.

Until very recent times, inegalitarian social structures were considered almost laws of nature. There were basically four dominant classes: the nobles, the military, the clergy, and a large class of very poor workers. In the 18th century, even Voltaire, considered an enlightened intellectual, was against the education of peasants. There was no notion of social mobility except in exceptional cases. It was thought that everyone should stay in their place and not try to change the established order.

The notion of economic growth is recent and has given a new meaning to social inequalities. The ancient world had no notion of widespread economic growth—in ancient times, the idea of expansion was always linked to military conquests. Trade offered opportunities for wealth, but wealth was still concentrated in the hands of a few.

A change came with the industrial revolution and with technology from the 19th century, particularly in the United States. The American Dream is a dream of continuous improvement resulting from continuous growth. In a situation of growth and opportunities, inequalities are not the focus because everyone feels that they have an opportunity to improve and to climb the social ladder. In the vision of the American Dream, inequalities become an engine of progress because they reward the most active, but all benefit under the idea that the wealth produced by capitalists trickles down and reaches everyone. Immigrants who made up the American population felt they were in a situation of unprecedented growth opportunities, where children can achieve a better standard of living than their parents and, if they are very good, can become rich and important; for their grandchildren, they can have high hopes of success.

De-growth deprives everyone of hope for improvement and exacerbates inequalities. Socially, de-growth would be tolerated only in a highly egalitarian society, with a wide sharing of simple values. It is, however, very difficult to believe that societies will become truly egalitarian any time soon.

Qualitative Growth

What alternative is there to de-growth? Purely quantitative economic growth is not sustainable. We need to move toward sustainable qualitative growth. The shift toward a qualitative and nonquantitative economy is already taking place for endogenous reasons, linked to technology and the symbolism associated with products but not linked to the need to protect the environment. The shift toward qualitative growth implies a change in the desires of consumers, who must genuinely appreciate quality and complexity. In parallel, economic theory and politics must recognize this change and accept at the theoretical level that qualitative changes are true growth and not a byproduct of quantitative growth.

The creation of qualitative demand and the recognition of qualitative growth are critical elements of the transition to a sustainable economy. The transition must be somewhat planned or at least facilitated. In fact, the shift toward a more qualitative and sustainable economy does not happen spontaneously. The economy depends on society and the culture expressed by society; without cultural change, the qualitative transition has little hope of success.

Spontaneous Growth

After World War II, economic growth was supported by desires, and therefore demand was very natural. In Europe, after the destruction of war, housing was in short supply, and the first consumer wish was to purchase a home with heating and hot and cold running water. Then came the car, a product naturally desired because everyone wanted the freedom and comfort it provided. The car brought along the economic development of roads, highways, gasoline stations, and other ancillary infrastructures. Then came appliances: the refrigerator, the washing machine, the dishwasher, the television, and the telephone. Then came the second house by the sea or in the mountains and cheap air travel that opened up previously unthinkable touristic horizons.

The European economic boom, like that of other non-European countries, was supported by spontaneous, simple, and unambiguous demand. US economic development had followed parallel lines, but well in advance of Europe. Even in the United States, however, demand had been simple and unambiguous, albeit different from that in Europe, as related to the environment, large spaces and great distances, and the fact that the transition to consumerism had begun much earlier.

However, in the last 30 years the situation has changed in both Europe and the United States. Technology has allowed products and services to be enriched with features that were previously unthinkable. Growth has become more qualitative than quantitative. An example is provided by the US automotive market. The number of vehicles per 1,000 inhabitants grew almost linearly in the second half of the 20th century, from 150 vehicles per 1,000 inhabitants to just over 800 vehicles per 1,000 inhabitants. Since the beginning of this century, however, the number of vehicles per 1,000 inhabitants has stopped growing and has stabilized at around 800–850 as new features of vehicles have multiplied.

It is not, however, just technology that has changed the demand for products and services: Products and services have acquired an increasingly symbolic character. An industry dedicated to creating the image of products and services has been created. Moreover, with the digital revolution, increasingly virtual products and services have appeared, for which demand is not so clearly defined.

Symbolic Consumption

At the end of the 19th century, an attentive observer such as Thorstein Veblen already pointed out that consumerism had a strong symbolic element. Veblen observed that consumption is not only linked to the real usefulness of products and services but also to the desire to express power and social prestige. In his 1899 book, *The Theory of the Leisure Class*, (Veblen 1899), he called *conspicuous consumption* that consumption primarily linked to the desire to gain social prestige. The notion of consumption as a way to keep up with others entered the popular culture in 1913 with a series of cartoons by Arthur Momand entitled *Keeping up with the Joneses*. The cartoon describes the McGinis family trying to keep up with its neighbors, the Jones family. It was a great success, and, in the English-speaking world, the phrase "keeping up with the Joneses" is now part of the daily lexicon.

Although the notion of the symbolic value of consumption dates back to Aristotle, Veblen was the first to insert it into a systematic economic theory. Over the last 30 to 40 years, the symbolic value of goods and services has become increasingly important and articulated. An entire industry has been formed whose task it is to create and manage the symbolism of consumption. Today we can say that goods and services constitute a language with its own grammar, syntax, and semantics. The symbolism associated with products and services is well analyzed in the work of Hirschman (1981).

These considerations are important because they point out the risks and difficulties related to cultural changes that result in changes of consumption habits. Moving a modern economy toward qualitative consumption paths requires a profound cultural change. These changes need to be managed and facilitated in some way.

The transition to a sustainable economy risks imprisoning society in a symbolic network that produces exacerbated social inequalities. This is what happened in the past with various forms of *sumptuary laws*—rules that forbade the display of wealth but that, in practice, created a network of symbolic inequalities. A genuine interest in quality and complexity needs to develop to launch widespread qualitative growth. However, the economy must become more egalitarian in order to appreciate that quality.

INVESTMENT MANAGEMENT AND THE GREEN TRANSITION

In this section, we discuss the central theme of this article: the impact of the green transition on investment management. Our key focus is to examine how the green transition affects returns and whether this should have an impact on portfolio formation and risk management. We further compartmentalize our discussion into three subtopics. First, we discuss the impact of actions to reduce carbon emissions. Second, we discuss the impact of actions to achieve sustainable growth, and finally we discuss the impact of potential social and financial changes related to financial sustainability and the green transition.

Reducing Carbon Emissions and Investment Management

Mitigating climate change is currently the top priority of the green transition. The 2018 World Economic Forum at Davos recognized climate change as one of the major risks (Martin 2018). The 2020 edition of the World Economic Forum at Davos again concluded that climate risk is a top risk for our civilization. The European Union R&I paper "Summary of Key Take-Aways from Davos, 2021"[5] lists as the first takeaway the need to mobilize action on climate change.

The European Union Green Deal[6] and the Biden Plan for a Clean Energy Revolution and Environmental Justice[7] in the United States call for strong actions to mitigate climate changes, in particular for reducing carbon emissions. The business community has realized that there is an urgent need to act.

Investment managers have started to analyze empirically the impact the green transition will have on returns. For example, Focardi and Fabozzi (2020) found that empirical studies on green portfolios reveal that investing in firms that respect green constraints does not reduce returns. After performing an empirical study, Tan, Wirjanto, and Fan (2018) further concluded that "climate change risk had not been fully recognized and priced by the European and North American markets and that carbon-intensive industries were not critical portfolio performance enhancers on a risk-adjusted basis. Both findings suggest a good potential for constructing optimal portfolios with minimal carbon and climate change risk exposure that should deliver a satisfactory performance in the long run as the risks unfold."

There is new evidence that environmental constraints do not harm returns. In May 2020, the Rockefeller Brothers Fund (RBF) released *Investing in Our Mission*,[8] a case study detailing how its investment returns beat market benchmarks since divesting from fossil fuels five years earlier. According to the study, RBF posted an average annual net return of 7.76% over the five-year period that ended December 31, 2019; over the same period, an index portfolio including coal, oil, and gas holdings returned 6.71% annually. An article in the January 11, 2020 issue of *The Economist*, reports

[5] https://ec.europa.eu/info/publications/summary-key-take-aways-davos-2021_en.
[6] https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en.
[7] https://joebiden.com/climate-plan/.
[8] https://www.rbf.org/annual-reports/investing-our-mission.

that Jeremy Grantham, co-founder and chief investment strategist at Grantham, Mayo & van Otterloo, published data showing[9] that excluding any single sector of the economy had no real effect on long-term financial returns.

According to an article by Bill McKibben that appeared in the April 3, 2021 edition of *The New Yorker*,[10] BlackRock carried out research over the past year for two major clients, the New York City teachers' and public employees' retirement funds, to assess divestment from polluting firms. The report concluded that the portfolios "experienced no negative financial impacts from divesting from fossil fuels. In fact, they found evidence of modest improvement in fund return."

The fact that returns are not affected by divesting from polluting firms should not come as a surprise. Reducing emissions of greenhouse gases is a major technology change; the generation of energy by burning fossil fuels will be replaced by green sources of energy such as solar panel and wind turbines. We still need technology breakthroughs to safely deploy wind turbines and solar panels on a large scale, in particular in the area of real-time management of networks. It is an unresolved question whether nuclear power will be allowed. Although nuclear fission does not pollute in the sense of carbon emission, it creates formidable problems in the storage of radioactive waste and in safety (Brook and Bradshaw 2015).

Technological progress is responsible for economic growth and for profit, although the relationship is complex. For example, if we look at the GDP figures in Exhibit 1, we observe a smooth trend. Nonethless, in the same period, 1950–2020, we witnessed fundamental technology changes. Informatics and communications are typical examples. The output of information technology, measured in units of information, has grown a millionfold, but the growth rate has remained stable. Therefore, it is reasonable to assume that, other things being equal, the transition to green technologies will not make returns deviate substantially from their historical averages.

However, the issue of climate change shapes our understanding of risk in two fundamental ways. First are the complex set of threats that climate change poses to individuals, businesses, and the financial ecosystem. Second is the extant and forthcoming regulatory response to cope with climate change as economies attempt to become low or no carbon. In terms of climate events, researchers and policymakers largely concentrate on extreme weather events such as increasing sea level, rising temperatures, hurricanes, droughts, and wild fires.[11] A recent report by the Climate-Related Market Risk Subcommittee and Market Risk Advisory Committee of the US Commodity Futures Trading Commission (2020) states that climate risks pose a substantial systemic and subsystemic risk to the US financial system.

Early on, the Stern Review on the Economics of Climate Change redirected attention to a significant market failure associated with mispricing of the GHG emissions, which were a negative externality that should have been priced into the production of goods and services (Stern 2007). Absent a price on carbon, markets have ineffectively estimated climate risks. Several programs and policies (e.g., the California Cap-and-Trade and the European Union Emission Trading Systems) attempted to remedy the pricing of GHG emissions. However, these efforts only capture 22% of the market, leaving carbon emissions systematically underpriced. Although several institutional investors have started paying attention to climate risks, accurate pricing of carbon emissions remains a thorny issue.

[9] https://www.economist.com/finance-and-economics/2020/01/09/jeremy-grantham-on-divesting-from-big-oil?.

[10] https://www.newyorker.com/news/daily-comment/the-powerful-new-financial-argument-for-fossil-fuel-divestment.

[11] See, for example, Ritchie and Rosner (2017), Christensen et al. (2018), Keenan and Bradt (2020), and Liang et al. (2017).

To understand how climate change exposes firms to new risks, it is helpful to compartmentalize the nature of risks into physical risk and transitory risk. The physical risk component is direct risk due to these natural disasters, whereas transitory risk includes regulatory risk, which may occur due to governmental response to curb emissions and litigation risks for firms that contribute to GHG and non-GHG emissions. The interlinkages among various asset classes (e.g., financial assets tied to real property, infrastructure, insurance coverage providers) or business operations directly affected by physical or transition risks encompass the entire financial system.

For example, the real estate sector is not only exposed to various location-specific risk, such as flooding from high sea levels, extreme heat, and icing, but also to related risks in the form of disruptions in energy, transportation, and communications sectors. Furthermore, with an associated increase in climate risks, it becomes harder for borrowers to provide cheap financing as they struggle to price these risks and insurance companies struggle to provide insurance products. The eventual decline in real estate value can collectively depress economic activity.

Transition risks affect economic agents as policymakers attempt to formulate policies to price carbon emissions. These policies are not without severe financial costs to affected firms. For example, a study by Mercure et al. (2018) projected a global loss of $1 trillion to $4 trillion resulting from disinvestment in fossil fuel assets. These problems are further complicated as institutional investors now screen firms to construct greener portfolios. Engle et al. (2020) showed that green portfolios significantly outperform, especially during periods with adverse climate news.

The preceding analysis highlights three key problems: mispricing of carbon emissions, risk emanating from physical climate risks, and risks emanating from policy responses that include but are not limited to coal phase-outs, bans on internal combustion vehicles, carbon pricing, carbon capture, and energy efficiency.

The estimation of physical risks is not straightforward either. Current techniques focus on representative concentration pathways that estimate how climate systems will react to a certain level of GHG in the atmosphere. However, because these models are based on assumptions that are sensitive to first-order conditions, they grossly over- or underestimate the physical risk (Ritchie and Dowlatabdi 2017; Christensen, Gillingham, and Nordhaus 2018). Given these constraints, access to reliable data can be critical as market participants try to estimate the extent of these risks.

Under these circumstances, and given the importance of estimating climate risks and challenges presented by models and data, voluntary disclosure by firms has gained traction. Identification of these risks not only helps businesses to adapt their operations and supply chain to the looming threat, but they also provide crucial information to capital providers, investors, regulators, and counterparties. In fact, in 2016 several investors proposed revisions to Regulation S-K in which the Securities and Exchange Commission should mandate that firms disclose their sustainability effort in accordance with the Sustainability Accounting Standards Board (SASB). A subsequent analysis of firms engaging in SASB-identified sustainability disclosure also showed an increase in stock price synchronicity and informativeness (Grewal, Hauptmann, and Serafeim 2020). This is just one example of the challenges associated with predicting the full range of implications of climate risks for both firms and the financial system.

Sustainable Growth and Asset Management

Mitigating climate change can be considered a major technology change that, if successful, will not change the structure of the economy. Making economic growth sustainable, however, is a more complex issue. Sustainable growth, in particular growth decoupled from use of resources, is a key objective of the European Green Deal.

In the previous sections, we argued that sustainable growth can be achieved through qualitative growth. Circularity will help in reusing resources but cannot guarantee growth. Qualitative growth offers this possibility. However, as stated in *Growth without Economic Growth*[12] by the EEA, "The European Green Deal and other political initiatives for a sustainable future require not only technological change but also changes in consumption and social practices." A qualitative economy works well only if households demand quality, and demand for quality is a significant cultural shift. These changes will require asset managers, as well as political decision-makers, to venture into a new economic framework.

Will returns change from their historical means? Other things being equal, there is no reason why returns should deviate, but economies based on qualitative growth imply some fundamental changes in the structure of the economy. Currently, qualitative improvements and innovation have been used to sell increasingly expensive products and services, creating a new web of symbols associated with those products and services. This type of growth has been very demanding in terms of natural resources.

Qualitative growth implies developing a new generation of products and services decoupled from using natural resources. These products and services will require a shift in demand that is not obvious. Asset management will require the ability to understand what shifts in demand will actually work, significantly changing valuation techniques.

Currently, many large firms use sophisticated marketing techniques to understand and anticipate demand for products and services. Firms also use sophisticated advertising and image-building campaigns to create demand, and financial analysts expend huge amounts of resources trying to analyze and predict which firms will be successful in their efforts to capture a dominant position in the market.

If we move to qualitative economies that do not use natural resources, corporate strategies and marketing efforts will have to change. No-use-of-resources will become an overarching constraint that will direct both supply and demand. The current drive to reduce prices needs to be inverted because economies should not be based on producing and selling large quantities of cheap products.

Asset management will have to understand these processes and anticipate new types of risk. In fact, the main risk of sustainable economies is that demand for quality will collapse. The EEA paper "Growth without Economic Growth," states that "Full decoupling of economic growth and resource consumption may not be possible." That is, there is always the risk that economies will precipitate into de-growth.

This consideration leads to another important consideration: Asset management must become an active force in the green transition. As discussed by Focardi and Fabozzi (2020), asset management investment policies can become a driving force in decarbonization. In fact, many major asset management firms and insurance companies have created decarbonization investment strategies. However, asset management should engage also in the more difficult task of investing for sustainable growth. This must be a concerted effort of the public and the private sectors. Investing for sustainability is a difficult endeavor because it involves a bet on demand for quality. Asset management must be very sensitive to invest for quality and to avoid investment that might make the demand for quality collapse.

[12] https://www.eea.europa.eu/publications/growth-without-economic-growth.

Financial Sustainability

There are two ways to define the concept of sustainability: environmental sustainability and social and financial sustainability. It is likely that the segmentation of modern capitalistic economies into sectors with diverging dynamics is socially and even financially nonsustainable. For example, for the 10-year period from April 13, 2011 to April 13, 2021 the S&P 500 Index rose almost five times, whereas the nominal per capita GDP rose slightly more than 40%. If this were to continue in the same way for another 11 years, the S&P 500 would grow 25 times from its 2011 value, whereas the nominal GDP would double. It is likely that this level of divergence between asset price growth and economic growth would be unsustainable.

The Buffett indicator is the ratio of total US market capitalization to US GDP. As of the first quarter of 2021, the US market capitalization was in the range of $50 trillion, whereas US GDP was in the range of $21.5 trillion. Therefore, the Buffet indicator was about 230% (data change daily). The historical average is 75%.

In his *Waiting for the Last Dance*[13] from January 5, 2021, Jeremy Grantham writes:

> The long, long bull market since 2009 has finally matured into a fully-fledged epic bubble. Featuring extreme overvaluation, explosive price increases, frenzied issuance, and hysterically speculative investor behavior, I believe this event will be recorded as one of the great bubbles of financial history, right along with the South Sea bubble, 1929, and 2000……..But this bubble will burst in due time, no matter how hard the Fed tries to support it, with consequent damaging effects on the economy and on portfolios. Make no mistake—for the majority of investors today, this could very well be the most important event of your investing lives.

Analyzing financial instability is beyond the scope of this article. The massive investment needed to decarbonize the economy might produce high returns without changing the structure of the economy. However, sustainable growth will need economies to change and to become more egalitarian. Demand for quality needs purchasing power: If households have to demand quality, they must have the financial means to do it. Asset managers must understand this point and adjust return expectations.

CONCLUSION

In this article, we claim that sustainability constraints, per se, will not reduce profits and returns, provided that developed economies follow a path of qualitative growth. Qualitative growth is already present in modern advanced economies, but it is not recognized as genuine growth. As the shift toward quality must increase to protect climate and reduce depletion of resources, it is important that economic theory recognize qualitative growth in order to offer guidance and support policymaking. However, asset managers will be forced to look more carefully to exogenous risks due to climate change and other environmental elements.

[13] https://www.gmo.com/americas/research-library/waiting-for-the-last-dance/.

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The Implications of Contemporary Research on COVID-19 for Volatility and Portfolio Management

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KEY FINDINGS

- We synthesize recent and ongoing research in the finance and economics literature on pandemic and disaster risk related to COVID-19 and discuss the implications for asset pricing, volatility, and risk management.
- Pandemic-induced uncertainty led to extreme market movements in early 2020. We explore possible channels, such as investor beliefs and behaviors and corporate strategies, through which this risk was transmitted to the financial markets.
- Lessons learned from the recent pandemic will continue to have implications for volatility and risk management, even after the pandemic ends.

ABSTRACT

This article synthesizes recent and ongoing finance and economics research on pandemic and disaster risk related to COVID-19. Characterized by pronounced market movements and extreme volatility, the unprecedented disruption to the economy in early 2020 has inspired a rich, burgeoning literature on the financial and economic ramifications of pandemic risk. Financial economists have cultivated fresh perspectives regarding the transmission of pandemic-induced uncertainty to financial markets via channels related to the beliefs and behaviors of investors as well as corporate strategies and outcomes. These findings also highlight the imperative role of government policy responses in regulating the market volatility triggered by large-scale disasters such as the pandemic. In this article, the authors take stock of this emerging literature, focusing on the implications for volatility and risk management. In doing so, they discuss the unique nature of the uncertainty induced by COVID-19 relative to that of past crises. They also review cutting-edge studies that use innovative analytical approaches and novel sources of data, offering fruitful avenues for future research.

TOPICS

*Tail risks, financial crises and financial market history, big data/machine learning**

*All articles are now categorized by topics and subtopics. **View at PM-Research.com**.

Early in 2020, the world was severely disrupted by COVID-19. Communities across the globe were forced to quickly adapt to an unknown, highly contagious virus, which rapidly evolved into a pandemic. Like prior epidemics, COVID-19 triggered extensive health, environmental, and social devastation. However, the scale of the effects quickly escalated, and for the first time, we witnessed a medical phenomenon have an enormous financial impact on businesses and investors worldwide. In late March 2020, the US stock market plunged and volatility peaked as a direct consequence of the infectious disease outbreak—a never-before-seen juncture. Market participants were forced to adapt with little to no guidance in the new landscape.

This unprecedented crisis led to a rich, burgeoning literature that is still rapidly developing. Collectively, these studies provide new insights on managing rare disasters and financial crises. Although there are many avenues to consider, our article synthesizes recent and ongoing research in the finance and economics literature on pandemic and disaster risk related to COVID-19. In particular, we focus on the implications for asset returns, volatility, and portfolio management.

It is important for investment professionals to gain a thorough understanding of the recent crisis because a number of unique aspects render it fundamentally different from previous crises, including the fact that our world is now more interconnected than ever before. COVID-19 forced nearly all activities across the globe to come to a sudden halt. Although the world has faced past pandemics (e.g., the Spanish Flu of 1918, Middle East respiratory syndrome, severe acute respiratory syndrome, H1N1, and Ebola) and large-scale disasters (e.g., earthquakes, tsunamis, terrorist attacks, and social and political instability), these types of events tend to be contained within a certain region. Therefore, they do not typically cause global, systematic shocks such as those observed in March of 2020. Although some similarities exist between COVID-19 and past global crises, namely the Great Depression of 1920 and the financial crisis of 2008, previous crises were endogenously generated by the economic and financial system. In comparison, COVID-19 is truly exogenous, and it cannot be neatly categorized as an aggregate supply shock or demand shock because it simultaneously triggered supply and demand constraints (Spatt 2020; Baqaee and Farhi 2021; Hassan et al. 2021). This exogenous shock led to widespread financial repercussions felt all over the world.

The recent crisis marks the first time in history that news outlets have explained major market jumps in relation to a pandemic (Baker et al. 2020a). Exposed to the abnormally high level of media coverage and rapidly increasing infection rates associated with COVID-19, individuals have been better informed about the day-to-day developments of the debacle than in previous pandemics. Virtually no one was immune to the barrage of new information.

The pandemic has also given rise to the emergence of innovative analytical approaches and sources of data. For instance, new research incorporates existing epidemiology models into economic estimations (Alon et al. 2020; Atkeson 2020; Alvarez, Argente, and Lippi 2021) and uses location and mobility data to capture evolving patterns in the behavior of individuals (Barrios and Hochberg 2021; Ozik, Sadka, and Shen 2021). Some have introduced an automatic pattern-based method of textual analysis to classify firms' primary concerns involving epidemic diseases (Hassan et al. 2021), and others have explored measures of risk perception based on search data from Google Health Trends (Barrios and Hochberg 2021). Recent studies attempting to establish a causal relationship between uncertainty, market volatility, and growth have examined the shock using novel measures of uncertainty, such as dividend futures (Gormsen and Koijen 2020), business survey responses (Meyer et al. 2020), newspaper coverage (Baker, Bloom, and Terry 2020),[1] Twitter

[1] Baker, Bloom, and Terry (2020) forecasted a 28% annualized decrease in GDP for Q2 of 2020. Consistent with this prediction, the United States Bureau of Economic Analysis reported a 32.9% annualized decrease in real GDP for Q2 of 2020. For more details, see: https://www.bea.gov/news/2020/gross-domestic-product-2nd-quarter-2020-advance-estimate-and-annual-update.

feeds, and dispersion in gross domestic product (GDP) forecasts (Altig et al. 2020). These uncertainty measures have proven to be especially valuable for policymakers and investors during this critical period when incorporating new information in real time is paramount.

Although some of the economic and financial effects of the pandemic are arguably transitory in nature, we also expect that COVID-19 will bring fundamental, potentially permanent shifts to the economy and society at large in terms of productivity, research and development expenditures, employers' standard work policies, and interindustry reallocation of resources, including human capital (Bloom et al. 2020; Barrero et al. 2021; Bernstein, Townsend, and Xu 2021). Furthermore, as employees across the globe were suddenly forced to adapt by working from home, many firms realized the efficiencies of remote work, a pattern indicating that work-from-home jobs may become more commonplace even after the pandemic clears. Consistent with this notion, Bloom, Davis, and Zhestkova (2021) found a significant increase in patent applications for technologies that enhance work-from-home capability.[2] Although some of the radical modifications to the way we live and work were perhaps inevitable, the pandemic surely accelerated their introduction and implementation. In fact, in an October 2020 McKinsey survey, executives reported that changes brought on by COVID-19 were already a part of their firms' long-term plans.[3] Thus, major transformations that were intended for gradual implementation over the course of many years happened over a brief three-month period.

As the economy and society struggled with the abrupt changes provoked by the pandemic, stock markets faced a new level of turmoil at the same time. We explore a few possible channels through which pandemic-induced uncertainty was transmitted to the financial markets. The emerging literature offers insights into how investors and corporations engaged in different behaviors and strategies, which also sheds light on some long-standing anomalies. There is new evidence involving the dynamism of beliefs and preferences across investor classes and how those beliefs and preferences shape investors' trading behaviors. Other studies focusing on cash flow uncertainty and external financing at the corporate level reveal how different firms have fared through the pandemic. Although the ability of businesses to adapt in the wake of the crisis certainly depends on the internal strategies they employ, empirical findings have also highlighted the noteworthy influence of external factors, such as the role of government policies in stabilizing the US Treasury market and the impact of bank liquidity provisions. By altering estimated cash flows and the discount rate, these factors collectively affect corporate valuations and, hence, stock returns.

Understanding these potential channels has important implications for asset prices and risk management. Asset-pricing models are now considering new risks, such as rare disaster risk, the infection rate of diseases, and the speed of vaccine arrivals. Furthermore, simple risk management strategies focusing on diversification are being augmented to incorporate the intensification of portfolio variances and correlations among different asset classes across the global financial markets.

The remainder of this article is organized as follows. We begin by discussing the extreme stock market movements and volatility observed during the pandemic. In the two sections that follow, we explore the possible channels through which pandemic-induced uncertainty is transmitted to the financial markets. In particular,

[2] In addition to major work–life adjustments, households shifted their spending and saving at the onset of the crisis to prepare for the difficult times ahead. In accordance with precautionary motives, savings increased considerably during periods of high market volatility (Baker et al. 2020b).

[3] Source: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/how-covid-19-has-pushed-companies-over-the-technology-tipping-point-and-transformed-business-forever#.

EXHIBIT 1

US Stock Indexes, January 2020 to April 2020

NOTE: S&P 500 and Russell 2000 are rescaled as 1 on January 2, 2020.

SOURCE: Bloomberg.

the first section reviews investor beliefs and behaviors, and the second focuses on corporate strategies and outcomes. Next, we turn our attention to the cross-sectional determinants of stock returns during the pandemic. We then discuss the implications for volatility and risk management strategies and finally provide concluding remarks.

STOCK MARKET REACTIONS

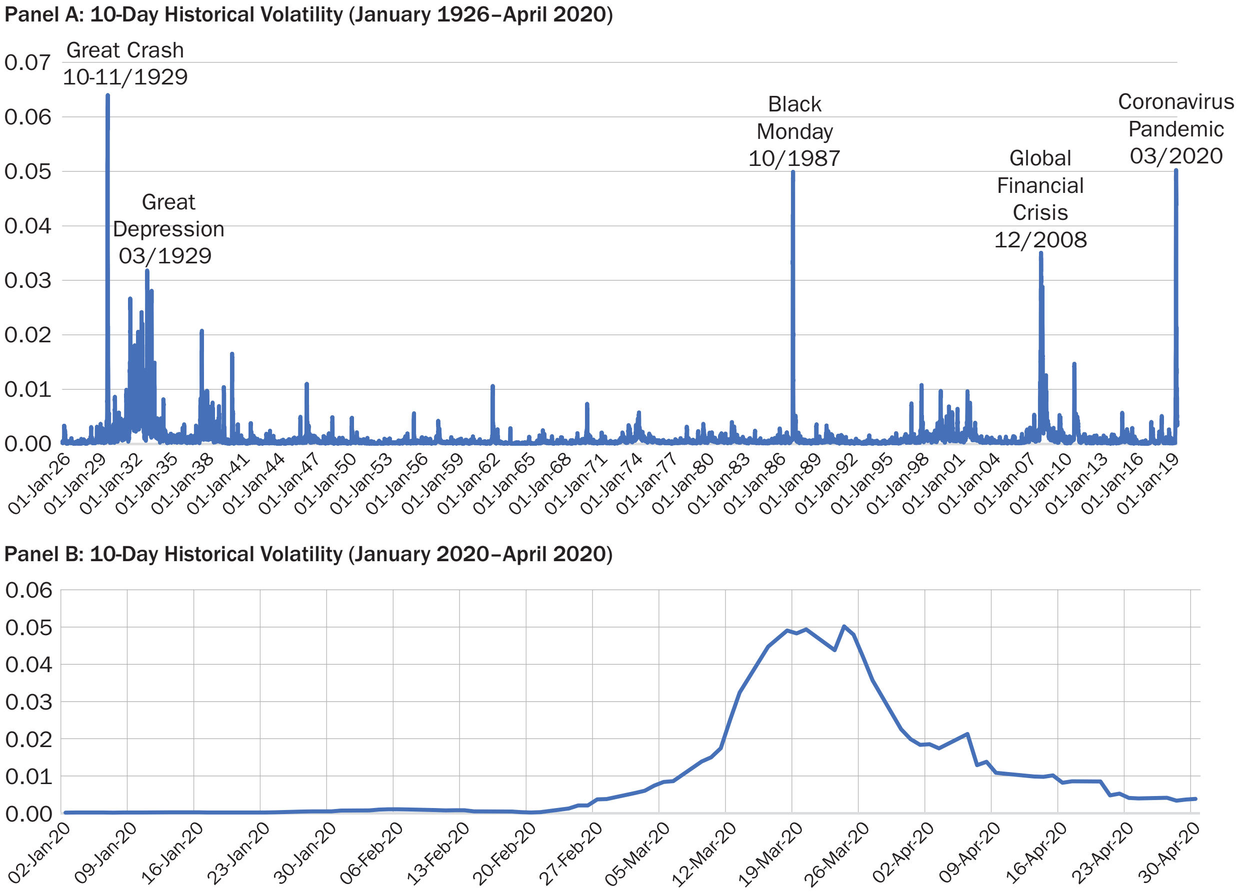
The outbreak of COVID-19 has brought unprecedented disruption to the economy. Its effects on stock markets are not only enormous in magnitude but also distinct from those of past crises in the scope and the economic channels through which they were transmitted. The US financial markets began to impound the economic impacts of the COVID-19 pandemic in late February 2020.[4] By the end of March, the US stock market had dropped more than 35% in value as stay-at-home measures were enforced and business activity shuttered (see Exhibit 1). Other major global financial markets experienced similar declines.[5] Market volatility peaked in March,

[4] Although the first confirmed case of COVID-19 in the United States was reported on January 20, 2020, S&P 500 index options did not reflect the impending crisis until one month later (Ampudia, Baumann, and Fornari 2020; Hanke, Kosolapova, and Weissensteiner 2020; Jackwerth 2020). This finding is consistent with the slowly unfolding disaster model developed by Ghaderi, Kilic, and Seo (2021).

[5] For example, measuring the performance of various stock market indexes from their highest levels in February 2020 to their lowest levels in March 2020 reveals that the declines were similar for the S&P/TSX (34%), FTSE 100 (34%), FTSE MIB (37%), DAX (39%), and Nikkei 225 (31%).

EXHIBIT 2

Realized US Stock Market Volatility, January 1926 to April 2020



NOTE: Based on Baker et al. (2020a), realized volatility is calculated as the sum of squared market returns over the past 10 trading days.

SOURCE: CRSP.

rivaling or surpassing levels last seen during the Great Depression and the 2008 financial crisis (see Exhibit 2). As an exogenous health emergency, COVID-19 provides an unfortunate, yet valuable, opportunity to examine how real shocks propagate through financial markets.

Following the outbreak of the virus, geographical exposure to COVID-19 risk was shown to directly predict stock market movements. Ramelli and Wagner (2020) found that internationally oriented firms, especially those with more export or supply chain exposure to China, underperformed in the first two months of 2020. As the situation in China improved toward the end of February, stocks exposed to China bounced back. Similarly, the domestic spread of the virus in the United States showed a negative and significant impact on local stock valuations. Using the first reported case of COVID-19 in a county as the event day, Bretscher et al. (2020) documented that firms headquartered in an affected county on average experienced a 27 bps decrease in returns in the 10-day post-event window, and this negative effect doubled for firms in counties with a higher infection rate.

Stock market volatility escalated in reaction to news of COVID-19, a unique feature that was not evident during previous infectious disease outbreaks. Baker et al. (2020a) showed that pandemic-related news, both positive and negative, was the dominant driver of large daily stock market moves from late February through April 2020. In comparison, other infectious diseases had limited effects on US stock market volatility. The authors pointed out that the dramatic market reaction to COVID-19 cannot be explained simply by the lethality of the virus; instead, it is attributable to news about the course of the pandemic and the corresponding policy actions. Similar findings are also documented in the global equity markets. Using daily updated news on global coronavirus cases,[6] Alan, Engle, and Karagozoglu (2020) found that both the number and the curvature (acceleration or deceleration) of active cases are significant predictors of the daily volatility of stock market indexes in 88 countries and that countries with stricter policy responses tend to have relatively lower stock market volatility.

Facing intensive media coverage during the rapid spread of COVID-19, investors and corporations were forced to adapt in this uncertain and unfamiliar circumstance. We have subsequently observed shifts in investor beliefs and trading behaviors as well as modifications to corporate cash flow expectations and the discount rate. Collectively, these changes represent the potential, but not mutually exclusive, channels through which COVID-19 pandemic risk has been transmitted to the financial markets. In the next two sections, we dissect the transmitting channels from the perspectives of investors and corporations, respectively.

INVESTOR BELIFS AND BEHAVIORS

The beliefs and responses of investors during the recent crisis represent one possible channel through which pandemic-induced uncertainty has been transmitted to the financial markets. The unprecedented pandemic triggered extreme reactions from investors and exacerbated market volatility.

Given that beliefs are time varying and heterogeneous across investor classes, it is important to incorporate the dynamism of investor beliefs into asset-pricing models (Brunnermeier et al. 2021). Giglio et al. (2021) confirmed the dynamism of beliefs using survey data from institutional and retail investors from Vanguard, one of the largest brokerage firms. The dataset offers the distinct advantage of also detailing the respondents' trading activity and portfolio performance from February to April 2020 to determine whether changes in beliefs explain investors' trading behaviors. Giglio et al. found that investors' trades are aligned with their beliefs and concluded that traditional asset-pricing models do not sufficiently capture the dispersion and time variance of beliefs. Recent studies provide further evidence by demonstrating that investors' risk perception and heterogeneous beliefs are shaped by their political affiliation (Barrios and Hochberg 2021; Cookson, Engelberg, and Mullins 2021). In fact, empirical evidence indicates that partisanship significantly affected the financial markets during the pandemic by affecting trading behaviors and stock turnover (Cookson, Engelberg, and Mullins 2021). These findings are particularly insightful considering that in the midst of the outbreak, the media publicized stark disagreements among politicians and constituents regarding the virus's origin and the appropriate level of government response.

As investor beliefs change over time, a burgeoning literature offers new insights into not only how beliefs are updated during a market crash but also the long-lasting impacts that follow. Given the magnitude of the systematic disruptions to day-to-day life brought on by COVID-19, combined with the heightened anxiety and arguably permanent shifts to our economy that ensued, it is expected that investors will update

[6] These data were extracted from the Johns Hopkins University website at https://coronavirus.jhu.edu/map.html.

their beliefs to incorporate rare disaster risk even after the pandemic ends (Sockin 2021). This will likely trigger a persistent increase in perceived tail risk, which reveals how investors weigh the probability of rare disaster events (Kozlowski, Veldkamp, and Venkateswaran 2020). Prior research has shown that investors tend to demand asset prices that reflect the tail risk of future disaster events, which offers insight into several puzzles in finance, such as excess volatility in the stock market and the high equity premiums (Wachter 2013).

In addition, we expect that investors will heterogeneously update their beliefs based on how severely they were affected by COVID-19.[7] For example, a restaurateur in New York City may weigh the tail risk more heavily than a software engineer working remotely in Honolulu. This heterogeneity in the belief-updating process further intensifies the dispersion of opinions and consequently elevates volatility.

Recent studies investigating how different investor classes respond to the same economic shock provide us with deeper insights on whether preferences shifted during the pandemic. Taking investors' environment, social, and governance (ESG) preferences as an example, Döttling and Kim (2020) found a sharper decline in retail mutual fund flows to high-ESG funds from February to April 2020, indicating that retail investors abandoned their preference for sustainability when confronted with a major shock. In contrast, Döttling and Kim showed that the sustainability preference remained prevalent among institutional investors, who face relatively fewer financial and attention constraints. Despite this difference between these two investor classes, Pastor and Voratz (2020) showed that investors, in the aggregate, display an unwavering preference for sustainability, particularly with an environmental focus. If the aggregate need for sustainability is relatively constant, then the volatility of portfolios with an environmental concentration should be lower compared to that of portfolios facing changes in investor preferences.

Furthermore, social interaction and connectedness among insiders and institutional investors seems to influence the trading behaviors of both parties, which could potentially amplify volatility in a crisis. For example, Henry, Plesko, and Rawson (2020) found that insiders of firms connected to China via the firms' supply chain and operations were more alert to the impending pandemic and the associated consequences, as evidenced by their personal trades. Moreover, insiders with Chinese and Korean backgrounds sold significantly more shares in the initial phases of the COVID-19 pandemic.[8,9] In addition to geographical connectedness, social media connectedness also appears to influence panic-driven trading by fund managers (Au, Dong, and Zhou 2020). Thus, institutional and informed investors who are more socially connected to the highly salient outbreak tend to oversell their stock holdings, intensifying market volatility.

In comparison to the rapid response from institutional investors, research suggests that retail investors' trading shows signs of delay. For example, John and Li (2021) designed an equilibrium model in which the reaction of behavioral traders to

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[7] This expectation is supported by Gao, Liu, and Shi (2020), who found that investors' risk perceptions vary based on how lucky they are following an earthquake. Other studies provide evidence of disaster risk affecting the risk tolerance and decision-making abilities of CEOs (Bernile, Bhagwat, and Rau 2017), firm managers (Dessaint and Matray 2017), and mutual fund managers (Bernile et al. 2021).

[8] Particularly useful for portfolio managers and investors is the informativeness of insiders' trades. Although insiders tend to be net sellers, Anginer et al. (2020) reported that insiders in aggregate purchased more shares after the stock market decline, suggesting that they viewed the March 2020 crash as transitory. Higher levels of insider purchasing are indicative of higher future returns, highlighting the informativeness of these trades.

[9] Another important group of sophisticated investors to consider during the pandemic is short sellers. Greppmair, Jank, and Smajlbegovic (2020) documented that short sellers targeting firms in countries with low credit ratings and low liquidity shortly before the crash yielded a profitable trading strategy.

certain types of pandemic-related news is delayed relative to that of sophisticated traders, who are more accurate when analyzing the payoff implications involved. In addition, Jackwerth (2020) demonstrated that although institutional investors purchased crash protection prior to the March 2020 crash, retail investors did not buy it until the market was already recovering.

Despite often being perceived as a peripheral, unsophisticated group, retail investors have become more notable in the markets with improved access to trading (through the rise of mobile platforms, zero commission fees, and so forth) and more time and attention to trade (as many are forced to be home) during the pandemic. Market maker Citadel Securities reports that retail investors account for as much as 25% of trades on the most active trading days.[10]

Although the March 2020 selloff was characterized by high volatility and low liquidity, Welch (2021) found that, in aggregate, retail investors display a preference for trading during such periods. In fact, retail investors trading on the Robinhood platform increased their holdings by approximately 3% per day in late March 2020, compared to 0.22% per day in the pre-crisis period. Welch showed that retail investors transferred more cash to their brokerage accounts to augment their stock positions, suggesting that they may have provided temporary market stabilization during the market downturn. Furthermore, retail investors' increased positions alleviated the illiquidity shock by nearly 40% during the lockdown, and stay-at-home orders were a major contributor to this pattern (Ozik, Sadka, and Shen 2021).

Retail investors have established themselves as an aggregate group of investors that should be closely observed. The 2021 GameStop frenzy is a very recent example demonstrating retail investors' ability to bring novel risk to financial markets. A portfolio that mimics the aggregate trades of Robinhood retail investors, which are publicly available in real time, yields a significantly positive alpha greater than 14% per year (Welch 2021).[11] As access to trading becomes more convenient and potentially permanent shifts are induced within the economy, we expect that some of the trends observed among retail investors during the pandemic will persist, presenting new challenges to asset-pricing models and portfolio risk management.

CORPORATE STRATEGIES AND OUTCOMES

Although both individual and institutional investors have been forced to update their beliefs and behaviors to a considerable extent as a direct consequence of COVID-19, corporate managers have been confronted by similar challenges that necessitate substantial modifications to their corporate strategies. Facing rapidly evolving economic fundamentals characterized by unprecedented levels of uncertainty, firms have had little choice but to adapt quickly to survive. The unique operating environment created by the pandemic has undoubtedly affected firms in a vast number of ways. Perhaps the most notable of these changes are the impacts on firm valuation and volatility attributable to cash flow expectations and financing costs.

The profound impact of the pandemic on economic fundamentals has triggered a direct and lasting shock to corporate cash flows. Survey evidence from the early stage of the crisis reveals that CFOs' expectations of revenue growth in 2020 dropped from roughly 10% in early March to nearly 0% by late March and early April, where it remained in subsequent months (Barry et al. 2021). Similarly, Landier and Thesmar

[10] Source: https://www.bloombergquint.com/onweb/citadel-securities-says-retail-is-25-of-the-market-during-peaks.

[11] Note that this portfolio performance extends beyond the pandemic because the data begin in May 2018.

(2020) documented a 16% reduction in 2020 earnings-per-share growth expectations based on implied analysts' earnings forecasts for US firms between mid-February and mid-May of 2020.

Unsurprisingly, expectations of shrinking sales quickly came to fruition as the effects of COVID-19 swept across the globe. Revenues for small US businesses were most severely affected during the second quarter of 2020, when these firms suffered a 29% plummet in sales on average. This negative effect is relatively persistent in that firms reporting the largest drop in sales also forecasted substantial losses during the following year (Barrero et al. 2021; Bloom, Fletcher, and Yeh 2021).

The cash flow crisis that ensued likely contributed to the unsurprising decline in corporate investment that emerged in response to COVID-19. Indeed, 2020 survey data revealed a noteworthy decrease in both actual and anticipated capital spending (Meyer et al. 2020). Barry et al. (2021) documented a similar drop in corporate investment activity, reporting that 30% of the CFOs they surveyed predicted that their willingness to pursue capital investments would not return to its pre-COVID level until after 2022, and some even expressed doubt that their pre-pandemic investment activities would ever resume. The survey results also shed light on how corporations updated their capital spending strategies in response to the pandemic. Firms with high investment flexibility appropriately exercised their ability to delay or reduce the scale of capital expenditures, and those with high workplace flexibility replaced their investments in physical assets with investments in their workforce and in intangible assets that accommodate remote collaboration.[12] This evolution in the nature of corporate investments surely affected the expected cash flows of many companies, suggesting that firm valuations were subsequently altered.

In addition to cash flow variations, corporate valuation is largely driven by financing decisions and the resulting cost of capital. The sudden spike in market risk at the onset of the pandemic triggered a sharp rise in the discount rates used in corporate valuations. In fact, Landier and Thesmar (2020) estimated that the average firm discount rate implicit in market valuations rose from 8.5% in mid-February of 2020 to 11% at the end of March. This pattern reflects the impact of the pandemic on several factors related to the sources and costs of corporate capital, including the risk-free rate, bank financing, and the capital markets. These factors have contributed to market volatility through their collective effects on the discount rate used for corporate valuation purposes.

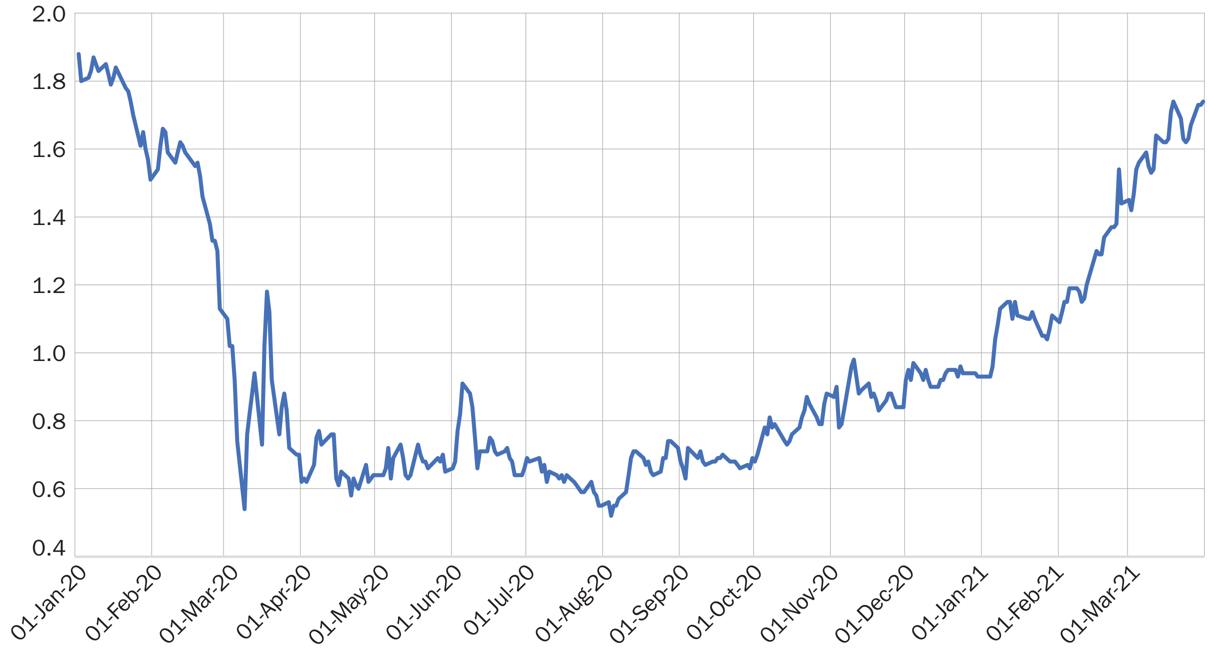
The risk-free rate represents an essential component of the required return for suppliers of corporate capital. Although this value should, by definition, remain relatively constant through time, evidence based on US Treasury yields suggests that it exhibited significant time variation during the COVID-19 pandemic (He, Nagel, and Song 2021).[13] In fact, the risk-free rate was disrupted during the early stages of the pandemic as the US Treasury market experienced severe stress and illiquidity (Ermolov 2020). He, Nagel, and Song documented that large owners of US Treasury securities dramatically reduced their holdings in March of 2020, and dealers unfortunately struggled to absorb the resulting demand shock. Market prices of US Treasuries plummeted in mid-March, causing yields to spike unexpectedly, as depicted in

[12] The advantages of workplace flexibility, specifically in regard to telework, are also evident in stock returns at the industry level during the pandemic (Favilukis et al. 2021).

[13] International evidence suggests similar signs of instability and risk during the pandemic within the sovereign debt market. For instance, Augustin et al. (2021) examined credit default swap premiums in 30 developed countries and reported that sovereign default risk is positively associated with the intensity of the virus's penetration for fiscally constrained governments.

EXHIBIT 3

Annualized 10-Year US Treasury Constant Maturity Rate, January 2020 to March 2021



SOURCE: Federal Reserve Economic Data, St. Louis Fed.

Exhibit 3.[14] At the same time, strong indications of market illiquidity emerged as bid–ask spreads grew wider and market depth plunged. Ermolov (2020) reported that measures of US government bond illiquidity began their ascent at the end of February 2020, and during the second week of March, they reached a peak that exceeded levels witnessed during the financial crisis of 2008. These extreme disruptions threaten the long-standing view of the US Treasury market as a safe haven. Fortunately, the US Federal Reserve played an enormous role in mitigating the crisis. Ermolov noted that the liquidity of government bonds improved tremendously following the launching of the Fed's aggressive interventions in March.

Despite the unprecedented volatility and liquidity shocks in the US Treasury market at the onset of the pandemic, most firms surprisingly managed to maintain access to external capital during the crisis. Thanks to the proper functioning of financial institutions and the capital markets, combined with important and timely government interventions, the financial constraints imposed on firms were rather limited during this time. Bank financing, in particular, remained quite stable as the pandemic unfolded. Li, Strahan, and Zhang (2020) found that firms relied on bank financing as a first resort, which led to pronounced growth in commercial and industrial loans on bank balance sheets during the pandemic. Banks were fortunately able to fulfill these spiking liquidity demands owing to their relatively strong financial position before the crisis escalated, combined with the benefit of massive and impeccably timed cash inflows from both the US Federal Reserve's liquidity injection programs and depositors. Levine et al. (2021) reported that total deposits in the United States increased from $13 trillion in January of 2020 to $15 trillion in April.

[14] This pattern sharply contrasts the behavior of Treasury yields during past crises (He, Nagel, and Song 2021).

Several studies have documented an enormous dash for cash as companies drew down on their preexisting credit lines to build up their precautionary cash holdings and mitigate future liquidity risk (Acharya and Steffen 2020; Bosshardt and Kakhbod 2020; Chodorow-Reich et al. 2021; Li, Strahan, and Zhang 2020).[15] This behavior was more pronounced among firms with lower credit ratings, whereas those with higher ratings relied on bank financing to a lesser extent because they managed to attain additional capital through the debt and equity markets (Acharya and Steffen 2020). Furthermore, Bosshardt and Kakhbod (2020) examined how firms used the excess liquidity produced by their credit line drawdowns. They found that most firms used the new funds to accumulate liquid assets, which is consistent with a precautionary motive to reduce future liquidity risk. However, firms operating in industries that were less affected by the shutdown, such as those specializing in professional services that can be performed remotely, used the capital for investment purposes.

Although bank financing was made readily available during the pandemic to US firms in the aggregate, not all companies were provided an equivalent opportunity to use this important source of capital. Chodorow-Reich et al. (2021) showed that small firms had reduced access to liquidity owing to the less favorable loan terms granted to them by banks. Fortunately, the government-sponsored Paycheck Protection Program helped to alleviate the liquidity shortfall to small firms during this vulnerable time.[16]

In contrast to the bank sector, which provided a reliable source of capital for most firms even during the most difficult times, the capital markets imposed temporary constraints on firms' financing activities as the pandemic intensified. The equity market was undeniably shaken in March 2020 as several broad US stock indexes plunged. Correspondingly, equity issuance activity slowed considerably during the first four weeks of the pandemic (Halling, Yu, and Zechner 2020). The corporate debt market exhibited similar signs of distress as bond prices fell dramatically, bond liquidity declined, and a number of price dislocations emerged. A major factor contributing to this instability in the bond market was the reluctance or inability of bond dealers to absorb the excess inventory of corporate debt created by persistent selling pressure from bond investors (Haddad, Moreira, and Mur 2021; Kargar et al. 2021; O'Hara and Zhou 2021). This extreme uncertainty deterred firms from raising funds in the bond market.

The US Federal Reserve fortunately introduced stabilization policies designed to boost liquidity and reduce transaction costs in the corporate bond market, reflecting a new role as "market maker of last resort" (O'Hara and Zhou 2021).[17] The government's interventions proved to be largely effective, as bond prices quickly rebounded and the dislocations dissolved (Haddad, Moreira, and Mur 2021). The equity market showed similar signs of recovery with increased stability shortly after the tumultuous period in March.

In the midst of reduced volatility following the adoption of the Federal Reserve's stabilization policies in late March, high-rated firms ventured into the capital markets once again, where they supplemented the cash obtained through credit line drawdowns by raising additional capital through debt and equity issues (Acharya and Steffen 2020). Halling, Yu, and Zechner (2020) noted that the equity market became more

[15] In addition, Acharya, Engle, and Steffen (2021) found that credit line drawdowns explain the banking sector's negative stock performance during the pandemic.

[16] Small companies in other countries received similar forms of federal aid. One such example is Italy's public guarantee scheme, which succeeded in granting small businesses access to bank credit (Core and Marco 2020).

[17] The Primary Dealer Credit Facility was launched on March 17 (see https://www.federalreserve.gov/newsevents/pressreleases/monetary20200317b.htm), and the Primary and Secondary Market Corporate Credit Facilities were established on March 23 (see https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm).

active after four straight weeks of limited activity from March 16 through April 10, and the corporate bond market experienced a substantial rise in the number of new issues, even for bonds rated BBB or lower. The pandemic was also marked by an increase in the maturities of new debt issues, reflecting an attempt by firms to avoid the rollover risk associated with short-term financing.

Despite the apparent availability of external capital throughout the COVID-19 pandemic, a potential rise in the cost of capital could render external financing unattainable in many cases. The increasing cost is partially attributable to the fact that an expanding proportion of firms was expected to encounter financial distress due to the damaging impact of the crisis on corporate cash flows. Based on a simulation conducted using data from Italy, Carletti et al. (2020) estimated that a three-month lockdown would cause 17% of sample firms to enter a state of financial distress. Similarly, Altman (2020) predicted that the pandemic will not only trigger a rise in corporate bankruptcies and elevated default rates on high-yield bonds but also render many BBB-rated bonds vulnerable to downgrades.

The mounting prevalence of financial distress has surely contributed to a rise in the cost of capital for a growing number of firms, suggesting that the discount rates applied when valuing these businesses have likewise increased. Even in the absence of financial distress, the cost of capital for most companies has been affected, at least temporarily, by higher risk premiums owing to extreme volatility in the capital markets and pronounced illiquidity in the debt market. In addition to the vast amount of risk surrounding several components of the discount rates, firms were simultaneously coping with depressed sales and immense cash flow uncertainty. These factors combined to form a perfect storm that shook the corporate landscape and introduced pandemic risk into the financial markets.

CROSS-SECTIONAL STOCK RETURNS

The fundamental changes in firm value, together with the shifts in investors' beliefs, have had a profound impact on stock markets. Although the pandemic's effects are systematic, some industries and firms have been hit harder than others. As of August 2020, the airline, recreation facility, gas and oil drilling, and restaurant industries were among those estimated to be the most affected from the perspective of default probability, whereas the insurance and real estate investment trust industries were among those least affected.[18] The effects of COVID-19 and the resulting government policy responses have caused large-scale reallocation of resources across industries and firms. Correspondingly, stock returns have differed enormously in terms of their reaction to news and policy interventions.

Generally speaking, firms with higher risk exposure or lower disaster resilience underperform their counterparties. Using textual analytics to characterize firm-level risk exposures in pre-pandemic 10-K filings, Davis, Hansen, and Seminario-Amez (2020) showed that risk exposures reveal information about how the pandemic affected future earnings and can explain up to half of the variation in the cross section of firm-level returns. The authors further adopted a supervised machine learning method to uncover and interpret risk factors. Terms including "restaurants," "hotels," "airline industry," and "jet fuel" are important predictors of negative returns. In a similar vein, Pagano, Wagner, and Zechner (2020) measured firms' disaster resilience based on survey data from the Occupational Information Network and found that firms that are more resilient to social distancing significantly outperformed those

[18] Source: https://www.spglobal.com/marketintelligence/en/news-insights/blog/industries-most-and-least-impacted-by-covid19-from-a-probability-of-default-perspective-september-2020-update.

with lower resilience during the COVID-19 outbreak. The authors also used option prices to infer expected future stock returns; they estimated that, as of March 2020, stocks of low-resilience firms would carry a premium of 5.5% over the following year and about 4% annually over the next two years.

The variations in cross-sectional stock returns can also be attributed to certain firm characteristics that are directly or indirectly associated with pandemic risk exposures. Cash holdings and leverage have emerged as important value drivers during the pandemic period. For example, Ramelli and Wagner (2020) showed that even within the same industry, firms with high corporate debt and low cash holdings performed poorly, and this result is more prominent in industries that suffered stronger stock price declines. The authors found that the effects of cash and leverage are economically sizeable. More specifically, one-standard-deviation changes in cash holdings and leverage both can explain the stock return variation by one-sixth of its standard deviation. Similar findings are documented by Alfaro et al. (2020), who showed that pandemic-related losses at the firm level tend to rise with capital intensity and leverage and are larger in industries that are more conducive to disease transmission. Furthermore, using cash to assets, short-term debt to assets, and long-term debt to assets as proxies for financial flexibility, Fahlenbrach, Rageth, and Stulz (2020) found that firms with high financial flexibility within an industry experienced a price decline that is 9.7% lower than that of firms with low financial flexibility.

In addition to managing financial risk, being socially responsible has provided continuing benefits for firms and their shareholders during the crisis. In particular, Albuquerque et al. (2020) estimated that stocks with higher environmental and social (ES) ratings earned an extra cumulative return of 7.2% during the March 2020 sell-off relative to firms with low ES ratings.[19] These results highlight the importance of customer and investor loyalty during the COVID-19 pandemic.

International financial markets exhibited confirmatory evidence similar to that documented in the US stock markets. For example, data from Italy show that distress is more frequent for small and medium-sized enterprises and those with high pre-pandemic leverage (Carletti et al. 2020). More comprehensively, using data on more than 6,700 firms across 61 countries, Ding et al. (2021) evaluated how corporate characteristics shaped stock price reactions to COVID-19. Their results show that the pandemic-induced declines in stock returns were milder among firms with stronger pre-pandemic finances, less geographic exposure to the pandemic, and more corporate social responsibility activities.

Overall, the evidence on cross-sectional stock return variations emphasizes the value of maintaining corporate financial strength and social responsibility, especially during crisis periods. Dissecting different drivers of stock returns offers implications for corporate risk management, including but not limited to liquidity (cash) and refinancing (leverage) risk management. A comprehensive understanding of these factors empowers businesses to identify ongoing and potential risks and better confront these challenges brought on by a pandemic or disaster.

VOLATILITY AND RISK MANAGEMENT

The breadth and depth of COVID-19's impact on global financial markets, together with the resulting business disruption and economic uncertainty, present new challenges to portfolio risk management. The shifts in risk factors induced by COVID-19

[19] The sample period extends from February 24, starting with the acceleration of the decline in the S&P 500 index, to March 17, when an aggressive fiscal and monetary policy response was initiated.

are highly correlated across countries, calling into question the benefits of diversification and the feasibility of hedging systematic risk during the crisis.

By examining 24 assets covering over 70% of the market value of global financial markets, Boudoukh et al. (2020) echoed this statement and showed that the structure of global risk factors changed more dramatically during the COVID-19 period compared to the past 15 years (including the 2008 financial crisis). These changes are tied directly to the abundance of COVID-19 news, which contains useful information in predicting the course and impacts of the pandemic. Their analyses identified a clear shock to systematic risk, coinciding with huge increases in portfolio volatility and large reductions in diversification benefits across markets and asset classes. More generally, Barro (2006) and Barro and Liao (2021) focused on the role of rare disasters in asset markets and found that disaster probability is highly correlated across countries and peaks during crises.[20] They also noted that rare disasters have great potential to explain the excess volatility anomaly.

With the escalation of portfolio variance and correlations of global financial assets, investors and portfolio managers need to look beyond diversification to manage portfolio risk during the pandemic. Strategies embedding risk management into investment decisions tend to be beneficial when facing sharp equity selloffs. Harvey et al. (2020) examined a series of such strategies and demonstrated that long–short profitability strategies performed well during the market selloff in February and March of 2020, as did faster-formulated time-series momentum (i.e., trend-following) strategies. Their analysis further showed that both responsive volatility targeting and strategic rebalancing rules appropriately suggested a reduction or underweight in equity positions ahead of the most volatile period in March. Other studies indicate that derivatives continue to serve as a useful tool in trading and risk management. For example, trading strategies based on estimated VIX futures premiums profited from the rise in market volatility and the equity market crash in early 2020 (Cheng 2020).

The importance of vaccine development and distribution is another unique feature of the COVID-19 crisis, delivering useful implications for managing pandemic risks. An emerging literature is mapping vaccine risks into asset prices by estimating the real value of a cure as opposed to that of fiscal or monetary policies. For instance, Hong, Wang, and Yang (2021) linked firm valuations to infections via an asset-pricing model with vaccines. They emphasized the value of engaging in COVID-19 mitigation activities, which, although costly, are optimal for firms from a long-run value-maximization perspective. Asset valuations are highly sensitive to the vaccine arrival rate, and stock market values would be down 15% absent mitigation and a high vaccine arrival rate. Similarly, by observing stock market responses to vaccine progress, Acharya et al. (2020) estimated that the economy-wide welfare gain attributable to a cure is worth 5%–15% of total wealth. This value rises substantially in the midst of uncertainty regarding the frequency and duration of pandemics. Their analysis indicates that variations in vaccine progress have profound implications for asset price volatility.

In sum, portfolio risk management faces new challenges as the risk factors continue to shift dramatically owing to the pandemic. These foundational changes offer rich opportunities for subsequent research. For instance, Hong et al. (2021) suggested that future studies could not only continue investigating the stock pricing framework with vaccines but also incorporate the resulting estimates into an asset-pricing model to measure the efficiency of stock prices, particularly within distressed industries.

[20] For rare disasters, Barro (2006) focused on the sharp contractions associated with World War I, the Great Depression, and World War II. Barro and Liao (2021) estimated the rare disaster probability using over-the-counter options prices for seven equity market indexes.

CONCLUSION

As the world embraces the potentially long-lasting effects of COVID-19 and adapts to a new normal, our article reflects upon the many lessons learned from the recent pandemic, including their applications to portfolio and risk management. The uniqueness of the COVID-19 pandemic's shock to market returns and volatility has shed light on several puzzles in finance and motivated the updating of asset-pricing models by incorporating novel risk factors. Financial economists now have fresh perspectives on the transmission of pandemic-induced uncertainty to the financial markets via channels pertaining to investor beliefs and behaviors and corporate strategies and outcomes. Although some of these effects on market volatility are transitory in nature, evidence suggests that there will be long-lasting impacts resulting from investors' updated risk perceptions and corporations' evolving approaches to investment and financing decisions. Recent findings also highlight the imperative role of government policy responses in regulating the market volatility triggered by large-scale disasters like the pandemic.

We anticipate that the topics reviewed in this synthesis of the emerging literature on the pandemic will not only provide practical insights to portfolio managers, investors, corporate insiders, and policymakers but also inspire fruitful avenues for future research. New questions will surely arise as COVID-19 continues to unfold and the nature and magnitude of its effects become more apparent. Using the growing set of pandemic-related data as it becomes available, researchers have a unique opportunity to enrich our comprehension of novel factors that induce volatility in the financial markets. An improved understanding of what drives asset prices will render us better equipped to devise portfolio strategies that effectively manage pandemic risk.

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Socially Responsible Investing Strategies under Pressure:
Evidence from the COVID-19 Crisis

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KEY FINDINGS

- On average, socially responsible investing (SRI) indexes neither significantly outperformed nor underperformed their conventional benchmark during the COVID-19 crisis.
- SRI strategies show substantial heterogeneity, with impact strategies delivering better performance.

ABSTRACT

By matching socially responsible (SR) stock indexes worldwide with their conventional benchmarks, the authors study the resilience of SR investment strategies during the COVID-19 crisis. Overall, SR indexes exhibited dynamics very similar to their benchmarks. The sample is composed of 573 SR stock indexes from MSCI, STOXX, and FTSE. In the first half of 2020, the average daily return was –0.11% for SR indexes and their benchmarks, with annualized volatility of 40% for each. SR indexes remained very close to their benchmarks during both the fever period (February 24–March 20) and the rebound period (March 23–May 29). The financial performance of SR strategies shows substantial heterogeneity, however, with SR impact strategies slightly outperforming their benchmarks. In addition, the resilience of SR strategies was a little stronger in countries and during periods in which the number of COVID-19 cases was increasing. In robustness checks, the authors control for public attention to the COVID-19 pandemic, as well as the economic effects of new policies implemented during the crisis, including lockdowns, and fiscal and monetary policy changes. Their findings call for careful SR investment selection because not all such investments have provided equal returns in the face of the COVID pandemic.

TOPICS

*Security analysis and valuation, mutual funds/passive investing/indexing, ESG investing, performance measurement**

For many, the COVID-19 pandemic has been an eye-opener to the ecological risks threatening humanity. These fears are not new, but this unprecedented crisis, which has seen almost four million dead (as of June 2021) and half of the world's population placed in lockdown, has revealed previously undetected fragilities in global economic systems. As a result, voices from all corners are increasingly calling for radical reform, including those from the heart of the economic system: the financial sector.

According to Mark Carney, the United Nations Special Envoy for Climate Action and Finance, investors have an "enormous strategic opportunity" to shift toward a sustainable future in the wake of the COVID-19 pandemic and "win the peace."[1] Similarly, for Larry Fink, BlackRock chief executive, "We are on the edge of a fundamental reshaping of finance,"[2] while according to a report issued by J.P. Morgan, "the Covid-19 crisis is accelerating the trend for a more sustainable approach to investing."[3]

It is certainly too early to claim that the COVID-19 pandemic will mark a turning point in favor of a better integration of environmental, social, and governance issues—the so-called ESG factors—into firms' valuation. Some evidence, however, seems to point in this direction. For instance, on April 3, 2020, in the midst of the COVID-19 crisis, *The Financial Times* reported that two-thirds of ESG investment funds outperformed the major indexes during the COVID-19 outbreak.[4] Similar observations have been reported by Standard & Poor's and MSCI.[5] Several recent academic papers also point in this direction; Albuquerque et al. (2020), Broadstock et al. (2020), Ding et al. (2020), and Garel and Petit-Romec (2021a, 2021b) showed that individual stocks with high ESG scores performed better during the COVID-19 pandemic than stocks with low ESG scores. In addition, Pastor and Vorsatz (2020) found that socially responsible (SR) funds performed better than conventional funds. However, Demers et al. (2020) found that ESG scores offer no significant explanatory power for stock returns during the COVID-19 and warned against a "premature celebration" of ESG factors as portfolio hedges in time of crisis.

This study is part of the strand of research aiming to analyze the resilience of different SR investment strategies in the time of the COVID-19 crisis. We offer three contributions to this evolving literature. First, we analyze stock indexes rather than individual stocks or mutual funds. Indeed, as opposed to individual stocks, SR indexes are portfolio strategies that are implemented by SR funds, which are the main investment vehicles for SR investing (Chen and Scholtens 2018). In addition, comparing SR and non-SR indexes instead of different mutual funds helps limit biases arising from sectoral and geographic factors, as well as from fund managerial ability. Controlling for these biases is all the more important in times of high volatility, when the performance of active funds diverges from their benchmarks (Agarwal, Arisoy, and Naik 2017). Second, we carry out the analysis on a global scale, covering most major stock markets, which allows us to improve the identification of the relationship between the severity of the COVID-19 pandemic and SR resilience. Third, in addition to comparing SR with conventional strategies, we also compare different SR strategies with one another. Indeed, the heterogeneity of SR investment is often overlooked. SR strategies differ in one or several of the following four criteria: (1) broad ESG indexes versus indexes focusing on environmental, social, or governance issues separately (Pastor, Stambaugh, and Taylor 2020; Pedersen, Fitzgibbons, and Pomorski 2020; Zerbib 2020); (2) demanding indexes versus less demanding ones in terms of ESG scores (Barnett and Salomon 2006; Capelle-Blancard and Monjon 2014); (3) best-in-class versus exclusion strategies (Hong and Kacperczyk 2009); and (4) indexes that seek to have an impact (i.e., with the intent to contribute to measurable positive ESG impact on companies' practices) versus those that do not (De Angelis, Tankov, and Zerbib 2020; Landier and Lovo 2020; Oehmke and Opp 2020; Barber, Morse, and Yasuda 2021).

[1] Abnett (2020).
[2] Fink (2020).
[3] J.P. Morgan (2020).
[4] Darbyshire (2020).
[5] See Whieldon, Copley, and Clark (2020) and Nagy and Giese (2020). See also Demers et al. (2020) for additional examples.

In this study, we examine 573 SR stock indexes provided by MSCI, STOXX Limited (STOXX), and the Financial Times Stock Exchange group (FTSE). We match each SR index with the benchmark index in its prospectus, which we use as a counterfactual conventional index. We classify all SR indexes according to the four main criteria listed previously. We also categorize the indexes with respect to the size of the firms (small, mid, or large capitalization) and the geographical areas (developed or developing countries) on which they focus. We then perform empirical analysis by estimating three types of specifications. First, we compute (model-free) performance and volatility measures based on raw returns. Second, we analyze the sensitivity of the SR indexes to their counterfactual conventional indexes by regressing the returns on the SR indexes on those of their benchmarks and the small-minus-big (SMB), high-minus-low (HML), and momentum (MOM) factors of the Carhart (1997) model. Third, we add to the previous specification the characteristics of the SR indexes and the country-level daily number of COVID-19 cases from the John Hopkins University (JHU) global database.

Our main results are the following. (1) Overall, we show that the SR indexes have exhibited dynamics very similar to their benchmarks. In the first half of 2020, the average daily return was –0.11% for SR indexes and their benchmarks, with annualized volatility of 40% for each. Specifically, SR indexes remained very close to their benchmarks during both the *fever period* (February 24–March 20, also referred to as *fever*) and the *rebound period* (March 23–May 29, also referred to as *rebound*). Our findings are consistent with the conclusions of Demers et al. (2020) in that it is unclear whether SR investment strategies have acted as an effective hedge in the time of the COVID-19 crisis. (2) Nevertheless, the resilience of SR strategies was a little stronger in countries and during periods in which the number of COVID-19 cases was increasing. (3) In addition, the financial performance of SR strategies shows substantial heterogeneity: Specifically, the few SR strategies aiming at having an impact showed stronger resilience than their conventional benchmarks during the COVID-19 crisis.

We support the results of our baseline analysis by implementing several robustness tests. First, we use several other controls (Capelle-Blancard and Desroziers 2020): (1) public attention to the COVID-19 pandemic over time and in each country using data from Google Trends; (2) a market volatility index linked to the publication of articles on infectious diseases (Baker et al. 2020); (3) variables capturing public authorities' responses to the COVID-19 crisis, including the Oxford Covid-19 Government Response Tracker on the degree of social, economic, and health domestic response to the pandemic, used as a proxy for lockdown policies; and (4) a combination of variables constructed from the Yale Program on Financial Stability on economic policy announcements by country, used as a measure of fiscal policy intervention. Second, we consider several subsamples based on different geographical regions (North America, Europe, and the rest of the world). We find that our main results are robust to these alternative specifications.

These results have several normative implications. First, they encourage SR investors seeking financial resilience to be very selective in their choice of investment vehicles and to favor impact funds when they can. Second, impact strategies have the advantage of diversifying the exposure of investors who do not necessarily have nonpecuniary preferences by providing potential benefit in time of crisis. Third, these conclusions remind investors that ESG ratings and labels are not necessarily predictive of financial performance (Peladan et al. 2020). A company can, for example, be very green but not show any particular outperformance. As such, although we are convinced that finance should care about corporate SR (CSR) in general and ecology in particular (Scholtens 2017), our results suggest that the decision to invest in SR strategies should not be based primarily on the search for financial

EXHIBIT 1

Academic Papers on SR Returns in the Time of the COVID-19 Crisis

Authors	Sample (period)	COVID-19 Data	Model	Main Results Regarding SR Investing
Albuquerque et al. (2020)	2,171 US firms (Q1: 2020)	No	CAPM + Firm controls	Daily AR = +0.45% (from February 24 to March 17) for high ES firms (top quartile, Eikon 2018), with a decrease in volatility.
Broadstock et al. (2020)	300 Chinese firms (February–March 2020)	No	Market model + Firm controls	$CAR_{[-2;+2]}$ = +0.1% around the Wuhan lockdown for high-ES firms (above the median, pre-2020), with a decrease in volatility.
Demers et al. (2020)	1,652 US firms (Q1: 2020)	No	Four-factor + Firm controls	ESG (Eikon 2018) was not significantly related to abnormal returns when controls are included—but was significant without controls—during the crisis, but was negatively associated with returns during the recovery.
Ding et al. (2020)	6,135 firms from 56 countries (Q1: 2020)	Yes (cumulative no. of cases)	Firm controls	Weekly returns = +0.23% for high-CSR firm (top quartile, pre-2020) compared to low-CSR firm (last quartile, pre-2020).
Garel and Petit-Romec (2021a)	1,626 US firms (February–March 2020)	No	Four-factor + Firm controls	Weekly returns = +1.41% if environmental scores (Eikon 2018) are one standard deviation higher.
Garel and Petit-Romec (2021b)	437 French firms (February–March 2020)	No	Firm controls	No evidence that social or environmental scores (Eikon 2018) influenced stock returns during the COVID-19 crisis.
Pastor and Vorsatz (2020)	3,626 US funds (February–April 2020)	No	Multifactor models	Funds with higher (Morningstar) sustainability ratings performed better and received larger net flows.
Current Article	574 indexes worldwide (January–May 2020)	Yes (cumulative no. of case)	Four-factor + Controls	SR indexes exhibited dynamics very similar to their benchmarks, but the resilience of SR investing was slightly stronger when the number of COVID-19 cases increased and for impact investing strategies.

performance (Pastor, Stambaugh, and Taylor 2020, 2021) but on the desire to have an impact on the environmental and social (ES) practices of firms (Capelle-Blancard and Monjon 2012).

LITERATURE AND HYPOTHESIS

Related Papers

The COVID-19 crisis has provided researchers with a unique opportunity to explore how SR investment strategies fare under stress (see Exhibit 1 for a synopsis). Albuquerque et al. (2020) noted that because the COVID-19 shock, unlike previous shocks, is totally exogenous to financial activity, it can likely provide a cleaner test of the effects of ES policies on stock market returns.[6]

[6]Previous authors also examined the resilience of SR indexes during the 2008 Global Financial Crisis (GFC). Erragragui et al. (2018) considered both developed (United States, United Kingdom, Japan, Canada, Australia) and emerging economies (Brazil, India, South Africa) from 2008 to 2014. They concluded that SR indexes have higher alpha despite the fact that they are more sensitive to systematic risks. Several other papers focus on mutual funds. Nofsinger and Varma (2014) showed that the 240

Albuquerque et al. (2020) considered 2,171 US firms to assess how companies with high ES scores performed during the first quarter of the COVID-19 crisis. Using Thomson Reuters Eikon ESG data, they measured the firms' ES performance as the average of the scores on both criteria in 2018. As a robustness test, they computed the difference between the number of strengths and concerns for each firm in 2016 using MSCI data. Their results showed that firms with ES ratings in the top quartile performed better. This result is confirmed by Garel and Petit-Romec (2021a), using a sample of over 1,626 US-listed firms from February 20 to March 20, 2020. Using the same Eikon ESG data, they showed that commitment to environmental matters reduced the impact of COVID-19 on stock prices.

Over the same period, Ding et al. (2020) collected data on 6,135 firms across 56 countries to observe how the COVID-19 crisis affected firms' financial performance. They also analyzed the resilience of best-in-class ESG companies. Using the Thomson Reuters Eikon ESG database—like Albuquerque et al. (2020) and Garel and Petit-Romec (2021b)—they constructed an environmental index and a social index, as well as an aggregated CSR score index. They also controlled for firms' governance through a set of dummy variables equal to 1 if the company under consideration has a board size or independence policy, or if an individual simultaneously has the roles of CEO and chairman. Their results suggested that firms with stronger commitment to CSR prior to the crisis overperformed during the outbreak.

Focusing on China, Broadstock et al (2020) considered the CSI 300 firms listed on the Shenzhen and Shanghai Stock Exchange. They performed an event study around the Wuhan lockdown (January 23–February 4, 2020) and showed that above-median ESG portfolios outperformed below-median ESG portfolios.

Contrary to the aforementioned studies, Demers et al. (2020) were more skeptical about the idea that ESG might be an "equity vaccine" against a fall in stock prices in times of crisis. They considered a sample of 1,626 US firms during the first quarter of 2020 and also used Thomson Reuters Eikon ESG scores. They showed that "consistent with all the hype, ESG is significantly positively related to returns *in the absence of other controls being included in the regression* [emphasis in original]." However, "once the firm's industry affiliation and accounting- and market-based measures of risk have been properly controlled for, ESG scores offer no such positive explanatory power for returns during Covid-19." Similarly, focusing on France, Garel and Petit-Romec (2021b) found no evidence that social or environmental scores influenced stock returns during the COVID-19 crisis.

All of the aforementioned studies consider individual stocks. At the portfolio level, Pastor and Vorsatz (2020) showed that actively managed mutual funds in the United States underperformed their passive benchmark during the outbreak. Nonetheless, they also demonstrated that SR funds outperformed conventional ones over the same period. They measured performance using benchmark-adjusted returns and factor-adjusted alphas. Investors favored funds with high ESG standards, especially environmental ones, and funds that applied exclusion criteria.

There are also studies that consider a specific dimension of CSR. Shan and Tang (2020) focused on Chinese firms with above-median employee satisfaction (using

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US SR mutual funds in their sample outperformed conventional funds during stock market crises (the dotcom crash in 2001 and GFC). Nakai, Yamaguchi, and Takeuchi (2016) confirmed this result using a sample of 62 Japanese mutual funds. However, Muñoz, Vargas, and Marco (2014) found no evidence of market outperformance by SR funds in the United States and Europe. Lastly, at the firm level, Lins, Servaes, and Tamayo (2017) showed that US nonfinancial firms with high ES ratings had greater stock returns (between +4% and +7%) and economic performances (higher profitability, growth, and sales per employee) compared to firms with low ES ratings. Bouslah, Kryzanowski, and M'Zali (2018) found that CSR strengths reduced volatility. Cornett, Erhemjamts, and Tehranian (2016) focused on US banks and showed that their financial performances (return on equity) is positively related to their ESG scores.

MioTech ESG data), and Cheema-Fox et al. (2020) focused on US firms protecting their workforce and supply chains (using Truvalue Labs ESG data). Both reported that, although still negative, SR firms experienced higher returns than conventional ones.[7]

Lastly, Döttling and Sehoon (2021) examined mutual fund flows during the COVID-19 crisis, especially from retail investors. Using ESG scores from Morningstar, they found that investor net demand for funds with high ESG scores significantly weakened during the crisis: Net outflows were higher both during the fever and the rebound periods. The authors suggested that retail investors perceive ESG as a luxury good, unaffordable under the stress induced by the COVID-19 pandemic.

Testable Hypothesis

This study uses variation unique to SR indexes to test to what extent, if any, SR investment strategies were immunized to financial shocks resulting from the COVID pandemic. To guide our investigation, we propose the following testable hypotheses.

> **H1:** *SR indexes were more resilient than their conventional benchmarks during the COVID-19 crisis.*

Although not unanimous (see Demers et al. 2020), most of the current literature shows that stocks with a good ESG rating, as well as SR funds, outperformed markets during the COVID-19 crisis. We therefore anticipate that this result will also apply to SR indexes.

> **H2:** *The most stringent SR strategies were more resilient than less stringent ones during the COVID-19 crisis.*

Although there are many different SR portfolio strategies, which differ by their stringency, most papers about the performance of SR investment compare SR funds or indexes to their conventional peers but neglect heterogeneity among the SR strategies. Our large dataset of SR indexes allows us to test whether some SR strategies fared better than others during the COVID-19 pandemic. Consistent with H1, we expect that SR strategy stringency will be associated with resilience in the face of the pandemic.

> **H3:** *Environmental indexes were more resilient than social and governance indexes during the COVID-19 crisis.*

Ding et al. (2020) and Pastor and Vorsatz (2020) suggested that stocks and funds, respectively, with good environmental ratings performed better during the crisis compared to their peers with good social or government ratings. Based on these findings, we expect that environmental indexes will offer higher returns during the crisis than social and governance indexes.

> **H4:** *SR indexes practicing exclusionary screening were more resilient than their conventional benchmarks during the COVID-19 crisis.*

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[7] Palma-Ruiz et al. (2020) showed that 12 of the 35 IBEX-35 companies that donated during the COVID-19 crisis improved their financial performance, compared to the 23 companies that gave nothing. They also surveyed 575 Spanish citizens: 50% indicated that their perception of the companies that donated would change after the lockdown, and 59% would not consume products from companies that did not behave responsibly during the crisis.

Pastor and Vorsatz (2020) suggested that funds practicing exclusionary screening outperformed during the COVID-19 crisis. We investigate this issue by exploiting variation in exclusionary strategies in our dataset and hypothesize that, like other dimensions of SR, greater exclusionary practices will be associated with stronger performance, relative to benchmarks.

DATA AND METHODOLOGY

SR Indexes

To build the database, we collect all ticker codes of the SR equity indexes listed by MSCI, STOXX, and FTSE that satisfy the following two criteria: (1) The index should not be based on religious criteria, which mostly excludes shariah-compliant indexes, and (2) the index should offer daily valuation data. Our final sample consists of 573 indexes, representing all major stock markets around the world (23 developed markets + 26 emerging markets). In our sample, 179 SR indexes (31%) have a worldwide scope, 161 (28%) focus on Europe, 139 (24%) on North America, and 94 (16%) on the rest of the world. In our final sample, in terms of the number of SR indexes, MSCI is the main provider (66.7%), followed by STOXX (28.3%) and FTSE (5.0%).

We match each index with its benchmark by analyzing the index prospectuses. This matching has the advantage of controlling for both geographic and sectoral biases.[8] We require the matching to comply with two criteria: (1) The types of returns (price or net returns) between the index and its benchmark are the same, and (2) the index and benchmark shares are denominated in the same currency.

We then download the valuation data for all 573 indexes and their matched benchmarks from the Reuters and Macrobond platforms. The number of benchmark indexes (250) is lower than the number of SR indexes because several SR indexes share the same benchmark. Our period of analysis is January 2, 2020 to May 20, 2020. Our final panel is unbalanced and consists of 58,925 index-days. On average, our sample consists of 102 trading days per index. A complete list of the SR indexes is provided in the online appendix. For each index i, we compute its rate of return as $R_{i,t} = 100 \times (\ln(Index_{i,t}) - \ln(Index_{i,t-1}))$, where $Index_{i,t}$ is the value of index i at the end of day t.

Heterogeneity of SR Indexes

One of our main contributions is an analysis of the relationship between different SR strategies and their financial performance. To this end, we construct the following variables.[9]

ESG stringency. Based on the index construction methodologies described in the prospectuses, we categorize indexes into three nonexclusive groups in terms of ESG stringency. For each group, a corresponding dummy variable is coded to indicate index group membership. (1) The first group is that of impact indexes (2.1% in our sample), which corresponds to the indexes intending to have a measurable, positive impact on a firm's ESG practices (see De Angelis, Tankov, and Zerbib 2020; Landier and Lovo 2020; Oehmke and Opp 2020; Barber, Morse, and Yasuda 2021). The term *impact* often appears either in the name of the funds or in the prospectus description.

[8] Limiting the sector bias between the SRI indexes and their benchmarks is often achieved by implementing best-in-class strategies, which consist of overweighing the most sustainable companies and underweighting or excluding the least sustainable ones within each sector.

[9] The descriptive statistics for the variables under consideration (Table A) as well as the correlation matrix between these variables (Table B) are presented in the Appendix.

We label this variable *Impact.* (2) The second group corresponds to the indexes that are demanding in terms of ESG rating (45.9%). We label this variable *ESG_High,* which includes all indexes in the *Impact* group. (3) Finally, the SR indexes that are the least demanding compared to their conventional benchmarks constitute the third group (54.1%). The dummy variable of this group is omitted as the reference group.

Exclusion. SR indexes can also be classified by the degree of exclusionary screening they implement. We denote by the dummy variables *ex_fossil* and *ex_nuclear* the indexes excluding firms involved in fossil fuels (47.1% of the sample) or firms involved in nuclear energy (34.1%), respectively. We denote by the dummy variable *ex_all* the indexes excluding companies involved in fossil fuels, nuclear energy, weapons, and tobacco (12.3%).

E, S, and G. Of the 573 indexes considered, 22.1% focus exclusively on environmental performance or low greenhouse gas emissions. We denote this group of indexes by the dummy variable *Env*. Similarly, we construct the dummy variables *Soc* and *Gov* to capture indexes that focus on firms with high social performance (four indexes, 0.7%) or governance performance (eight indexes, 0.14%), respectively. Because the three groups *Env*, *Soc,* and *Gov* are not perfectly collinear, we include all three dummies in our estimation.

Geographical coverage. The use of a global dataset allows us to identify which SR indexes focus on developed countries. For each index, we identify the country in which each component firm is headquartered. The dummy variable *DEV* is equal to 1 if all firms included in the index under consideration are located in developed countries (58.2% of the sample).

Index style. We construct the variable *Large* that is 1 when the SR index contains large-cap companies (95.6% of the sample). We omit as a baseline the dummy that characterizes indexes focusing on small- and mid-cap companies. We also consider the dummy variable *Value*, which is equal to 1 if the index exhibits value style characteristics (2.4%),[10] and the dummy *Low vol*., which is equal to 1 for low-volatility indexes (5.8%). This information is collected from the prospectus.

Tracking error. Although the dynamics of SR indexes are often close to those of their benchmarks (e.g., best-in-class strategies), some SR indexes may deviate substantially. All of the previous information to assess the stringency of our SR indexes is inferred from the prospectus published by the index providers. However, to complement these de jure variables, we also rely on a de facto variable.[11] To this end, we consider the tracking error (i.e., the standard deviation of the difference between the returns on the SR index and those on its benchmark). To avoid endogeneity issues, we consider the tracking error measured during the pre-crisis period (January–December 2019). The tracking error is 0.13 on average and ranges from zero[12] to 0.77.

[10] We did not include a similar dummy variable *Growth* because we have only two indexes with such an investment style.

[11] We also attempted to consider the number of firms in the SR index compared to its benchmark: The lower the relative number, the more demanding the SR index is expected to be. However, this information is only available for 413 SR indexes, and the ratio between the number of stocks in the SR index and the number of stocks in its benchmark index includes some extreme values: Although the average is 56%, the range spans from 0.3% (the MSCI World IMI Select Sustainable Impact Top 20 includes only 20 firms, whereas its benchmark, the MSCI World IMI, includes 5,806 firms) to 109% (the STOXX USA Low Carbon includes 547 firms, whereas its benchmark, the STOXX USA 500, includes 500 firms).

[12] The smallest tracking error in our sample is for the MSCI Denmark, Mid & Large Cap, ESG Screened Index, which is not surprising because such ESG indexes propose precisely to limit exclusions "to lead to manageable tracking error vs parent index" (MSCI website).

COVID-19

To measure the number of COVID-19 cases, we use the COVID-19 Global Cases Database managed by Dong, Du, and Gardner (2020) at the JHU.[13] For a given geographical area *i* at time *t*,[14] variable $COVID_{i,t}$ is constructed as the log-growth in the number of cumulative cases in that area.[15] Because most indexes cover geographical areas larger than countries, we identify all countries *j* in region *i* and define the cumulative case variable in *t* as

$$COVID_{i,t} = \ln\left(\sum_{j \in Region_i} Cumulative\ cases_{j,t}\right) - \ln\left(\sum_{j \in Region_i} Cumulative\ cases_{j,t-1}\right)$$

Period

The spread of the COVID-19 pandemic in the first quarter of 2020 was a violent exogenous shock to the global financial system, providing a unique analytical framework for studying the resilience of sustainable investing. We follow Ramelli and Wagner (2020) in breaking down the first five months of 2020 into three phases: outbreak, fever, and rebound. The outbreak phase runs from January 1, 2020 to February 20, 2020. It corresponds to the lack of adverse reaction in financial markets to the gradual increase in the number of COVID-19 cases in China. During the fever phase, which begins on February 24, 2020 and ends on March 20, 2020, the COVID-19 pandemic affected Europe and the United States and led to a collapse of the financial markets (e.g., the S&P 500 dropped by 28.5% over the period). For our analysis of the resilience of the SR indexes, the fever phase is key. Finally, the rebound phase begins on March 23, 2020 with the intervention of the Fed, which led to a strong market rally. We stop our analysis on May 29 (for comparison, the S&P 500 rose by 36.1% during this period).[16]

Methodology

We analyze the resilience of SR strategies during the COVID-19 crisis in four steps. First, we directly compare the raw returns and volatilities of SR indexes to those of their benchmarks. Second, we estimate a Carhart model by regressing SR index returns, $R_{i,t}^{ESG}$, on their benchmarks returns, $R_{i,t}^{Bench}$, as well as the SMB, HML (Fama and French 1993), and MOM (Carhart 1997) factors.[17] We include an index fixed effect, μ_i, to capture time-invariant characteristics of the SR indexes. The specification is written as follows:

[13] The JHU database is completed with data from Owid-COVID when needed. In particular the latter provides information from January 1, 2020.

[14] Because the number of cases is often known after the stock market close, we use the first lag. For weekends and holidays, we divide the log-growth of COVID-19 cumulative cases by the numbers of calendar days between two nonconsecutive business days.

[15] Following Ding et al. (2020), we use growth in the number of cumulative cases to proxy for the spread of the crisis. However, our results do not differ when using the number of cumulative deaths.

[16] Pastor and Vorsatz (2020) considered approximately the same periods, although they are labeled differently: crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); and pre-crisis (October 1, 2019 to January 31, 2020).

[17] The factors are downloaded from Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html.

$$R_{i,t}^{ESG} = \alpha + \beta_1 R_{i,t}^{Bench} + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \mu_i + \varepsilon_{i,t} \quad (1)$$

where $\varepsilon_{i,t}$ is the error term. We estimate this model using White robust standard errors.[18] This model allows us to study the sensitivity of the SR index to its benchmark, β_1, and the alpha of the SR index during the COVID-19 crisis. However, it does not allow us to capture the dynamics of the pandemic spread or analyze the heterogeneity of SR strategies. Thus, as our third step, we add to the previous specification the *COVID* variable:

$$R_{i,t}^{ESG} = \alpha + \beta_1 R_{i,t}^{Bench} + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \delta COVID_{i,t} + \mu_i + \varepsilon_{i,t} \quad (2)$$

Fourth, we include a set of variables aiming to capture heterogeneity among SR strategies[19]:

$$R_{i,t}^{ESG} = \alpha + \beta_1 R_{i,t}^{Bench} + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \delta COVID_{i,t} + \varphi \times SR_i + \varepsilon_{i,t} \quad (3)$$

The set of variables accounting for the features of the SR indexes includes *Impact*, *ESG high*, *Environmental*, *Social*, *Governance*, developed countries (*Dev*), large-cap (*Large*), exclusion (*all*, *fossil*, and *nuclear*), *Value*, *Low vol.*, and the *tracking error* in 2019. Hence, SR_i is a 573×13 (indexes × variables) matrix.

Finally, we carry out a series of robustness tests on the econometric specification and the variables used, which are presented later.

EMPIRICAL RESULTS

Returns and Volatility

Exhibit 2 presents the comparative performance of the SR indexes and their benchmarks during each subperiod of the COVID-19 crisis (Panel A), by geographical coverage (Panel B), and by category (Panel C[20]).[21] Overall, no substantial difference between the returns on SR indexes and their conventional benchmarks is found. Regardless of how we subdivide the sample, *t*-tests of the difference in mean between the SR indexes and their benchmarks fail to reject the null hypothesis of zero difference. In addition, SR indexes and their benchmarks have similar volatilities over time.

Over the entire sample period (Panel A), the average daily return was –0.11% for both SR and conventional indexes, whereas their annualized volatilities were 39.18% and 39.41%, respectively. When we compute these quantities by phase of the crisis, the dynamics of SR indexes remain very close to those of their benchmarks whether in bearish or bullish markets. During the fever period (February 24–March 20), the average daily return was –1.84% for SR indexes and –1.86% for their benchmarks, whereas during the rebound period (March 23–May 29) the average daily returns were +0.42 and +0.43, respectively.

Exhibit 3 shows the performance (mean and first and third quartiles) of the 573 SR indexes (in black) and their conventional benchmarks (in red) during the first semester of 2020. Indexes are normalized to 100 at the beginning of the year. No difference

[18] The estimates are robust to the use of clustered standard errors at the SR index, benchmark, and regional levels.

[19] In this last specification, we remove the index fixed effect, which becomes collinear with the independent variables when we add the set of controls. However, we include an index provider fixed effect.

[20] SR indexes can be included in more than one category because they may have different characteristics at the same time.

[21] Additional descriptive statistics (percentiles, Table C) and the density of returns (Figure A) are provided in the online appendix.

EXHIBIT 2

SR versus Benchmark Indexes during the COVID-19 Crisis

		Daily	Returns	Mean	Test	Volatility			
	No.	SR	Bench.	*t*-Stat	*p*-Value	SR	Bench.	% Days $r_{SR} > r_B$	Tracking Error
Panel A: All Indexes, by Period									
Crisis	573	–0.11	–0.11	–0.01	0.99	39.18	39.41	50.9	0.27
Outbreak	573	0.05	0.04	0.66	0.51	12.16	12.14	52.0	0.13
Fever	573	–1.84	–1.86	0.26	0.79	69.28	70.13	55.3	0.39
Rebound	573	0.42	0.43	–0.51	0.61	36.62	36.52	48.4	0.29
Pre–crisis	573	0.09	0.08	0.29	0.77	14.69	11.72	50.6	0.15
Panel B: All of the Periods (Crisis: January 2 to May 29, 2020), by Geographical Coverage									
World	179	–0.10	–0.10	–0.18	0.86	36.77	37.57	54.0	0.54
Europe	161	–0.15	–0.15	0.10	0.92	38.62	38.92	49.9	0.38
North America	139	–0.12	–0.12	0.11	0.92	34.38	34.41	49.2	0.33
RoW	94	–0.06	–0.06	–0.02	0.98	49.83	49.34	49.1	0.32
Panel C: All of the Periods (Crisis: January 2 to May 29, 2020), by Type of SR Index									
Impact	12	–0.09	–0.09	0.04	0.97	39.18	40.54	46.6	0.47
ESG High	264	–0.12	–0.11	–0.16	0.87	39.40	39.58	49.9	0.57
ESG Low	309	–0.11	–0.11	0.14	0.89	39.00	39.26	51.7	0.21
Environment	127	–0.10	–0.10	–0.08	0.93	38.74	38.81	51.7	0.55
Social	4	–0.22	–0.11	–0.44	0.66	38.90	38.99	48.6	1.21
Governance	8	–0.14	–0.09	–0.26	0.79	38.59	39.28	47.1	0.83
Excl. all	70	–0.11	–0.11	0.05	0.96	38.44	39.08	49.0	0.64
Excl. fossil	272	–0.12	–0.12	–0.03	0.98	39.61	39.87	50.5	0.48
Excl. nuclear	194	–0.10	–0.11	0.18	0.85	39.21	39.60	50.6	0.48
Dev. and Em.	151	–0.12	–0.11	–0.31	0.75	36.64	37.37	51.8	0.63
Dev.	333	–0.10	–0.10	0.18	0.86	40.93	41.05	50.9	0.29
Em.	89	–0.15	–0.15	0.00	1.00	36.55	36.35	49.0	0.36
Large cap.	548	–0.11	–0.11	0.01	0.99	38.81	39.05	51.1	0.42
Mid cap.	524	–0.11	–0.11	0.00	1.00	38.48	38.78	51.0	0.42
Small cap.	181	–0.13	–0.11	–0.34	0.74	40.08	40.34	49.5	0.57
Value	14	–0.13	–0.16	0.19	0.85	41.86	43.53	51.5	0.38
Low vol.	34	–0.16	–0.10	–0.70	0.48	38.64	40.49	49.1	1.00

NOTES: This exhibit presents, for each SR index and its benchmark, the number of indexes (No.), the daily raw returns, the annualized volatility, a nonparametric test of equality of the average returns under the assumption of unequal variances and the associated *p*-value, the percentage of days on which the SR indexes outperformed their benchmarks, and the tracking error. The sample includes 573 SR indexes from MSCI, STOXX, and FTSE between January 2, 2020 and May 29, 2020. In Panel A, results are for all SR indexes and are broken down by time periods: crisis (January 2–May 29, 2020); outbreak (January 2–February 21), fever (February 24–March 20), and rebound (March 23–May 29); and pre-crisis (January to December 2019). In Panels B and C, results are for the whole period (crisis). In Panel B, results are broken down by geographical coverage (RoW = rest of the world). In Panel C, results are broken down by type of SR index (the categories are defined in the text).

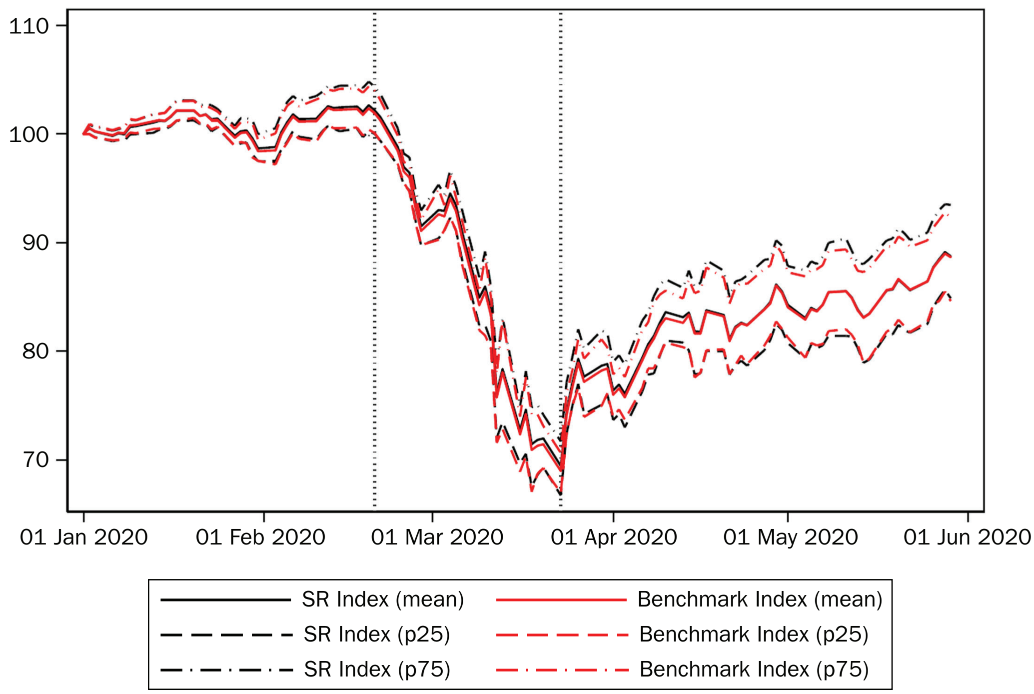
SOURCE: Authors' computation.

can be discerned. Overall, these findings are consistent with those of Demers et al. (2020), who did not identify any significant outperformance of companies with high ESG scores during the COVID-19 crisis.

Focusing on the indexes broken down by geographical coverage (Panel B), average returns are found to be lower in Europe (–0.15%) and in the United States (–0.12%) than in world SR indexes (–0.10%). SR indexes focusing on other countries (mainly in Asia) have a higher average return (–0.06%), but at the expense of greater volatility. Whatever the geographical coverage, however, the performance of SR indexes during the COVID-19 crisis appears to be similar to that of conventional indexes.

EXHIBIT 3

Performance of SR Indexes and Their Benchmarks during the COVID-19 Crisis



NOTES: This exhibit shows the performance of the SR strategies (in black) compared to that of their conventional benchmarks (in red). Indexes are initialized at 100 at the beginning of the period. The sample includes 573 SR indexes from MSCI, STOXX, and FTSE between January 2, 2020 and May 29, 2020. The dotted lines correspond to the first and the third quartiles.

SOURCE: Authors' computation.

Decomposing SR indexes by their strategy features (Panel C), the least negative average return is found among impact indexes (–0.09%). Average returns are the same (–0.12%) for the most stringent SR indexes (ESG high) and the less stringent ones (ESG low). Similarly, the same average return is found whatever the exclusion criteria. Note also that, on average, small-cap indexes, value indexes, and low-volatility indexes performed worse than their benchmarks during the COVID-19 crisis (–0.13%, –0.13%, –0.16%, respectively). Lastly, impact SR indexes and ESG high indexes have higher tracking errors, as do SR indexes focusing only on one ESG dimension.

Heterogeneous Resilience of SR Strategies to the COVID-19 Crisis

Exhibit 4 presents the estimates of the Carhart model without (Equation 1, columns 1–4) and with controls (Equation 2, columns 5–8) for the COVID-19 crisis. The R^2 between 0.8 and 1 underscores the strong explanatory power of the four-factor model, mainly due to the use of the index benchmark as the market factor. Because SR indexes are, by definition, very close to their benchmark, we ran the estimation on the whole sample (573 SR indexes, Panel A) but also on a smaller subsample corresponding to the last quartile in terms of the pre-crisis tracking error (144 SR indexes with the largest tracking error, Panel B).[22] We first consider the full sample period, January 2, 2020 to May 29, 2020, and then the three subperiods: outbreak (January 2–February 21), fever (February 24–March 20), and rebound (March 23–May 29).

The SR indexes have a sensitivity to their benchmarks slightly lower than that when the whole period is considered (0.978 in Panel A and 0.926 in Panel B), as

[22] As expected, the beta and the R^2 are lower in Panel B.

EXHIBIT 4

Performance of SR Indexes during the COVID-19 Crisis

	Periods	Outbreak	Fever	Rebound	All Period	Outbreak	Fever	Rebound
Panel A: All Sample (573 SR indexes)								
Constant	–0.0009	0.0094***	–0.0313***	0.0021	0.0031**	0.0093***	–0.0384***	0.0074**
	(0.0008)	(0.0009)	(0.0073)	(0.0022)	(0.0013)	(0.0012)	(0.0085)	(0.0030)
Benchmark	0.9778***	0.9692***	0.9826***	0.9785***	0.9779***	0.9693***	0.9844***	0.9795***
	(0.0032)	(0.0042)	(0.0036)	(0.0039)	(0.0032)	(0.0043)	(0.0034)	(0.0038)
SMB	0.0052*	0.0081*	0.0216***	–0.0064**	0.0071**	0.0078*	0.0228***	–0.0020
	(0.0027)	(0.0048)	(0.0043)	(0.0025)	(0.0028)	(0.0047)	(0.0045)	(0.0025)
HML	0.0095***	0.0072**	–0.0352***	0.0310***	0.0076***	0.0072**	–0.0356***	0.0284***
	(0.0028)	(0.0033)	(0.0046)	(0.0039)	(0.0027)	(0.0033)	(0.0047)	(0.0037)
MOM	0.0036*	0.0059	–0.0052	0.0168***	0.0027	0.0058	–0.0093	0.0161***
	(0.0020)	(0.0038)	(0.0053)	(0.0018)	(0.0020)	(0.0037)	(0.0061)	(0.0018)
COVID					–0.0040***	0.0004	0.0096***	–0.0042***
					(0.0009)	(0.0017)	(0.0031)	(0.0010)
No. Obs.	58,822	20,035	10,882	27,905	58,822	20,035	10,882	27,905
R^2	0.972	0.937	0.9762	0.9654	0.972	0.937	0.975	0.965
Panel B: Subsample: Large Pre-Crisis Tracking Error (144 SR indexes)								
Constant	–0.0176***	0.0218***	–0.1662***	0.0114	–0.0007	0.0269***	–0.2021***	0.0345***
	(0.0032)	(0.0030)	(0.0241)	(0.0076)	(0.0045)	(0.0039)	(0.0283)	(0.0094)
Benchmark	0.9260***	0.8907***	0.9426***	0.9166***	0.9270***	0.8899***	0.9507***	0.9209***
	(0.0108)	(0.0151)	(0.0117)	(0.0139)	(0.0108)	(0.0151)	(0.0109)	(0.0136)
SMB	0.0320***	–0.0000	0.0870***	–0.0183*	0.0402***	0.0150	0.0928***	0.0015
	(0.0098)	(0.0179)	(0.0151)	(0.0094)	(0.0099)	(0.0174)	(0.0159)	(0.0093)
HML	0.0436***	0.0125	–0.0969***	0.1114***	0.0350***	0.0097	–0.0983***	0.0999***
	(0.0102)	(0.0127)	(0.0165)	(0.0134)	(0.0101)	(0.0125)	(0.0168)	(0.0128)
MOM	–0.0001	–0.0245*	–0.0212	0.0363***	–0.0038	–0.0170	–0.0407*	0.0335***
	(0.0072)	(0.0142)	(0.0193)	(0.0063)	(0.0074)	(0.0138)	(0.0221)	(0.0065)
COVID					–0.0172***	–0.0188***	0.0483***	–0.0183***
					(0.0032)	(0.0064)	(0.0106)	(0.0034)
No. Obs.	14,761	5,036	2,734	6,991	14,761	5,036	2,734	6,991
R^2	0.9065	0.7994	0.9176	0.886	0.906	0.794	0.914	0.887

NOTES: This exhibit shows the estimations of Equations 1 and 2. The sample period is January 2, 2020 to May 29, 2020. It is broken down into three subperiods: outbreak (January 2–February 21), fever (February 24–March 20), and rebound (March 23–May 29). The main dependent variable is daily the SR index returns, and the control variables are *Benchmark*, which is the return on each SR's benchmark index, and the Carhart factors (SMB, HML, MOM). The key independent variable is *COVID*, which is the growth of the cumulative COVID-19 log-cases in the investment area of the SR index. Panel A includes all of the SR indexes in our sample. Panel B includes only the lowest quartile in terms of tracking error (computed in 2019). All regressions include index fixed effect. White robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

SOURCE: Authors' computation.

well as during the bearish fever period (0.982 and 0.942) and the bullish outbreak rebound period (0.978 and 0.917). The SR indexes therefore have a slightly defensive profile compared to their conventional benchmarks. However, this effect is offset by slightly positive and negative alphas, respectively. Overall, we do not find substantially different dynamics between the SR indexes and their benchmarks, and betas close to 1 validate the quality of our index-benchmark matches.

These estimates show that the dynamics of the SR indexes and their benchmarks are tightly interwoven, but they do not show the relationship between SR index returns and the evolution of the COVID-19 pandemic through time. When considering this relationship, we observe a cushioning effect on SR indexes. During the fever period, for a given benchmark performance, the resilience of the SR indexes was greater when the number of COVID-19 cases was increasing in the investment area. Relative to their benchmarks, a doubling of cumulative COVID-19 cases (i.e., +100%) increased the average daily performance of the SR indexes by +0.96% for the full sample (Panel A) and +4.83% for the subsample with the largest pre-crisis tracking errors (Panel B). During the rebound period, the effect was reversed, but the loading was only half as large as during the fever period (–0.42% for Panel A and –1.83% for Panel B). These results, therefore, complement the findings regarding H1: The difference in financial performance between SR and non-SR indexes is not significant but is slightly in favor of SR indexes in the areas most affected by COVID-19.

Exhibit 5 presents the estimates of the Carhart model with controls for the COVID-19 crisis and the strategic characteristics of SR indexes (Equation 3). The inclusion of control variables does not alter our previous results: The benchmark beta is close to one; the alpha is negative during the bearish fever phase but not significant during the bullish rebound phase; and the COVID-19 coefficient is positive during the fever period and negative during the rebound. The extended model allows us to further test the resilience of some types of SR indexes.

The estimate of the dummy variable *ESG High* is not significant (except for the fever period, albeit at the 10% level only—see also the Robustness section). Contrary to what Pastor and Vorsatz (2020) identified for US funds and Ding et al. (2020) for global equities, we do not find that global SR indexes with a high ESG score perform better than those with a low score over the whole sample period. In addition, the coefficient associated with *Tracking error* (measured in 2019), which we interpret as a proxy for the stringency of SR indexes,[23] is negative during the fever period. However, the subcategory of SR impact indexes shows a substantial daily average outperformance of +0.13% relative to nonimpact indexes during the fever period and –0.04% during the rebound period.

Hypothesis H2 is therefore partly verified: The impact strategies, which are the most stringent ones, are the more resilient. The effect of stringency is not straightforward, however; SR indexes with high ESG scores or high tracking error do not outperform SR indexes with lower ESG scores or those that closely tracked their benchmark in 2019. This suggests the need to go beyond the selection of funds with high ESG scores when investing in an SR strategy. For example, impact strategies benefited from a buffer during the COVID-19 financial crisis.

None of the coefficients associated with the dummy variables *Environment*, *Social*, *Governance* or related to exclusion criteria (*Excl. all*, *Excl. fossils*, *Excl. nuclear*) are consistently significant. Therefore, hypotheses H3 and H4 are not verified.

The SR indexes investing in large-cap and value stocks enjoyed slight financial outperformance compared to their benchmarks during the whole period. This result is consistent with those of Ding et al. (2020), who found that the firms with the most cash, including many large companies, were better positioned to absorb the shock of the COVID-19 financial crisis. Indexes investing in developed countries also benefited from slight outperformance during the rebound period, whereas low-volatility indexes benefited less from the rebound.

Robustness Checks

We implement several robustness checks whose results are detailed in the online appendix. Findings were in line with those of our main analysis overall, but some differences appeared. We comment on these differences in this section.[24]

[23] An SR index that deviates from its conventional benchmark tends to be more selective regarding the companies included and, therefore, more demanding from a responsible-investment point of view.

[24] We also considered alternative dependent variables and specifications. First, we used the abnormal returns, defined as the excess returns with respect to the Carhart model, as the dependent variable. Second, we considered a model-free approach and used the return differentials between the SR indexes and their benchmarks. Third, we considered the baseline model but without index fixed effects. All results are consistent with those of the baseline estimation.

EXHIBIT 5

Performance of SR Indexes during the COVID-19 Crisis: Additional Determinants

	All Period	Outbreak	Fever	Rebound
Constant	–0.0252***	–0.0381***	–0.0902***	0.0010
	(0.0076)	(0.0090)	(0.0336)	(0.0100)
Benchmark	0.9779***	0.9695***	0.9833***	0.9795***
	(0.0032)	(0.0043)	(0.0034)	(0.0038)
COVID	–0.0040***	0.0007	0.0085***	–0.0043***
	(0.0009)	(0.0017)	(0.0032)	(0.0010)
Impact	0.0057	0.0016	0.1276***	–0.0389***
	(0.0094)	(0.0157)	(0.0455)	(0.0105)
ESG High	0.0030	–0.0015	0.0398*	–0.0083
	(0.0047)	(0.0059)	(0.0213)	(0.0070)
Environment	0.0033	0.0111**	–0.0301	0.0097*
	(0.0040)	(0.0052)	(0.0185)	(0.0054)
Social	–0.0563	0.0094	–0.1744	–0.0583*
	(0.0440)	(0.0440)	(0.1074)	(0.0336)
Governance	–0.0174	0.0054	–0.0144	–0.0353
	(0.0255)	(0.0224)	(0.0772)	(0.0236)
Dev.	0.0045*	0.0046	–0.0084	0.0123***
	(0.0025)	(0.0030)	(0.0118)	(0.0035)
Large	0.0185***	0.0211***	0.0416	0.0070
	(0.0064)	(0.0076)	(0.0308)	(0.0087)
Excl. all	–0.0049	0.0040	–0.0259	–0.0039
	(0.0078)	(0.0103)	(0.0319)	(0.0106)
Excl. fossil	0.0106**	0.0044	0.0322**	0.0065
	(0.0042)	(0.0043)	(0.0161)	(0.0048)
Excl. nuclear	0.0114**	0.0027	0.0211	0.0139*
	(0.0055)	(0.0061)	(0.0243)	(0.0077)
Value	0.0427***	0.0081	0.0927	0.0474***
	(0.0112)	(0.0089)	(0.0579)	(0.0159)
Low vol.	–0.0445***	–0.0151	0.0666	–0.1103***
	(0.0146)	(0.0146)	(0.0602)	(0.0178)
Tracking error	–0.0767***	0.0471*	–0.3205***	–0.0661*
	(0.0218)	(0.0277)	(0.1081)	(0.0364)
No. Obs.	58,822	20,035	10,882	27,905
No. SR index	573	573	573	573
R^2	0.972	0.937	0.975	0.965

NOTES: This exhibit shows the estimation of Equation 3. The sample period is January 2, 2020 to May 29, 2020. The dependent variable is daily SR index return and the control variables are *Benchmark,* which is the return of each SR's benchmark index, and the Carhart factors (SMB, HML, MOM) included, but not reported. The key explanatory variable is *COVID*, which is the growth of the cumulative COVID-19 log-cases in the investment area of the SR index. The regression also includes specific observable features of SR indexes: *Impact*, *ESG High*, *Environmental*, *Social*, *Governance*, developed countries (*Dev*), large-cap (*Large*), exclusion (*all*, *fossil,* and *nuclear*), *Value*, *Low vol.*, and the *tracking error* in 2019. All regressions include index provider fixed effect (not reported). White robust standard errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

SOURCE: Authors' computation.

Subsamples. We break down our indexes by their geographical area of investment in four categories: world, North America, Europe, and rest of the world (Table F, online appendix). For the North America and Europe categories, results are similar to our main results reported in Exhibits 4 and 5. However, for SR indexes focusing on the rest of the world—mainly Asia and emerging countries—returns are higher over the whole period compared to their benchmarks' returns. In addition, for the rest of the world, faster growth in COVID-19 was associated with weaker performance.

Additional independent variables. We consider several additional control factors related to public attention, governmental response to the COVID-19 pandemic, and monetary policies implemented during the crisis (Table H, online appendix).[25]

First, the varying attention to COVID-19 within each geographical area and over time may have an impact on market sentiment and, thus, on index returns. We therefore control for public attention using the number of queries on Google for the terms "Covid-19" and "coronavirus," as measured by Google Trends. These query terms have the advantage of being written similarly in most languages. Thus, we are able to construct a country-specific, daily variable that is comparable across countries. Between January 1, 2020 and May 29, 2020, these two terms were among the most searched terms worldwide. For SR Indexes investing in a region, rather than a single country, we use a gross domestic product–weighted average of all national Google Trends in the regions under consideration. We then consider the daily growth of this search trend variable in each region or country as a proxy for public attention to the COVID-19 pandemic.

Second, we consider the growth rate of the Infectious Disease Equity Market Volatility tracker provided by Baker et al. (2020), which reflects the frequency of articles about stock market volatility in leading US newspapers, multiplied by the share of those articles that contain words related to diseases or epidemics.

Third, for the crisis response variables, we use the growth rate of the Oxford Covid-19 Government Response Tracker, which takes into account external and internal movement restrictions, fiscal support, and measures supporting the healthcare system, by country.

Fourth, for fiscal and monetary policy responses, we add a variable that is a sum of dummies constructed from the Yale Program on Financial Stability, reflecting economic policy daily announcements about asset purchases, government credit guarantees or facilities for nonfinancial firms, support to the financial system, tax reduction and public spending increase, interest rate changes, changes in bank supervisory rules, swap lines, and other monetary policy decisions. We consider a daily aggregated tracker of the policy reaction to the COVID-19 crisis in each country.[26] For regions, we collect all announcements in the countries included in the region under consideration. The average number of daily announcements across the whole sample is 2.2, with a maximum of 8.

All additional controls for the COVID-19 crisis are mostly significant. In all cases, however, the main conclusions of the baseline model are unchanged: The beta is just below one; the alpha is negative during the fever (but not always) and nonsignificant during the rebound. Estimated coefficients associated with the variables *COVID-19* and *Impact* are positive during the fever and negative during the rebound, with values similar to those of the baseline. Moreover, although *ESG High* was barely significant in the baseline, with the additional controls it is positive and significant at the 5% level, strengthening the validation of hypothesis H2.

Cross-sectional analysis. In addition to the previous panel data models, we consider several cross-sectional specifications to investigate the impact of the COVID-19 crisis on buy-and-hold benchmark-adjusted returns, abnormal returns, the volatility spread (i.e., the difference between the volatility of the SR index and its benchmark), and the tracking error over either the whole period or during the fever period (Exhibit 1). For SR returns, the results are in line with our previous estimates and, overall, do not differ significantly from their benchmark. More precisely, for benchmark-adjusted

[25]See Capelle-Blancard and Desroziers (2020) for a detailed investigation of the impact of the policy reactions to the COVID-19 crisis on stock market worldwide.

[26]We also test each of these economic policy announcements separately, and this does not change the results.

returns, the constant is nonsignificant, whereas for abnormal returns, the constant is now positive but the loading of the number of COVID-19 crisis is negative and the difference is very small. The only exception is for impact indexes, which, as in the baseline panel model, perform better during the fever phase. In addition, *ESG High* is also positive and significant, as in the case where additional controls (i.e., policy variables) are included in the panel data model. Interestingly, impact indexes also have a lower volatility during the fever period. Unsurprisingly, low-volatility indexes indeed have significantly lower volatility, and the most stringent SR indexes (*ESG High* and *Excl. All*) have a significantly higher tracking error.

In brief, whatever the measure of asset returns (raw returns, benchmark-adjusted returns, abnormal returns), the controls (including or not including interactions or proxies for policies implemented during the COVID-19 crisis), or the specifications (panel data or cross section), our main results hold: SR indexes have a slightly defensive profile, but their performance was very similar to that of their benchmark during the COVID-19 crisis, except for impact indexes, which performed better with higher returns and lower volatility during the fever.

CONCLUSION

In this study, we use SR indexes to analyze the resilience of SR strategies during the COVID-19 crisis. Matching SR indexes from a worldwide sample with their conventional benchmarks allows us to rigorously control for sectoral and geographic biases and to avoid the potential bias associated with fund managers' abilities. By controlling for factors related to the COVID-19 crisis and by breaking down the indexes according to their investment strategies, we show that, on average, SR indexes were not spared from large market downturns during the COVID-19 pandemic, nor did they disproportionally benefit from market rallies. SR indexes invested in the regions most affected by COVID-19 were, however, slightly more resilient relative to other SR indexes from the other regions. Nevertheless, except for the SR indexes following an impact strategy, the other SR strategies did not outperform their conventional benchmarks. The findings of this study should prompt sustainable investors to rigorously select their SR investment vehicles and arm themselves with the knowledge that impact funds may offer greater resilience in times of crisis.

Future research can investigate sustainable investors' motives to arbitrate from one strategy to another depending on economic conditions and analyze the consequences in terms of financial returns. Another research avenue would consist of breaking down the relative performance of SR indexes compared to their benchmarks according to the flows induced by sustainable investors' nonpecuniary motives and those induced by investors' pecuniary motives. Indeed, some SR strategies may have outperformed because they focused on firms that were financially resilient to the crisis and not necessarily because they were more sustainable.

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Measuring and Managing ESG Risks in Sovereign Bond Portfolios and Implications for Sovereign Debt Investing

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KEY FINDINGS

- Higher environmental scores for developed countries and higher social scores for emerging countries are associated with lower costs of borrowing for issuers and consequently with lower yields for investors.
- A minimum variance optimization approach leads in general to better performance compared to a negative screening strategy for the same level of E, S, and G score improvements.
- ESG momentum strategies generate additional value, suggesting the presence of some form of underreaction to news related to changes in ESG scores.

ABSTRACT

This article shows that implementation choices matter with respect to how environment, social, and governance (ESG) constraints are incorporated in sovereign bond portfolio construction. In particular, the authors confirm that negative screening leads to more diversified portfolios and lower levels of tracking error, whereas positive screening leads to higher levels of improvement of ESG scores, at the cost of an increase in absolute and relative risk budgets. The authors also find that a dedicated focus on absolute or relative risk reduction at the selection stage allows investors to reduce the opportunity costs along the dimension that is most important to them. Overall, the results suggest that sound risk management practices are critically important in allowing investors to incorporate ESG constraints in investment decisions at an acceptable cost in terms of dollar or risk budgets.

TOPICS

*ESG investing, fixed income and structured finance, global markets, portfolio construction**

In just under 10 years, the global bond markets increased from $87 trillion in 2009 to over $115 trillion in mid-2019, according to the International Institute of Finance. This growth was mostly seen in the sovereign bond market. Sovereign bonds are one of the most important asset classes held by investors around the world, representing 47% of global bond markets, compared to 40% in 2009. Although it is traditionally considered a risk-free asset class, this perception has been challenged since 2008, and there is a critical need for a better understanding of the full range of risks, including nonfinancial risks, involved in sovereign bonds.

Over the past decade, sustainable and responsible investing have gained momentum and continue to grow in popularity among investors, and it is increasingly recognized that the financial system has a particularly important role to play in the transition toward a low-carbon and climate-resilient economy. The integration of sustainability considerations into the decision-making process for investments, as measured by environmental, social, and governance (ESG) indicators, has been driven by investor demands, fiduciary duty, climate change, and the development of new regulations and values. Sustainability in the financial sector is becoming mainstream and is reshaping global markets.

Nevertheless, the integration of ESG factors into sovereign bond investment analysis and investment decision-making is not systematic owing to a lack of understanding among investors of how to integrate ESG issues into sovereign debt analysis and a lack of consistency in defining and measuring material ESG factors. The absence of a coherent investment framework for such integration is consistent with the relative scarcity of available academic research, which has focused more on ESG investing in equity markets.

In this article, we explore the impact of ESG factors on the risk and return of sovereign bonds from an investor perspective, in particular investigating how to measure and manage ESG risks in sovereign bond portfolios and their implications for sovereign bond portfolio strategies. We first analyze the materiality and impact of ESG scores, taken individually, on key risk and return indicators of relevance to asset owners in both developed and emerging markets. In the second step, we explore the portfolio implications of these findings. In particular, we analyze how to minimize the efficiency loss involved in the introduction of ESG constraints in a robust sovereign bond portfolio construction process. We also analyze the benefits and limits of ESG momentum strategies in sovereign bond markets. The main objective of this second part of the article is to assess whether a significant improvement in the portfolio ESG score or ESG momentum score can be achieved without a substantial increase in absolute and relative risk budgets or a substantial decrease in expected performance.

ANALYSIS OF THE IMPACT OF ESG ON RISK AND RETURN

We first seek to analyze whether cross-sectional differences in the risk and return of sovereign bonds from various developed or emerging issuing countries can be explained partly by cross-sectional differences in E, S, or G scores. We draw an important distinction between the perspective of long-term buy-and-hold investors, for whom performance can be captured by bond yield spreads, and that of shorter-term investors, who will not hold the bond until maturity and as such cannot use bond yield as a measure of expected performance because of the uncertainty regarding the selling price of the sovereign bonds held in their portfolios. In the latter case, we will instead use average annualized return as a measure of performance.

For ESG indicators, we use the Verisk database, which contains 58 risk indexes and 371 indicators available from 2010–2020 for a total of 35 countries (20 developed, 15 emerging) and eventually aggregated for the following themes: economics, environment, and climate change (which we use as a proxy for the E dimension); human rights and development (which we use as a proxy for the S dimension); and governance (which we use as a proxy for the G dimension).[1] The Verisk Maplecroft

[1] We would like to express our gratitude to Verisk Maplecroft for providing us with access to their database.

Economics index, which aggregates macroeconomic indicators, will be used as a control variable in our different regression analyses to isolate the impact of the E, S, and G dimensions on a given dependent variable.[2]

ESG Scores and Sovereign Bond Yield Spreads

We first explore the impact of cross-sectional differences in ESG scores on the performance characteristics of sovereign bonds from the perspective of a long-term investor for whom sovereign bonds are held to maturity. In particular, we want to answer the following questions:

- What is the relationship between ESG scores and the premium investors demand to invest in the sovereign bond market?
- How can ESG performance affect sovereign bond yield spreads?
- Is better ESG associated with lower bond yield spreads?

From the Thomson Reuters and ICAP Datastream databases, we extract yield on 12-month, 5-year, and 10-year sovereign bonds for 35 countries (20 developed, 15 emerging countries) from 2010 to 2020. The countries are classified based on the MSCI 2019 market classification. We define government bond yield spreads as the difference between the yield on sovereign bonds for a given country and the yield on the US sovereign bond with the corresponding maturity. In other words, we use the yield on the US sovereign bond as the risk-free rate.

Our main analysis consists of estimating a (dynamic) fixed-effects panel regression model including ESG scores as explanatory variables, in line with Capelle-Blancard et al. (2019) and Berg, Margaretic, and Pouget (2016). The economic score is used as a control variable to isolate the impact of the three extra-financial dimensions on bond yield spreads, as suggested by the literature on the determinants of sovereign bond yield spreads (see, in particular, Cantor and Packer 1996; Eichengreen and Mody 1998; Attinasi, Checherita, and Nickel 2009; Barbosa and Costa 2010; Afonso, Arghyrou, and Kontonikas 2012; D'Agostino and Ehrmann 2014). Our dataset is a panel that includes a group of 19 developed countries (United States excluded) and 15 emerging countries observed over a period of 10 years. The structure of the dataset includes a country dimension. We performed a Hausman test, which indicates that a fixed-effects model needs to be estimated, instead of a random-effects model. Indeed, the test for the non-existence of fixed effects rejects the null hypothesis and concludes with the existence of country-specific effects. Because of the persistency of the spread, we also included lagged sovereign bond spreads on the right-hand side. The three Verisk dimensions that are used as proxies for ESG criteria are also lagged for robustness. To estimate our model, we use the least square dummy variable corrected (LSDVC) estimator of Bruno (2005a) as done by Capelle-Blancard et al. (2019). The lagged sovereign bond spreads added on the right-hand side of the model might be serially correlated and hence correlated with the error term, which makes the ordinary least squares (OLS) and least square dummy variable (LSDV) estimators biased and inconsistent (Baltagi and Chang 1994). The LSDVC estimator of Bruno (2005b) derives an approximation for the bias of the LSDV estimator for the standard autoregressive panel data model and extends the results of Bun and Kiviet (2003) and Kiviet (1995, 1999) to unbalanced panels.

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[2] We prefer to use the Verisk Maplecroft Economics index rather than credit ratings because credit rating agencies might already incorporate ESG criteria into their analyses.

The dynamic panel regression model is of the following form[3]:

$$Spread_{i,t} = \beta_0 + Spread_{i,t-1} + \beta_{Eco}Eco_{i,t-1} + \beta_{Env}Env_{i,t-1} + \beta_{Soc}Soc_{i,t-1} + \beta_{Gov}Gov_{i,t-1} + \alpha_i + \varepsilon_{i,t} \tag{1}$$

where

i = 1 to n (the number of countries) and t = 1 to T (the number of periods)

$Spread_{i,t}$: sovereign bond yield spreads of country i at time t defined as $Spread_{i,t}$ $Yield_{i,t} - Yield_{USA,t}$ (the sovereign bond spreads can be either 1 year, 5 year, or 10 year)

$Spread_{i,t-1}$: lagged sovereign bond yield spreads of country i to account for the persistent nature of spreads

$Eco_{i,t-1}$: lagged economic dimension obtained from Verisk database

$Env_{i,t-1}$: lagged E dimension obtained from Verisk database

$Soc_{i,t-1}$: lagged S dimension obtained from Verisk database

$Gov_{i,t-1}$: lagged G dimension obtained from Verisk database

α_i : (unobserved) country-specific fixed effect allowing us to take into account unobservable variables that are specific to country i and time invariant

$\varepsilon_{i,t}$: error term

β_0: constant

The results of the panel regression model (Equation 1) are presented in Exhibit 1 for developed countries and emerging countries.

Our estimation results allow us to extract two key conclusions on the relationship between ESG scores and yield spreads. For developed countries, after controlling for economic scores as well as other variables and fixed effects, we first find that differences in E scores help explain differences in bond yield spreads, with a higher E score associated with a lower spread. Regardless of bond maturity, the coefficient associated with the E dimension is negative and statistically significant. S and G scores are both associated with a positive coefficient but do not appear significant, except G for one-year sovereign bond maturity, which appears significant with a positive coefficient (0.013). Although the results are similar across bond maturities (in terms of significance), the magnitude of the E score coefficients changes with the bond maturity: –0.013 for 1-year, –0.025 for 5-year, and –0.023 for 10-year bond yield spreads. The impact of the E dimension on bond yield spreads is more pronounced in the medium run. Hence, from an issuer standpoint, better E scores can lead to reduced borrowing costs, everything else being equal. From the investor standpoint, this result suggests that a lower yield is to be expected when investing in countries with higher E performance, which tells us that a negative premium is associated with this reduction in E risk. Interestingly, these results differ from previous studies; for example, Capelle-Blancard et al. (2019) showed that the E dimension has no impact on bond yield spreads, whereas G has the strongest negative relationship with bond yield spreads, followed by the S dimension.

For emerging countries, after controlling for economic scores as well as other variables and fixed effects, we first find that differences in S scores help explain differences in bond yield spreads, with a higher S score associated with a lower spread. For 5-year and 10-year maturity bonds, the coefficient associated with the S dimension

[3] We evaluate the performance of the LSDVC estimator of Bruno (2005) by comparing the coefficient estimate of the first lagged dependent variable with the one that would be obtained estimating our model with a simple linear regression (OLS estimation) or the within-panel transformation (LSDV estimation). The coefficient of our estimator lies between the coefficient estimates of the alternative two estimators, meaning that it is a consistent estimate. We also performed cross-sectional dependence autocorrelation and heteroskedasticity tests, as well as an overidentification test and tests of endogeneity for each explanatory variable.

EXHIBIT 1

Model Estimates of Equation 1 for Developed Countries and Emerging Countries

	Developed Countries			Emerging Countries		
	Bond Yield Spreads $Spread_{(i,t)}$			Bond Yield Spreads $Spread_{(i,t)}$		
	1Y	5Y	10Y	1Y	5Y	10Y
$Spread_{(i,t-1)}$	0.713***	0.686***	0.661***	0.710***	0.852***	0.604***
	(0.065)	(0.066)	(0.067)	(0.073)	(0.079)	(0.090)
$Eco_{(i,t-1)}$	–0.003	–0.002	–0.003	–0.003	–0.003	–0.005**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
$Env_{(i,t-1)}$	–0.013**	–0.025***	–0.023***	0.001	0.002	0.002
	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)	(0.004)
$Soc_{(i,t-1)}$	0.003	0.005*	0.003*	–0.007***	–0.004**	–0.001
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)
$Gov_{(i,t-1)}$	0.013**	0.013*	0.009*	0.004	0.004	0.002
	(0.005)	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)
Observations	190	190	190	150	150	150
Countries	19	19	19	15	15	15
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.651	0.629	0.633	0.676	0.602	0.419

NOTES: Standard deviation in parentheses. Level of significance: *10%, **5%, ***1%.

is negative and significant. E and G scores are associated with a positive coefficient but do not appear significant. Although the results are similar across bond maturities (in terms of significance), the magnitude of the S score coefficients changes with the bond maturity, reaching a value of –0.007 for one-year and –0.004 for five-year bond yield spreads. The impact of the S dimension on bond yield spreads is more pronounced in the short run. Hence, from an investor standpoint, a lower yield is to be expected when investing in countries with higher S performance, suggesting that a negative premium is associated with this reduction in S risk. These results are in line with those of Berg, Margaretic, and Pouget (2016) in terms of the negative impact of this S dimension on bond yield spreads. However, Berg, Margaretic, and Pouget (2016) found that the link between the S score and bond yield spread is stronger in the long term. Moreover, they also found that the E dimension affects the spread with a strong negative long-term link.

One straightforward explanation for why the S dimension may have a higher explanatory power is that it is the variable that exhibits the highest degree of cross-sectional dispersion. Looking at the cross-sectional dispersion of each of the E, S, and G dimensions, it indeed turns out that S is the most dispersed for both developed and emerging countries, with a standard deviation of 0.92 and 1.57, respectively. The dispersion of the S dimension for emerging countries is particularly high, meaning that the S scores are more spread out within emerging countries. It should be noted that there is higher heterogeneity in terms of S performance within emerging countries, compared to developed countries. In comparison, the standard deviation for the G dimension is 0.85 and 0.86 for developed and emerging countries, respectively, whereas for the E dimension the respective figures are 0.80 and 0.91.

From an economic perspective, it can be argued that if emerging countries appear more vulnerable to S risks, it is because these risks may be more material in emerging countries, in which governments have fewer resources available to manage them. The S dimension is closely linked to political stability, governance, and a country's ability to raise taxes or introduce reforms. Key social factors include human rights, labor standards, education system, health care, and so on. As already noted, our result regarding the S dimension for emerging countries is in line with that of Berg, Margaretic, and Pouget (2016), who analyzed 52 emerging economies from 2000 to 2012. Their results indicate that emerging economies seem to be more vulnerable to E and S risks. They found that G is not significant in explaining sovereign bond spreads, whereas the E and S factors are.

Moreover, a strand of the literature on sovereign bonds and ESG indicators focuses on the link between sovereign bond spreads and/or credit ratings and one particular dimension of the ESG criteria (either E, S, or G). Regarding the S factor, Bundala (2013) found that the inequality-adjusted human development index and the unemployment rate, respectively, negatively and positively influence the probability of a country defaulting and dishonoring its debt obligation. Therefore, they recommended using these factors as a prerequisite when assessing a country's creditworthiness. Hoepner et al. (2016) investigated the link between the sustainable development culture of a country and country risk. They showed that high ratings for culture, in terms of social, environment, and political issues, reduce government bond yields, meaning that culture is priced by sovereign bond markets.

ESG Scores and Risk and Expected Return on Sovereign Bonds

We now explore the impact of cross-sectional differences in each E, S, and G dimension on the performance characteristics of sovereign bonds from the perspective of a short-term investor, who will not hold the bonds until maturity and for whom bond yields are not sufficient statistics for expected returns. In particular, we want to answer the following questions:

- What is the relationship between each ESG score and sovereign bond risk and performance from an investor perspective?
- How can each ESG performance dimension affect sovereign bond returns?
- Is better ESG associated with lower sovereign bond returns and/or lower risk?

We answer these questions, exploring the impact of each ESG score on bond returns for different bond maturities (1 year, 5 year, and 10 year) and level of country development (developed versus emerging markets). To this end, for every time period (year), we sort sovereign bonds based on their economic/E/S/G scores and form four quartiles. Quartile Q1 corresponds to the 25% lowest-ranked bonds, whereas quartile Q4 corresponds to the 25% best-rated bonds. The selected bonds are then equally weighted, and each quartile is rebalanced on an annual basis (note: Verisk indexes are updated on an annual basis).

We also want to explore the impact of cross-sectional differences in each dimension on sovereign market risk; for each sovereign bond quartile, in addition to annualized expected returns, we report the average value of the following indicators: volatility and Sharpe ratio, max drawdown, kurtosis, and skewness. We perform the analysis for both developed and emerging countries and for different maturities (1 year, 5 year, and 10 year).

Exhibits 2 and 3 report for developed countries and emerging countries, respectively, the annualized expected returns in percentage, the volatility in percentage, the max drawdown in percentage, the Sharpe ratio, skewness, and kurtosis for each ESG quartile over the period 2010–2020, as well as the difference between the quartiles with the best and poorest ESG profiles (Q4 – Q1).

EXHIBIT 2

Annualized Expected Returns, Volatility, Max Drawdown, Sharpe Ratio, Skewness, and Kurtosis for Each Developed Country's ESG Quartiles (2010–2020) and Difference between the Quartiles with the Best and Poorest ESG Profiles (Q4 – Q1)

		Economics					Environment				
	Bond Maturity	Q1 (worst)	Q2	Q3	Q4 (best)	Q4 – Q1	Q1 (worst)	Q2	Q3	Q4 (best)	Q4 – Q1
Annualized Return (%)	1Y	2.36	2.97	2.10	1.69	–0.67	2.66	1.94	2.98	1.53	–1.13
	5Y	5.82	6.81	5.38	4.92	–0.89	6.40	5.79	6.55	4.21	–2.19
	10Y	8.44	11.03	9.87	8.86	0.42	10.56	9.32	10.91	7.49	–3.07
Volatility	1Y	0.07	0.09	0.08	0.08	0.01	0.08	0.08	0.08	0.09	0.01
	5Y	0.14	0.11	0.10	0.10	–0.04	0.13	0.11	0.11	0.11	–0.02
	10Y	0.19	0.15	0.15	0.14	–0.05	0.17	0.17	0.15	0.14	–0.03
Maximum Drawdown (%)	1Y	21.99	28.02	24.71	23.64	1.64	23.33	23.72	25.08	26.23	2.90
	5Y	33.04	32.05	29.47	27.50	–5.54	31.42	30.87	29.99	29.78	–1.63
	10Y	41.33	39.12	37.72	35.22	–6.11	39.34	39.63	37.64	36.78	–2.55
Sharpe Ratio	1Y	0.25	0.28	0.18	0.10	–0.15	0.22	0.22	0.28	0.09	–0.14
	5Y	0.43	0.55	0.45	0.39	–0.03	0.51	0.46	0.52	0.32	–0.18
	10Y	0.43	0.65	0.63	0.56	0.14	0.62	0.53	0.65	0.48	–0.14
Kurtosis	1Y	3.27	3.14	2.73	3.12	–0.16	3.02	2.92	3.00	3.32	0.30
	5Y	3.05	3.00	2.62	3.20	0.16	3.13	2.93	2.49	3.31	0.18
	10Y	2.97	3.46	3.35	3.94	0.97	3.49	3.59	2.80	3.85	0.36
Skewness	1Y	0.18	–0.39	–0.28	0.27	0.09	0.10	–0.29	–0.25	0.22	0.12
	5Y	0.40	–0.18	–0.10	0.60	0.20	0.23	0.12	–0.05	0.43	0.20
	10Y	0.43	0.41	0.59	1.02	0.58	0.48	0.76	0.34	0.87	0.39
		S					G				
Annualized Return (%)	1Y	1.24	0.37	0.79	1.24	0.00	2.48	2.17	1.35	3.13	0.64
	5Y	6.63	2.60	4.00	4.06	–2.58	6.74	6.01	4.04	6.14	–0.60
	10Y	11.14	6.03	8.10	7.22	–3.92	10.06	10.06	7.70	9.64	–0.43
Volatility	1Y	0.07	0.08	0.08	0.09	0.02	0.08	0.07	0.08	0.09	0.01
	5Y	0.12	0.11	0.11	0.11	0.00	0.14	0.10	0.10	0.11	–0.03
	10Y	0.17	0.16	0.16	0.15	–0.02	0.20	0.14	0.14	0.15	–0.06
Maximum Drawdown (%)	1Y	20.30	24.98	25.20	27.87	7.57	23.89	21.16	24.73	28.57	4.68
	5Y	29.27	30.62	30.14	32.02	2.75	35.28	26.64	27.76	32.38	–2.90
	10Y	37.95	38.18	38.91	38.34	0.39	43.90	36.27	34.91	38.31	–5.59
Sharpe Ratio	1Y	0.22	0.14	0.24	0.23	0.01	0.27	0.20	0.09	0.26	–0.01
	5Y	0.57	0.34	0.47	0.43	–0.14	0.45	0.53	0.37	0.47	0.01
	10Y	0.61	0.51	0.61	0.54	–0.07	0.50	0.65	0.53	0.59	0.09
Kurtosis	1Y	3.16	3.15	2.95	3.01	–0.16	2.74	3.15	3.27	3.10	0.36
	5Y	3.08	3.20	2.68	2.90	–0.18	3.47	2.46	2.91	3.03	–0.43
	10Y	3.62	3.66	3.16	3.30	–0.32	4.04	3.10	3.24	3.36	–0.68
Skewness	1Y	0.24	–0.03	–0.26	–0.17	–0.41	–0.16	–0.04	0.09	–0.11	0.04
	5Y	0.52	0.23	–0.03	0.00	–0.52	0.62	–0.04	0.09	0.05	–0.57
	10Y	0.81	0.71	0.49	0.45	–0.36	1.01	0.49	0.50	0.45	–0.56

For both developed and emerging countries, we find that annualized returns are lower for the best ESG quartiles (Q4) than for the worst ESG quartiles (Q1). Moreover, the difference is greater for emerging countries than for developed countries. Regarding bond maturities, the difference between the two quartiles is greater for long-term bonds (10-year maturity), an intuitive result given that the longer maturity magnifies the effect under consideration. In other words, we confirm that a negative risk premium is associated with each ESG dimension for both developed and

EXHIBIT 3

Annualized Expected Returns, Volatility, Max Drawdown, Sharpe Ratio, Skewness, and Kurtosis for Each Emerging Country's ESG Quartiles (2010–2020) and Difference between the Quartiles with the Best and Poorest ESG Profiles (Q4 – Q1)

		Economics					Environment				
	Bond Maturity	Q1 (worst)	Q2	Q3	Q4 (best)	Q4 – Q1	Q1 (worst)	Q2	Q3	Q4 (best)	Q4 – Q1
Annualized Return (%)	1Y	10.01	8.72	5.82	4.28	–5.73	6.52	11.43	6.78	3.83	–2.69
	5Y	12.90	12.46	10.29	6.68	–6.23	9.71	15.61	10.31	6.56	–3.15
	10Y	14.64	15.71	13.59	7.97	–6.67	12.05	17.98	13.09	9.07	–2.98
Volatility	1Y	0.12	0.12	0.12	0.13	0.01	0.12	0.16	0.10	0.11	–0.01
	5Y	0.12	0.12	0.12	0.13	0.01	0.11	0.14	0.11	0.13	0.02
	10Y	0.15	0.16	0.15	0.14	–0.01	0.13	0.18	0.14	0.16	0.03
Maximum Drawdown (%)	1Y	32.44	31.25	30.31	33.27	0.84	31.34	37.96	27.10	30.07	–1.28
	5Y	31.37	31.06	31.23	33.88	2.51	28.96	33.96	30.39	34.37	5.41
	10Y	35.81	35.12	35.12	37.00	1.19	33.05	36.93	33.68	40.18	7.13
Sharpe Ratio	1Y	0.63	0.63	0.38	0.25	–0.37	0.43	0.60	0.55	0.31	–0.11
	5Y	0.88	0.92	0.70	0.43	–0.44	0.75	0.95	0.77	0.47	–0.29
	10Y	0.82	0.90	0.79	0.52	–0.31	0.80	0.90	0.81	0.51	–0.29
Kurtosis	1Y	3.15	3.12	2.78	2.60	–0.55	2.65	3.53	2.73	2.79	0.15
	5Y	3.62	3.76	3.13	2.76	–0.86	3.37	4.05	2.98	2.90	–0.47
	10Y	2.55	3.41	3.49	3.28	0.73	2.75	3.46	3.23	3.27	0.52
Skewness	1Y	0.02	0.37	0.13	–0.01	–0.03	0.22	0.71	–0.05	–0.50	–0.71
	5Y	–0.70	0.11	0.11	–0.13	0.57	–0.55	0.06	0.12	–0.26	0.29
	10Y	–0.39	0.65	0.55	0.04	0.44	–0.13	0.30	0.43	0.33	0.45
		S					G				
Annualized Return (%)	1Y	8.21	10.42	5.83	4.06	–4.15	7.50	10.58	6.15	4.48	–3.02
	5Y	12.34	14.22	9.40	6.13	–6.20	11.66	14.54	9.07	6.95	–4.70
	10Y	14.59	16.88	12.22	8.26	–6.32	14.38	17.11	12.02	8.29	–6.09
Volatility	1Y	0.15	0.13	0.12	0.09	–0.06	0.14	0.13	0.10	0.12	–0.01
	5Y	0.13	0.12	0.13	0.11	–0.03	0.12	0.13	0.12	0.13	0.00
	10Y	0.16	0.15	0.16	0.14	–0.02	0.16	0.16	0.15	0.13	–0.03
Maximum Drawdown (%)	1Y	35.66	33.32	30.81	25.55	–10.12	33.44	33.01	28.49	32.02	–1.43
	5Y	32.39	30.01	34.02	30.21	–2.18	30.47	32.16	31.98	32.62	–2.15
	10Y	36.03	33.35	36.86	36.76	0.73	35.67	35.42	37.13	34.10	–1.58
Sharpe Ratio	1Y	0.46	0.46	0.49	0.35	–0.11	0.44	0.66	0.50	0.29	–0.14
	5Y	0.78	0.78	0.66	0.49	–0.29	0.83	0.95	0.68	0.48	–0.34
	10Y	0.75	0.75	0.70	0.54	–0.22	0.81	0.91	0.73	0.60	–0.21
Kurtosis	1Y	3.31	2.99	2.55	2.88	–0.43	3.26	2.98	2.65	2.83	–0.43
	5Y	3.70	3.77	2.89	2.95	–0.76	3.83	3.45	2.99	3.07	–0.76
	10Y	3.37	2.78	3.38	3.16	–0.21	3.24	3.00	3.56	2.80	–0.44
Skewness	1Y	0.66	0.44	–0.12	–0.63	–1.29	0.53	0.31	–0.31	–0.03	–0.56
	5Y	0.09	–0.44	0.10	–0.41	–0.49	–0.18	–0.20	–0.14	–0.05	0.14
	10Y	0.39	–0.18	0.54	0.13	–0.26	0.46	0.13	0.34	–0.11	–0.56

emerging countries. This result implies that investors seeking to improve the E, S, and/or G scores of their portfolio will face an opportunity cost that will translate into lower performance.

This lower performance is naturally associated with lower risk. Indeed, we find that on average bonds in the best ESG quartiles (Q4) are less volatile than those in the worst (Q1) for all maturities and for both developed and emerging countries. We also find that on average bonds in the best ESG quartiles (Q4) have a lower max drawdown than those in the worst (Q1), a result that again holds for all maturities and for both developed and emerging countries. Combining the impact on risk and performance, we also find that on average bonds in the best ESG quartiles (Q4) have a higher Sharpe ratio than those in the worst (Q1), a result that is robust to changes in bond maturities and regions (both developed and emerging countries).

In the online appendix, we present a complementary analysis intended to control for differences in economic scores so as to better isolate the impact of nonfinancial dimensions. This analysis allows us to reach two main conclusions. On one hand, E and G scores have a significant and negative impact on bond returns for developed countries after controlling for economic scores and other fixed effects. On the other hand, S scores have a significant and negative impact on bond returns for emerging countries after controlling for economic scores and other fixed effects.

MEASURING AND MANAGING THE OPPORTUNITY COSTS OF ESG CONSTRAINTS

The previous results suggest that cross-sectional differences in E, S, or G scores translate into cross-sectional differences in the risk and performance characteristics of sovereign bond portfolios. Although ESG investing is sometimes presented as an opportunity for higher performance, it has to be recognized that ESG scores are, strictly speaking, to be regarded instead as performance constraints, which need to be applied at the security selection and/or portfolio construction stages. As such, the integration of ESG dimensions in an investment decision framework suggests that an opportunity cost should be incurred, compared to a portfolio that would be optimally formed in the absence of ESG considerations. The main focus of this analysis is how implementation choices regarding how ESG criteria are incorporated into a portfolio can have a direct impact on this opportunity cost.

To the best of our knowledge, only three academic papers and one practitioner study have focused on analyzing the risk and performance of sovereign bond portfolios based on ESG criteria (Drut 2010; AXA Investment Managers 2013; Badia, Pina, and Torres 2019; Hübel 2020). Their results provide evidence that integrating ESG scores into the investment process does not necessary mean sacrificing returns.

Integrating ESG Constraints at the Selection Stage

A first approach to introducing ESG criteria into the investment process is to include them at the selection stage. In this context, an investor or portfolio manager may wish to increase the E, S, and/or G score of a portfolio by applying a set of investment screens, designed to either exclude (negative screening) or select (positive screening) sovereign bonds from the investment universe on the basis of their ESG scores.

In other words, a negative screening, or ESG worst-in-class exclusion, approach involves excluding from a portfolio a number of countries (say, the last decile or quartile) that perform poorly in terms of ESG scores. A drawback of this negative exclusion approach is that it tends to have a relatively modest impact on the global ESG score of the portfolio because relatively few assets are excluded. On the other hand, it allows the investor to enjoy a relatively high level of diversification. Conversely, a positive screening, or ESG best-in-class inclusion, approach involves only including in the portfolio countries with the highest ESG scores (say, the top decile or quartile). A drawback of this positive screening approach is that it can be too exclusive, and

EXHIBIT 4

Benchmark Results over the Sample Period (2010–2020) for Developed and Emerging Countries

	Developed Countries				Emerging Countries			
Annualized Return (%)	7.46				12.60			
Annualized Volatility (%)	8.76				6.68			
Sharpe Ratio	0.85				1.89			
Max Return (%)	8.62				7.75			
Min Return (%)	–6.18				–3.27			
Max Drawdown (%)	71.66				42.20			
Benchmark Score (mean)	Economics	E	S	G	Economics	E	S	G
	6.15	7.00	7.68	7.83	6.04	5.47	4.55	5.84

focusing only on better ESG countries can easily result in a pool of highly correlated and geographically concentrated countries, with lower associated diversification benefits. However, the impact in terms of improvement on ESG scores is expected to be greater given the focus on the relatively few sovereign bonds that have the highest ESG scores.

There is a key distinction to make between an ESG approach based on negative/positive screening with a regional neutrality constraint and one without such a constraint. In the latter case, geographical biases would arise from a straightforward positive or negative screening process. For this reason, in what follows we build portfolios of five-year maturity sovereign bonds separately for developed and emerging countries, as opposed to selecting sovereign bonds in a global universe mixing developed and emerging economies.

More precisely, for each region (developed and emerging) we sort sovereign bonds based on the four available dimensions, namely economic, E, S, and G, and for each one we form four quartiles. Quartile Q1 corresponds to the 25% lowest-ranked bonds, whereas quartile Q4 corresponds to the 25% best-rated bonds. Our negative screening strategy is to exclude the 25% lowest-ranked bonds (Q1). The selected bonds, corresponding to the 75% best-ranked bonds (Q2, Q3, and Q4), are then equally weighted, and the portfolios are rebalanced on an annual basis, which is consistent with the fact that Verisk scores are updated on an annual basis. Our positive screening strategy consists of selecting the 25% best-ranked bonds (Q4). The selected bonds are then equally weighted, and the portfolios are rebalanced on an annual basis. We use an equally weighted portfolio of all quartiles, which is also rebalanced on an annual basis, as a benchmark portfolio for developed and emerging countries.

In Exhibits 4 to 6, for each sovereign bond portfolio (benchmark portfolios and negative and positive screening strategies) associated with each selection/exclusion criterion, we report the following indicators: annualized mean return, annualized volatility, Sharpe ratio, information ratio, maximum return, minimum return, and maximum drawdown over the period 2010–2020. We also report the economic, E, S, and G scores associated with each portfolio over the period.

Starting with the negative screening strategy, we find that for each dimension the annualized performance of the ESG-enhanced portfolio remains close to or slightly lower than the annualized return of the benchmark portfolio for both developed and emerging countries. On the other hand, the annualized volatility is systematically higher than that of the benchmark portfolios, reflecting a lower level of diversification without a strong corresponding impact on ESG scores (see the following). For each dimension, the Sharpe ratio for both developed and emerging countries is equal to or slightly lower than their benchmarks.

EXHIBIT 5

Results of the Negative Screening Strategy over the Sample Period (2010–2020) for Developed and Emerging Countries

Negative Screening								
Economics								
	Developed Countries				Emerging Countries			
Annualized Return (%)	7.20				11.54			
Annualized Volatility (%)	9.32				7.15			
Portfolio Annualized Return—Benchmark (%)	−0.25				−1.06			
Sharpe Ratio	0.77				1.61			
Tracking Error (%)	1.40				1.36			
Information Ratio	−0.18				−0.78			
Max Return (%)	9.50				7.76			
Min Return (%)	−6.74				−3.62			
Max Drawdown (%)	70.80				46.62			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	**6.45**	7.15	7.88	8.04	**6.37**	5.47	4.58	5.90
Benchmark Score (mean)	**6.15**	7.00	7.68	7.83	**6.04**	5.47	4.55	5.84
Diff Score/Benchmark Score (%)	**4.92**	2.18	2.64	2.71	**5.51**	0.17	0.56	1.03
E								
	Developed Countries				Emerging Countries			
Annualized Return (%)	7.78				12.80			
Annualized Volatility (%)	9.14				7.69			
Portfolio Annualized Return—Benchmark (%)	0.32				0.20			
Sharpe Ratio	0.85				1.66			
Tracking Error (%)	1.11				1.96			
Information Ratio	0.29				0.10			
Max Return (%)	9.20				8.80			
Min Return (%)	−5.84				−4.43			
Max Drawdown (%)	63.50				50.32			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	6.27	**7.30**	7.92	7.94	5.91	**5.92**	5.01	6.02
Benchmark Score (mean)	6.15	**7.00**	7.68	7.83	6.04	**5.47**	4.55	5.84
Diff Score/Benchmark Score (%)	1.90	**4.31**	3.19	1.44	−2.13	**8.39**	10.11	3.08
S								
	Developed Countries				Emerging Countries			
Annualized Return (%)	7.48				11.92			
Annualized Volatility (%)	9.60				7.63			
Portfolio Annualized Return—Benchmark (%)	0.02				−0.68			
Sharpe Ratio	0.78				1.56			
Tracking Error (%)	1.15				1.89			
Information Ratio	0.02				−0.36			
Max Return (%)	9.42				9.34			
Min Return (%)	−6.99				−4.35			
Max Drawdown (%)	74.20				46.57			

(continued)

EXHIBIT 5 *(continued)*

Results of the Negative Screening Strategy over the Sample Period (2010–2020) for Developed and Emerging Countries

	S							
	Developed Countries				Emerging Countries			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	6.33	7.24	**8.08**	8.16	6.03	5.71	**5.15**	6.19
Benchmark Score (mean)	6.15	7.00	**7.68**	7.83	6.04	5.47	**4.55**	5.84
Diff Score/Benchmark Score (%)	2.98	3.39	**5.24**	4.22	–0.13	4.47	**13.15**	5.94
	G							
	Developed Countries				Emerging Countries			
Annualized Return (%)	7.23				12.05			
Annualized Volatility (%)	9.05				7.96			
Portfolio Annualized Return—Benchmark (%)	–0.23				–0.55			
Sharpe Ratio	0.80				1.51			
Tracking Error (%)	1.47				1.98			
Information Ratio	–0.16				–0.28			
Max Return (%)	9.56				9.75			
Min Return (%)	–5.98				–4.60			
Max Drawdown (%)	62.59				47.15			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	6.32	7.22	8.00	**8.22**	5.99	5.78	5.09	**6.24**
Benchmark Score (mean)	6.15	7.00	7.68	**7.83**	6.04	5.47	4.55	**5.84**
Diff Score/Benchmark Score (%)	2.74	3.14	4.14	**4.96**	–0.78	5.78	11.65	**6.76**

EXHIBIT 6

Results of the Positive Screening Strategy over the Sample Period (2010–2020) for Developed and Emerging Countries

	Positive Screening							
	Economics							
	Developed Countries				Emerging Countries			
Annualized Return (%)	5.77				11.37			
Annualized Volatility (%)	9.22				8.15			
Portfolio Annualized Return–Benchmark (%)	–1.68				–1.23			
Sharpe Ratio	0.63				1.40			
Tracking Error (%)	2.69				1.36			
Information Ratio	–0.63				–0.28			
Max Return (%)	10.99				9.85			
Min Return (%)	–6.26				–4.13			
Max Drawdown (%)	56.97				41.90			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	**7.19**	7.47	7.78	8.16	**6.89**	4.96	4.39	5.78
Benchmark Score (mean)	**6.15**	7.00	7.68	7.83	**6.04**	5.47	4.55	5.84
Diff Score/Benchmark Score (%)	**16.93**	6.68	1.28	4.19	**13.97**	–9.18	–3.52	–0.97

(continued)

EXHIBIT 6 *(continued)*

Results of the Positive Screening Strategy over the Sample Period (2010–2020) for Developed and Emerging Countries

	E							
	Developed Countries				**Emerging Countries**			
Annualized Return (%)	6.55				9.49			
Annualized Volatility (%)	6.71				11.05			
Portfolio Annualized Return–Benchmark (%)	–0.90				–3.11			
Sharpe Ratio	0.98				0.86			
Tracking Error (%)	6.58				1.96			
Information Ratio	–0.14				–0.56			
Max Return (%)	7.34				12.63			
Min Return (%)	–3.73				–7.83			
Max Drawdown (%)	50.78				61.96			
	Economics	**E**	S	G	Economics	**E**	S	G
Score (mean)	6.98	**8.00**	8.26	8.49	6.49	**6.46**	6.27	6.55
Benchmark Score (mean)	6.15	**7.00**	7.68	7.83	6.04	**5.47**	4.55	5.84
Diff Score/Benchmark Score (%)	13.41	**14.28**	7.58	8.51	7.38	**18.21**	37.76	12.12
	S							
	Developed Countries				**Emerging Countries**			
Annualized Return (%)	8.19				8.73			
Annualized Volatility (%)	10.00				10.85			
Portfolio Annualized Return–Benchmark (%)	0.73				–3.87			
Sharpe Ratio	0.82				0.80			
Tracking Error (%)	2.67				1.89			
Information Ratio	0.27				–0.74			
Max Return (%)	10.59				11.17			
Min Return (%)	–6.98				–7.25			
Max Drawdown (%)	65.95				64.94			
	Economics	E	**S**	G	Economics	E	**S**	G
Score (mean)	6.55	7.57	**8.52**	8.64	5.96	6.27	**6.83**	6.60
Benchmark Score (mean)	6.15	7.00	**7.68**	7.83	6.04	5.47	**4.55**	5.84
Diff Score/Benchmark Score (%)	6.41	8.11	**10.89**	10.35	–1.33	14.72	**50.03**	13.03
	G							
	Developed Countries				**Emerging Countries**			
Annualized Return (%)	8.58				10.31			
Annualized Volatility (%)	10.39				9.02			
Portfolio Annualized Return–Benchmark (%)	1.12				–2.29			
Sharpe Ratio	0.83				1.14			
Tracking Error (%)	3.39				1.98			
Information Ratio	0.33				–0.49			
Max Return (%)	10.82				12.16			
Min Return (%)	–6.45				–4.70			
Max Drawdown (%)	59.62				38.70			
	Economics	E	S	**G**	Economics	E	S	**G**
Score (mean)	6.60	7.67	8.46	**8.70**	6.43	5.72	5.05	**7.00**
Benchmark Score (mean)	6.15	7.00	7.68	**7.83**	6.04	5.47	4.55	**5.84**
Diff Score/Benchmark Score (%)	7.21	9.60	10.11	**11.12**	6.42	4.65	10.93	**19.86**

Moreover, for each dimension we confirm that, as expected, the E, S, and G scores are systematically higher for the negative screening strategy, compared to their benchmarks. Excluding the 25% worst-ranked bond results only has a relatively modest impact in terms of E, S, or G criteria. For both developed and emerging countries, among these criteria the highest increase is for the S dimension (+5.24% and +13.15%, respectively), and the lowest increase is for the E dimension for developed countries (+4.31%) and the G dimension for emerging countries (+6.76%).

These results imply that increasing the sustainability (E, S, and G criteria taken separately) of a portfolio using negative screening does not do much harm to returns and increases volatility by 0.5% on average for developed countries and 0.9% for emerging countries. However, the increase in the E, S, and G scores remains quite small, up to 4.8% on average for developed countries and 8.4% on average for emerging countries.

Regarding the positive screening strategy, for developed countries the annualized return and volatility are both lower for the E dimension whereas they are both higher for the S and G dimensions, compared to the benchmark. For emerging countries, all portfolios have lower annualized returns and higher annualized volatility than the benchmark portfolio.

For each dimension, we confirm that the scores are systematically higher than the benchmark portfolios and with respect to the less aggressive negative screening strategy, which makes sense because these portfolios only include the 25% best-ranked bonds. For developed countries the highest increase in ESG scores is for the E dimension (+14.28%), and for emerging countries the highest increase is for the S dimension (+50%). For developed countries the lowest increase is for the G dimension (+11.12%), and for emerging countries it is for E dimension (+18.21%).

These results allow us to draw two conclusions. First, for developed countries, increasing the sustainability of a portfolio using positive screening comes at a cost for the E dimension, whereas it slightly enhances returns and increases volatility for the S and G dimensions. Second, for emerging countries, increasing the sustainability of a portfolio using positive screening comes at a cost for all dimensions because it leads to a lower annualized return and higher volatility. The higher the increase in the score (the more sustainable a portfolio is, based on our different criteria taken individually), the higher the cost.

Integrating ESG Constraints at the Optimization Stage

In contrast to including ESG criteria at the selection stage, one may also attempt to incorporate ESG constraints at the allocation stage.[4] In this context, an investor or portfolio manager may wish to increase the E, S, and/or G score of a portfolio by introducing a minimum score target as a constraint in a formal portfolio optimization process. In what follows, we adopt a relative performance focus, in which the optimization objective relates to the risk or risk-adjusted performance of the portfolio subject to ESG constraints. We refer the interested reader to the online appendix for an absolute performance focus, in which the optimization objective relates to the tracking error of the portfolio with respect to the benchmark, again subject to ESG constraints.

More precisely, we investigate the impact of integrating E, S, and G criteria as part of the global minimum variance (GMV) portfolio optimization approach. In what follows, we perform an in-sample analysis because our main motivation is not to

[4] Obviously, the approaches of incorporating ESG constraints at the selection and allocation stages are not mutually exclusive. In this article, we analyze these approaches separately so as to better identify the impact of ESG integration in selection and optimization procedures taken in isolation.

provide a horse race out-of-sample analysis of competing optimization strategies, which would not lead to robust conclusions given the relatively short sample history, but instead to measure the opportunity cost involved in the introduction of ESG constraints. In other words, we are interested in measuring the increase in variance of the ESG-constrained portfolio with respect to the corresponding unconstrained portfolio.

As before, we build separate portfolios of five-year-maturity sovereign bonds for developed and emerging countries. For each region, we first the minimum variance portfolios with no E, S, or G constraints. For each portfolio, in addition to the constraint that the sum of the weights allocated to the assets must be equal to 1, we add a minimum weight constraint so that the minimum weight of each asset must be greater than or equal to $\frac{1}{2N}$, with N being the total number of assets in a portfolio (20 for developed countries and 15 for emerging countries). This is meant to avoid corner solutions that are typical of straightforward optimization procedures. We then calculate the E, S, and G scores of each of the portfolios at the initial date (2010) as the weighted average of each country's scores.

Given the lack of robustness of expected return estimates, we focus on a variance minimization problem subject to the constraint that the portfolio is fully invested in the N assets. The GMV portfolio is defined by the following program:

$$\min_{w} \sigma^2(w) = w' \Sigma w, \quad \text{subject to} \begin{cases} 1'_N w = 1 \\ w \geq \dfrac{1}{2N} \end{cases}$$

We want to improve the E, S, and G scores of the minimum variance portfolios. To this end, in the second step we integrate E, S, and G constraints into the optimization process. The level of E, S, and G constraints is set in terms of a given improvement with respect to the E, S, and G scores of the previously built minimum variance portfolios with no E, S, or G constraints.

We denote the reference scores by $Score_{MSR}$ and $Score_{GMV}$ and the percentage increase from a reference score by P%. For each dimension, we test different target levels for P (from 5% to 60%). For each score dimension, the maximum percentage increase depends on the range of scores within the underlying universe as well as the weight and minimum weight constraints. We report the results for the maximum increase we obtained for each dimension.

The minimum variance portfolio with E, S, or G constraints is defined by the following program:

$$\min_{w} \sigma^2(w), \quad \text{subject to} \begin{cases} 1'_N w = 1 \\ w \geq \dfrac{1}{2N} \\ Score \geq Score_{GMV} \times (1 + P\%) \end{cases}$$

In Exhibit 7, for each dimension we report the following indicators for the minimum variance strategies: annualized mean, annualized volatility, Sharpe ratio, information ratio, maximum return, minimum return, and maximum drawdown over the period 2010–2020. We also report the economic, E, S, and G scores associated with each portfolio at the initial date (2010).[5]

[5] In this analysis we compare the E, S, and G scores of each portfolio based on the E, S, and G scores of each country at the initial date (2010).

EXHIBIT 7

Results of the Minimum Variance Strategy over the Sample Period (2010–2020) for Developed and Emerging Countries

	Minimum Variance							
	Developed Countries				Emerging Countries			
Annualized Return (%)	5.74				13.01			
Annualized Volatility (%)	5.05				4.47			
Sharpe Ratio	1.14				2.91			
Max Return (%)	4.76				5.30			
Min Return (%)	–3.02				–2.07			
Max Drawdown (%)	63.54				39.00			
Minimum Variance Score (mean)	Economics	E	S	G	Economics	E	S	G
	5.60	6.52	6.92	7.93	6.07	4.96	3.85	5.45
Benchmark Score (mean)	6.15	7.00	7.68	7.83	6.04	5.47	4.55	5.84

In Exhibit 8, we report for each dimension over the period 2010–2020 the following indicators for the minimum variance portfolios with E, S, and G constraints: annualized mean, annualized volatility, Sharpe ratio, information ratio, maximum return, minimum return, and maximum drawdown. We also report the economic, E, S, and G scores associated with each portfolio at the initial date (2010).

Regarding the minimum variance strategy with E, S, and G constraints, for developed countries we managed to increase the E score by 10%, the S score by 15%, and the G score by 5%. The annualized performance for the E dimension is less than that for the portfolio with no E constraints as well as the benchmark, whereas in both cases it is higher for the S and G dimensions. For the E, S, and G dimensions, respectively, the volatility is 52.55%, 87.83%, and 69.38% higher and the Sharpe ratio is 42.53%, 23.08%, and 18.74% lower, compared to the portfolio with no E, S, and G constraints. Here again, there is a trade-off between increasing E, S, and G scores and generating low variance for the portfolio.

For emerging countries, we managed to increase the E score by 15%, the S score by 50%, and the G score by 15%. The annualized returns of these portfolios are lower than those for the portfolio with no E, S, and G constraints and the benchmark, whereas the annualized volatility is higher. For the E, S, and G dimensions, respectively, the volatility is 85.34%, 68.47%, and 49.55% higher and the Sharpe ratio is 52.80%, 57.90%, and 49.70% lower, compared to the portfolio with no E, S, and G constraints. There is a clear trade-off between increasing E, S, and G scores and maintaining a focus on minimizing the portfolio variance. In the case of emerging countries, increasing the E, S, and G scores of a minimum variance portfolio also comes with an opportunity cost in terms of performance, as expected.

Comparing the Opportunity Cost of ESG Constraints with an Optimization Versus Selection Approach

Increasing the E, S, and G scores of a minimum variance strategy portfolio by adding an E, S, and G constraint equal to the maximum percentage increase achievable does not allow us to draw a direct comparison with the improvement in ESG scores obtained with a selection approach. Furthermore, setting the improvement target at the highest level is likely to hamper the optimization process because exceedingly

EXHIBIT 8

Results of the Minimum Variance Strategy with E, S, and G Constraints over the Sample Period (2010–2020) for Developed and Emerging Countries

	Minimum Variance + E/S/G Constraints							
	Economics							
	Developed Countries				**Emerging Countries**			
Annualized Return (%)	4.83				9.64			
Annualized Volatility (%)	8.76				6.10			
Portfolio Annualized Return–Benchmark (%)	–2.63				–2.96			
Sharpe Ratio	0.55				1.58			
Tracking Error (%)	3.28				5.00			
Information Ratio	–0.80				0.67			
Max Return (%)	11.81				4.94			
Min Return (%)	–5.59				–3.22			
Max Drawdown (%)	47.30				65.12			
Diff Ret/Min Var (%)	–15.77				–25.89			
Diff Vol/Min Var (%)	73.37				36.50			
Diff SR/Min Var (%)	–51.42				–45.71			
Diff MDD/Min Var (%)	–25.55				66.97			
	Economics (+25%)	E	S	G	**Economics (+10%)**	E	S	G
Score (mean)	**7.00**	7.35	7.45	7.93	**6.68**	4.56	3.44	5.17
Minimum Variance Score (mean)	**5.60**	6.52	6.92	7.93	**6.07**	4.96	3.85	5.45
Benchmark Score (mean)	**6.15**	7.00	7.68	7.83	**6.04**	5.47	4.55	5.84
Diff Score/Min Variance Score (%)	25.00	12.78	7.57	0.02	10.00	–8.06	–10.76	–5.01
Diff Score/Benchmark Score (%)	13.72	5.00	–3.02	1.32	10.59	–16.63	–24.47	–11.44
	E							
	Developed Countries				**Emerging Countries**			
Annualized Return (%)	5.03				11.38			
Annualized Volatility (%)	7.71				8.28			
Portfolio Annualized Return–Benchmark (%)	–2.43				–1.22			
Sharpe Ratio	0.65				1.37			
Tracking Error (%)	2.78				5.53			
Information Ratio	–0.87				–0.48			
Max Return (%)	10.02				9.88			
Min Return (%)	–4.64				–4.71			
Max Drawdown (%)	46.35				47.71			
Diff Ret/Min Var (%)	–12.33				–12.51			
Diff Vol/Min Var (%)	52.55				85.34			
Diff SR/Min Var (%)	–42.53				–52.80			
Diff MDD/Min Var (%)	–27.05				22.33			
	Economics	**E (+10%)**	S	G	Economics	**E (+15%)**	S	G
Score (mean)	6.66	**7.17**	7.34	7.95	6.23	**5.70**	5.23	6.11
Minimum Variance Score (mean)	5.60	**6.52**	6.92	7.93	6.07	**4.96**	3.85	5.45
Benchmark Score (mean)	6.15	**7.00**	7.68	7.83	6.04	**5.47**	4.55	5.84
Diff Score/Min Variance Score (%)	19.06	10.00	5.99	0.21	2.64	15.00	35.63	12.21
Diff Score/Benchmark Score (%)	8.32	2.41	–4.45	1.51	3.19	4.29	14.79	4.62

(continued)

EXHIBIT 8 *(continued)*

Results of the Minimum Variance Strategy with E, S, and G Constraints over the Sample Period (2010–2020) for Developed and Emerging Countries

	S	
	Developed Countries	**Emerging Countries**
Annualized Return (%)	8.29	9.22
Annualized Volatility (%)	9.49	7.53
Portfolio Annualized Return–Benchmark (%)	0.83	–3.38
Sharpe Ratio	0.87	1.22
Tracking Error (%)	2.07	2.81
Information Ratio	0.40	–1.20
Max Return (%)	9.46	9.48
Min Return (%)	–5.86	–4.27
Max Drawdown (%)	61.94	45.07
Diff Ret/Min Var (%)	44.47	–29.13
Diff Vol/Min Var (%)	87.83	68.47
Diff SR/Min Var (%)	–23.08	–57.94
Diff MDD/Min Var (%)	–2.52	15.56

	Economics	E	**S (15%)**	G	Economics	E	**S (+50%)**	G
Score (mean)	6.19	7.14	**7.96**	8.37	5.67	5.42	**5.78**	6.29
Minimum Variance Score (mean)	5.60	6.52	**6.92**	7.93	6.07	4.96	**3.85**	5.45
Benchmark Score (mean)	6.15	7.00	**7.68**	7.83	6.04	5.47	**4.55**	5.84
Diff Score/Min Variance Score (%)	10.59	9.52	15.00	5.60	–6.69	9.43	50.00	15.52
Diff Score/Benchmark Score (%)	0.62	1.96	3.67	6.98	–6.19	–0.76	26.96	7.71

	G	
	Developed Countries	**Emerging Countries**
Annualized Return (%)	7.80	9.78
Annualized Volatility (%)	8.56	6.68
Portfolio Annualized Return–Benchmark (%)	0.34	–2.82
Sharpe Ratio	0.91	1.46
Tracking Error (%)	2.20	2.41
Information Ratio	0.15	–1.17
Max Return (%)	9.33	8.26
Min Return (%)	–4.80	–4.29
Max Drawdown (%)	51.45	51.87
Diff Ret/Min Var (%)	35.94	–24.78
Diff Vol/Min Var (%)	69.38	49.55
Diff SR/Min Var (%)	–19.74	–49.71
Diff MDD/Min Var (%)	–19.03	33.00

	Economics	E	S	**G (+5%)**	Economics	E	S	**G (+15%)**
Score (mean)	5.98	7.01	7.68	**8.33**	6.02	5.32	4.83	**6.26**
Minimum Variance Score (mean)	5.60	6.52	6.92	**7.93**	6.07	4.96	3.85	**5.45**
Benchmark Score (mean)	6.15	7.00	7.68	**7.83**	6.04	5.47	4.55	**5.84**
Diff Score/Min Variance Score (%)	6.79	7.58	10.98	5.00	–0.81	7.44	25.25	15.00
Diff Score/Benchmark Score (%)	–2.84	0.16	0.05	6.37	–0.28	–2.57	6.01	7.22

high levels of E, S, and G constraints will tend to leave little room for optimization. In this context, and in an attempt to compare the integration of ESG constraints via selection versus optimization strategies, we set the E, S, and G constraint in the optimization process so that the E, S, and G scores are equal to the scores obtained previously with the negative screening strategy.

More precisely, we build minimum variance portfolios with the following constraints (in addition to the constraint that the sum of the weights allocated to the assets must be equal to 1 and the minimum weight of each asset must be greater than or equal to $\frac{1}{2N}$, where N is the total number of assets in a portfolio): Our target level for the economic, E, S, and G scores is set at 6.45, 7.30, 8.08, and 8.22, respectively, for developed countries and at 6.37, 5.92, 5.15, and 6.24, respectively, for emerging countries.

In Exhibit 9, for each dimension we report the following indicators for the minimum variance portfolios with E, S and G constraints: annualized mean, annualized volatility, Sharpe ratio, information ratio, maximum return, minimum return, and maximum drawdown over the period 2010–2020. We also report the economic, E, S, and G scores associated with each portfolio at the initial date (2010).

Regarding the minimum variance strategies with E, S, and G constraints, for developed and emerging countries we managed to obtain the same E, S, and G scores as for the negative screening strategy—except for E in the case of emerging countries, in which the score achievable is 2.68% lower than its target for both strategies. This is due to the presence of strictly positive minimum weight constraints that can be binding in some cases.

We are now able to compare the performance of portfolios whose E, S, and G score improvement results from a selection approach versus an optimization approach. For developed countries, for the same S and G score (8.08 and 8.22, respectively), the minimum variance strategy performs better than the negative screening strategy not only in terms of volatility, as expected, but also in terms of performance and risk-adjusted performance. For the same S score, the GMV strategy has a 22.46% higher annualized return and a 15.73% higher Sharpe ratio. For the same G score, the strategy has a 0.33% higher annualized return and a 21.00% higher Sharpe ratio. Regarding the E dimension, for the same E score (7.30), the minimum variance strategy underperforms the negative screening strategy with a 31.23% lower annualized return and a 31.58% lower Sharpe ratio.

For emerging countries, for the same S or G scores (5.15 and 6.24, respectively), the GMV strategy underperforms the negative screening strategy in terms of raw performance but outperforms in terms of risk-adjusted performance. For the same S score, the GMV strategy has a 12.31% lower annualized return and an 8.18% higher Sharpe ratio. For the same G score, the GMV strategy has a 16.87% lower annualized return and a 2.28% higher Sharpe ratio.

Interestingly, for developed countries, for the same E score, the S score (nontargeted) is lower and the G score (nontargeted) is higher for the GMV strategy compared to the negative screening strategy (the economic score is also higher). For the same S score, the nontargeted scores are higher for the GMV strategy (except economics), whereas for the same G score the nontargeted scores are lower for the GMV strategy.

Overall, our results show that optimization approaches can be useful for integrating ESG constraints while minimizing the opportunity cost measured in terms of either lower performance or higher volatility.

EXHIBIT 9

Results of the Minimum Variance Strategy with E, S, and G Constraints over the Sample Period (2010–2020) for Developed and Emerging Countries

	Minimum Variance + E/S/G Constraints							
	Economics							
	Developed Countries				Emerging Countries			
Annualized Return(%)	5.17				11.04			
Annualized Volatility (%)	7.08				4.85			
Portfolio Annualized Return–Benchmark (%)	–2.29				–1.56			
Sharpe Ratio	0.73				2.28			
Tracking Error (%)	2.71				3.42			
Information Ratio	–0.84				–0.46			
Max Return (%)	8.88				4.90			
Min Return (%)	–4.18				–2.39			
Max Drawdown (%)	47.04				48.79			
Diff Ret/Min Var (%)	–9.92				–15.09			
Diff Vol/Min Var (%)	40.19				8.49			
Diff SR/Min Var (%)	–35.74				–21.74			
Diff MDD/Min Var (%)	–25.96				25.09			
Diff Ret/Negative Screening (%)	–28.27				–4.31			
Diff Vol/Negative Screening (%)	–24.02				–32.17			
Diff SR/Negative Screening (%)	–5.59				41.07			
Diff MDD/Negative Screening (%)	–33.63				4.64			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	**6.45**	7.04	7.26	7.94	**6.37**	4.86	3.71	5.37
Minimum Variance Score (mean)	**5.60**	6.52	6.92	7.93	**6.07**	4.96	3.85	5.45
Negative Screening Score (mean)	**6.45**	7.15	7.88	8.04	**6.37**	5.47	4.58	5.90
Benchmark Score (mean)	**6.15**	7.00	7.68	7.83	**6.04**	5.47	4.55	5.84
Diff Score/Min Variance Score (%)	4.94	2.59	1.55	0.05	5.51	–2.44	–4.52	–1.69
Diff Score/Negative Screening Score (%)	0.00	–1.55	–7.94	–1.21	0.00	–11.18	–19.08	–8.98
Diff Score/Benchmark Score (%)	–4.54	–4.50	–8.46	1.36	6.07	–11.53	–19.18	–8.34
	E							
	Developed Countries				Emerging Countries			
Annualized Return(%)	4.88				13.80			
Annualized Volatility (%)	8.39				5.56			
Portfolio Annualized Return–Benchmark (%)	–2.57				1.19			
Sharpe Ratio	0.58				2.48			
Tracking Error (%)	3.08				4.04			
Information Ratio	–0.84				–0.62			
Max Return (%)	11.20				10.05			

(continued)

EXHIBIT 9 *(continued)*

Results of the Minimum Variance Strategy with E, S, and G Constraints over the Sample Period (2010–2020) for Developed and Emerging Countries

	E	
	Developed Countries	**Emerging Countries**
Min Return (%)	–5.25	–6.37
Max Drawdown (%)	46.91	63.42
Diff Ret/Min Var (%)	–14.84	6.07
Diff Vol/Min Var (%)	66.01	24.50
Diff SR/Min Var (%)	–48.70	–14.81
Diff MDD/Min Var (%)	–26.17	62.62
Diff Ret/Negative Screening (%)	–37.23	7.81
Diff Vol/Negative Screening (%)	–8.25	–27.68
Diff SR/Negative Screening (%)	–31.58	49.07
Diff MDD/Negative Screening (%)	–26.12	26.04

	Economics	**E**	**S**	**G**	**Economics**	**E**	**S**	**G**
Score (mean)	6.88	**7.30**	7.42	7.95	6.27	**5.76**	5.52	6.00
Minimum Variance Score (mean)	5.60	**6.52**	6.92	7.93	6.07	**4.96**	3.85	5.45
Negative Screening Score (mean)	6.27	**7.30**	7.92	7.94	5.91	**5.92**	5.01	6.02
Benchmark Score (mean)	6.15	**7.00**	7.68	7.83	6.04	**5.47**	4.55	5.84
Diff Score/Min Variance Score (%)	8.23	4.32	2.58	0.09	–0.71	8.39	12.58	5.94
Diff Score/Negative Screening Score (%)	9.76	0.00	–6.34	0.11	6.01	–2.69	9.98	–0.41
Diff Score/Benchmark Score (%)	–1.55	–2.89	–7.52	1.39	–0.18	–1.71	–4.72	–1.23

	S	
	Developed Countries	**Emerging Countries**
Annualized Return(%)	9.16	10.45
Annualized Volatility (%)	10.15	6.18
Portfolio Annualized Return–Benchmark (%)	1.70	–2.15
Sharpe Ratio	0.90	1.69
Tracking Error (%)	3.50	2.09
Information Ratio	0.49	–1.03
Max Return (%)	9.96	8.12
Min Return (%)	–5.89	–3.25
Max Drawdown (%)	59.16	40.02
Diff Ret/Min Var (%)	59.73	–19.64
Diff Vol/Min Var (%)	101.02	38.35
Diff SR/Min Var (%)	–20.54	–41.92
Diff MDD/Min Var (%)	–6.89	2.61
Diff Ret/Negative Screening (%)	22.46	–12.31
Diff Vol/Negative Screening (%)	5.82	–18.94
Diff SR/Negative Screening (%)	15.73	8.18
Diff MDD/Negative Screening (%)	–20.27	–14.06

(continued)

EXHIBIT 9 *(continued)*

Results of the Minimum Variance Strategy with E, S, and G Constraints over the Sample Period (2010–2020) for Developed and Emerging Countries

	S							
	Developed Countries				Emerging Countries			
	Economics	E	S	G	Economics	E	S	G
Score (mean)	6.21	7.29	**8.08**	8.43	5.79	5.33	**5.15**	6.04
Minimum Variance Score (mean)	5.60	6.52	**6.92**	7.93	6.07	4.96	**3.85**	5.45
Negative Screening Score (mean)	6.33	7.24	**8.08**	8.16	6.03	5.71	**5.15**	6.19
Benchmark Score (mean)	6.15	7.00	**7.68**	7.83	6.04	5.47	**4.55**	5.84
Diff Score/Min Variance Score (%)	3.54	3.59	5.24	1.96	–2.26	4.61	13.15	4.73
Diff Score/Negative Screening Score (%)	–1.98	0.67	0.00	3.31	–4.10	–6.58	0.00	–2.46
Diff Score/Benchmark Score (%)	–5.81	–3.57	–5.13	3.29	–1.74	–5.13	–4.23	–2.35

	G	
	Developed Countries	Emerging Countries
Annualized Return(%)	7.25	10.02
Annualized Volatility (%)	7.50	6.47
Portfolio Annualized Return–Benchmark (%)	–0.21	–2.58
Sharpe Ratio	0.97	1.55
Tracking Error (%)	2.43	2.73
Information Ratio	–0.09	–0.94
Max Return (%)	7.99	7.75
Min Return (%)	–4.09	–4.25
Max Drawdown (%)	51.16	54.80
Diff Ret/Min Var (%)	26.38	–22.96
Diff Vol/Min Var (%)	48.49	44.81
Diff SR/Min Var (%)	–14.89	–46.80
Diff MDD/Min Var (%)	–19.47	40.52
Diff Ret/Negative Screening (%)	0.33	–16.87
Diff Vol/Negative Screening (%)	–17.09	–18.73
Diff SR/Negative Screening (%)	21.00	2.28
Diff MDD/Negative Screening (%)	–18.25	16.24

	Economics	E	S	G	Economics	E	S	G
Score (mean)	5.85	6.87	7.47	**8.22**	6.16	5.28	4.46	**6.24**
Minimum Variance Score (mean)	5.60	6.52	6.92	**7.93**	6.07	4.96	3.85	**5.45**
Negative Screening Score (mean)	6.32	7.22	8.00	**8.22**	5.99	5.78	5.09	**6.24**
Benchmark Score (mean)	6.15	7.00	7.68	**7.83**	6.04	5.47	4.55	**5.84**
Diff Score/Min Variance Score (%)	6.74	7.53	10.89	4.96	–0.80	5.41	6.97	6.76
Diff Score/Negative Screening Score (%)	–7.42	–4.81	–6.59	0.00	2.73	–8.60	–12.37	0.00
Diff Score/Benchmark Score (%)	–2.90	0.10	–0.03	6.33	–0.27	–4.41	–9.47	–0.46

EXHIBIT 10

Long–Short ESG Momentum Strategy (2010–2020) Based on Economic, E, S, and G Dimensions for Developed Countries

	Economics	E	S	G
1-Year Maturity Bonds				
Average Return (%)	–7.99	6.87	–2.08	5.35
Maximum Return (%)	13.07	29.11	13.65	22.09
Minimum Return (%)	–41.21	–17.63	–13.28	–9.96
5-Year Maturity Bonds				
Average Return (%)	1.13	14.54	–2.48	6.75
Maximum Return (%)	53.06	34.29	30.93	23.70
Minimum Return (%)	–38.47	–16.63	–27.35	–18.80
10-Year Maturity Bonds				
Average Return (%)	14.55	20.24	–4.53	8.13
Maximum Return (%)	102.92	39.02	32.26	48.77
Minimum Return (%)	–39.33	–13.86	–49.68	–28.91

EXPLORING THE BENEFITS OF ESG MOMENTUM STRATEGIES

Our ambition is to explore the benefits of using information about differences over time in ESG cores, as opposed to cross-sectional differences in ESG scores. More specifically, our ambition is to build portfolios of "improving countries," rather than of countries that are already leaders from an ESG perspective.

We define E, S, and G *momentum scores* by the year-on-year change in each dimension, and we consider the following strategy for economic, E, S, and G dimensions. Every year we sort sovereign bonds based on these momentum scores (i.e., based on improvement or deterioration in their economic, E, S, and G scores). We then form an ESG momentum portfolio that is long the 15% best-ranked countries (i.e., countries showing the greatest improvement) and short the 15% worst-ranked countries (i.e., those showing the lowest improvement). The selected bonds for both strategies are then equally weighted, and each portfolio is rebalanced on an annual basis.

In Exhibits 10 and 11, for each dimension we report the average return and maximum and minimum return for the corresponding ESG momentum strategy for developed and emerging countries, respectively. For more details, in the online appendix, we show the yearly return of the strategies for 1-year, 5-year, and 10-yeear bonds based on economic, E, S, and G dimensions from 2011 to 2020 for developed and emerging countries, respectively.

We find that for developed countries, regardless of bond maturity, the top 15% of bonds exhibiting positive changes in E and G scores outperformed the bottom 15% on average over the period 2010–2020. Moreover, the long–short ESG momentum strategy based on the E dimension offers attractive levels of performance, substantially higher than the strategy based on changes in G scores. The difference between the two strategies increases with bond maturity: 6.87% versus 5.35% for 1-year bond maturity, 14.54% versus 6.75% for 5-year bond maturity, and 20.24% versus 8.13% for 10-year bond maturity. The average return for the long–short strategy based on the E dimension increases much faster across bond maturities than that for the long–short strategy based on the G dimension. On the other hand, we find that the top 15% of bonds exhibiting the highest change in scores on the S dimension underperformed the bottom 15%. The average return remains almost the same for 1-year and 5-year

EXHIBIT 11

Long–Short ESG Momentum Strategy (2010–2020) Based on Economic, E, S, and G Dimensions for Emerging Countries

	Economics	E	S	G
1-Year Maturity Bonds				
Average Return (%)	–7.78	–4.57	4.45	12.01
Maximum Return (%)	63.08	31.61	50.82	52.43
Minimum Return (%)	–65.62	–44.67	–44.72	–14.34
5-Year Maturity Bonds				
Average Return (%)	9.66	–4.55	21.14	4.87
Maximum Return (%)	73.70	32.29	64.12	24.96
Minimum Return (%)	–62.10	–40.60	–17.03	–29.61
10-Year Maturity Bonds				
Average Return (%)	22.52	–4.46	37.30	–2.28
Maximum Return (%)	66.44	22.18	92.09	50.26
Minimum Return (%)	–57.43	–34.28	–23.52	–69.82

bond maturity (–2.08% and –2.48%, respectively) and increases up to 4.53% for 10-year bond maturity.

For emerging countries, regardless of bond maturity, the top 15% of bonds exhibiting positive changes in S scores outperformed the bottom 15%. Regarding G, the top 15% of bonds exhibiting the highest score differences outperformed the bottom 15% for one-year and five-year bond maturity only. For five-year bond maturity, the long–short strategy based on the S dimension offers a higher average return (21.14%) compared to that based on G (4.87%). Regarding E, the top 15% of bonds exhibiting positive signals underperformed the bottom 15% for all bond maturities. The average return for the long–short strategy based on the E dimension from 2011 to 2020 remains almost the same across bond maturities, on average –4.5%.

Overall, these results suggest that additional value can be added by implementing portfolio decisions informed not only by cross-sectional differences in ESG scores but also by variations in these scores over time, suggesting the presence of some form of underreaction to news related to changes in ESG scores.

CONCLUSION

The integration of ESG constraints into investment decisions a priori involves an opportunity cost with respect to the outcome that would be optimally achieved in the absence of ESG considerations. This cost can be measured in terms of a possible increase in risk and reduction in performance (particularly meaningful for the benchmark-free investor) or in terms of an increase in tracking error with respect to the benchmark (particularly meaningful for the benchmark-driven investor). The main contribution of our article is its analysis of how competing implementation choices with respect to incorporation of ESG constraints into a sovereign bond portfolio construction process may affect these measures of opportunity cost.

We begin by analyzing the impact of cross-sectional or time-series differences in E, S, and G scores on key risk and return indicators for sovereign bonds in both developed and emerging markets. We find that for developed countries, after controlling for economic scores and other fixed effects, a higher E score is associated with a lower spread, whereas the impact of other dimensions is less pronounced. From an issuer standpoint, this result suggests that better E scores can lead to reduced borrowing costs, everything else being equal. From the investor standpoint, this result suggests that a lower yield is to be expected when investing in countries with higher E performance, which tells us that a negative premium is associated with this reduction in E risk. On the other hand, for emerging countries, after controlling for economic scores and other fixed effects, we find that a higher S score is associated with a lower spread, whereas the impact of other dimensions is less pronounced. Hence, from an investor standpoint, a lower yield is to be expected when investing in countries with higher S performance, suggesting that a negative premium is associated with this reduction in S risk.

In the second step, we explore the portfolio implications of these findings, analyzing how to minimize the efficiency loss involved in introducing ESG constraints to a robust sovereign bond portfolio construction process. We confirm that negative screening leads to more diversified portfolios and a lower level of tracking error, but also lower levels of improvement in ESG scores compared to positive screening. We also find that a dedicated focus on absolute or relative risk reduction at the selection stage allows investors to reduce opportunity costs along the dimension that is most important to them. We finally provide evidence that ESG momentum strategies in sovereign bond markets can reduce some of the aforementioned opportunity costs. Overall, our results suggest that sound risk management practices are critically important in allowing investors to incorporate ESG considerations into investment decisions at an acceptable cost in terms of dollar or risk budgets.

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