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Factor based commodity investing☆

Athanasios Sakkas[a,*], Nikolaos Tessaromatis[b]

[a] Nottingham University Business School, University of Nottingham, Nottingham, United Kingdom
[b] EDHEC Business School and EDHEC Risk Institute, Nice, France

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ABSTRACT

A multi-factor commodity portfolio combining the momentum, basis, basis-momentum, hedging pressure and value commodity factor portfolios outperforms significantly, economically and statistically, widely used commodity benchmarks. We find evidence that a variance timing strategy applied to commodity factor portfolios generates timing gains for the commodity momentum factor but not the other commodity factors. Dynamic commodities strategies based on commodity factor return prediction models provide little value added.

1. Introduction

There is growing evidence that commodity investment strategies based on exposures to commodity fundamental characteristics earn significant risk premiums, in addition to the premium offered by a broadly diversified commodity index. Choosing among the proposed commodity factors those that are priced is important for both commodity pricing and commodity portfolio management. Building on existing research on the pricing of commodity factors we identify priced commodity factors, use them to create an optimal passive multifactor commodity portfolio and examine the efficiency gains achieved compared to widely used commodity benchmarks. Assuming that commodity risk premiums are time varying, we also explore the possible benefits from dynamic strategies that rotate between commodity factors based on commodity variance timing and commodity return forecasting models.

Research shows that commodity investment strategies based on exposures to commodity fundamental characteristics such as the basis, momentum, basis-momentum, value, inflation, hedging pressure, volatility, speculative pressure, skewness, dollar beta and liquidity outperform commercially available commodity indices such as the S&P GSCI or a passive equally weighted index of all commodities.[1] A number of recent studies provide evidence on pricing of the basis (Szymanowska et al., 2014), the basis and the average commodity (an equally weighted portfolio of all commodities) factor (Yang, 2013), the basis,[2] commodity momentum and the average commodity factor (Bakshi et al, 2019), and the average commodity factor and basis-momentum[3] (defined as the difference in

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* Corresponding author.
E-mail address: athanasios.sakkas@nottingham.ac.uk (A. Sakkas).

[1] Miffre (2016), provides a comprehensive review of the literature of the performance of various investment strategies in commodity futures markets. Fernandez-Perez, Fuertes and Miffre (2019), examine the performance of the combination of five long/short strategies in equity index, fixed income, currency, and commodity futures markets.

[2] Bakshi, Gao and Rossi (2019) argue that the basis factor provides to investors compensation for the low returns of the factor during periods of high global equity volatility while the momentum factor tends to do well when aggregate activity increases.

[3] The basis-momentum factor proposed by Boons and Prado (2019) cannot be explained by the classical theories of storage (Kaldor, 1939), backwardation (Keynes, 1930) or hedging pressure (Cootner, 1960, 1967) but represents compensation for commodity volatility risk.

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momentum signals of first and second nearby futures contracts) factor (Boon and Prado, 2019) in the cross section of commodity returns. In contrast, Daskalaki et al. (2014), in a comprehensive study of the pricing of commodity futures, find that neither macroeconomic nor equity nor commodity factors price commodity futures. They attribute the difference in results obtained compared with other studies to the use as test assets commodity portfolios rather than individual commodities. Identifying a small number of priced commodity factors from many possible factor candidates remains a challenge (see also Skiadopoulos, 2013).

While capturing commodity risk premia requires the construction of passive portfolios with the desired exposure to commodity factors, timing commodity returns presupposes the ability to predict commodity returns and risk and calls for the design of dynamic trading strategies that rotate between the factors. Hong and Yogo (2012) provide evidence on the predictability of individual commodity futures using the short-term interest rate and the term premium, financial variables used in the stock and bond forecasting literature.[4] In an out-of-sample study of individual commodity and a basis-based commodity portfolio predictability, Ahmed and Tsvetanov (2016) find weak evidence that conditional and unconditional forecasts of the average commodity portfolio and the basis factor, predict future commodity returns. Commodity return forecasts generate no economic gain to investors who use the predictions to build commodity timing strategies. Daskalaki et al. (2017) test the predictive ability of the dividend yield, Treasury bill yield, default spread, term spread, industrial production, money supply growth and the growth in the Baltic Dry Index for equities, bonds and commodity indices. They find that equities and bonds can be predicted by some of the predictors but no evidence of commodity index return predictability. Gao and Nardari (2018) in contrast, using a forecast combination approach to predict equity, bond and commodity returns and the dynamic conditional correlation model of Engle (2002) to predict risk, find that the addition of commodities to the traditional stock-bond-cash asset mix improves utility. The evidence on the predictability of commodity returns is as controversial as the evidence on the predictability in equity markets.

Our study focuses on four questions. First, which commodity factors are priced? Existing evidence on commodity pricing supports a four-factor model that includes the average commodity factor and the basis, momentum and the basis-momentum factors. Whether the other proposed factors are priced or are redundant in the presence of the factors from the four-factor model is an open question. The question is particularly important when considering the implications of multiple priced factors in the creation of optimal multifactor portfolios. We use the testing methodology proposed by Barillas and Shanken (2017) and applied in Fama and French (2018), and the methodology developed by Harvey and Liu (2019) to test whether four or more commodity factors are priced in commodity markets. Based on the evidence and theoretical justification provided by Yang (2013), Szymanowska et al. (2014), Bakshi et al. (2019), and Boons and Prado (2019) we (a) use as baseline a four-factor model to confirm the pricing of the average commodity portfolio, the basis, momentum and basis-momentum factors and (b) test the pricing of commodity factor portfolios exposed to value, inflation, open interest, hedging pressure, volatility and skewness.

Second, what is the optimal commodity portfolio when commodity returns are driven by multiple commodity factors? In the presence of multiple priced commodity factors the investor should hold a multi-factor portfolio (Fama, 1996; Cochrane, 1999). The task of the paper is to use the commodity priced factors to build a well-diversified commodity portfolio. To address the issue of estimation risk, we use alternative portfolio construction methodologies in the factor combination. Consistent with the current practice in benchmark creation, we create portfolios without short positions in individual commodities but we also consider long-short versions that allow for short positions especially since shorting is inexpensive and straight forward in the commodities futures market.

Third, how does the performance of a multi-factor commodity portfolio compare with the performance of existing commodity indices? To address this question, we compare the performance of the multifactor commodity portfolio to existing commodity benchmarks and in particular the S&P GSCI which represents the leading fully collateralized investable index and is the preferred benchmark for the majority of professionally managed portfolios. We also test whether second and third generation commodity indices used by practitioners as passive commodity investment strategies are spanned by the commodity priced factor portfolios identified in this study.

Fourth, are commodity factor portfolio returns predictable and if so, is it possible to create dynamic factor strategies that outperform passive commodity factor strategies? To assess the economic benefits of risk and returns predictability we create dynamic investment strategies based on risk or return prediction signals and measure the improvement in performance compared to passive investment strategies.

Our study supports the following conclusions. First, the spanning regressions of Barillas and Shanken (2017) and Fama and French (2018) and the methodology developed by Harvey and Liu (2019) confirm the pricing of the equally weighted portfolio of all commodities, and portfolios based on the basis, momentum and basis-momentum commodity factors. The evidence is consistent with a four-factor pricing model for commodities which nests the one-factor model of Szymanowska et al. (2014), the two-factor models of Yang (2013) and Boons and Prado (2019), and the three-factor model of Bakshi, Gao and Rossi (2019). Boons and Prado (2019) also test the pricing performance of a four-factor model that includes, in addition to the average and basis-momentum factors, the basis and momentum. Our paper is the first to study whether commodity factors such as value, inflation, hedging pressure, volatility, open interest and skewness are priced against the four-factor model. Spanning tests suggest that from the six additional factors we consider, only value and hedging pressure provide marginal information about commodity average returns and are therefore also priced commodity factors. In the spirit of Huberman and Kandel (1987) we interpret the evidence as suggesting that the mean-variance efficient tangency commodity portfolio is a combination of the average commodity factor and the basis, basis-momentum, momentum, value and hedging pressure long/short commodity factor portfolios.

Second, an equally weighted commodity factor portfolio combining the low basis, high momentum, high basis-momentum, high value and high hedging pressure factor portfolios, achieves over the period 1970–2018 a Sharpe ratio of 0.716 that represents a major improvement compared with the return to risk offered by the S&P GSCI (0.198) and an equally weighted portfolio of all commodities (0.377). The improvement in return-to-risk is significantly better when short positions are allowed in the construction of the commodity factor portfolios (Sharpe ratio 1.253). The multifactor commodity portfolio is superior whether we use portfolio construction methodologies that combine stand-alone commodity factor portfolios (mean-variance, minimum variance, maximum diversification or risk parity) or combine individual commodity char-

[4] Chen, Rogoff and Rossi (2010) show that "commodity currencies" predict the price of the commodity produced by the countries of these currencies. Bork, Kaltwasser and Sercu (2014) argue that the results are not robust to variations in the test design and the use of average rather than end of period prices of the commodity indexes used.

acteristics following the cross-sectional regression methodology of Lewellen (2015), to construct the multifactor portfolio. Combining individual characteristics into a composite valuation signal enables netting out of trades in individual commodities associated with the rebalancing of different characteristics. DeMiguel et al. (2019) find significant reductions in turnover and transaction costs when considering all characteristics simultaneously rather than combining standalone factors in the context of stock portfolios.

Third, the factor-based portfolio represents a dramatic improvement compared with the S&P GSCI, the benchmark used by most institutional investors, ETFs, ETNs and mutual funds. In particular, over the 1970–2018 period the S&P GSCI achieved an annual excess return of 3.90% compared with an annual excess return of 10.62% of an equally weighted long-only commodity factor portfolio. The significant outperformance has been achieved with much lower volatility (14.82% vs.19.64%) and is robust across sub-periods, the business cycle and volatility states. The evidence suggests that the S&P GSCI is unlikely to be on the mean-variance efficient frontier and that switching to the factor-based commodity benchmark increases the return to risk from investing in commodities significantly. The long-only commodity multifactor portfolio offers a better return to risk trade-off than the Dow-Jones-UBS Commodity Index, the Deutsche Bank Liquid Commodity Index (DBLCI), the DBLCI-Optimum Yield, and the Morningstar Long-only Commodity Index.

Finally, we build dynamic factor portfolio timing strategies based on predictions of factor returns and volatility. We find strong evidence suggesting that variance timing works out-of-sample for the long-short commodity momentum premium, consistent with the findings of the success of variance-based timing for equity momentum reported in Barroso and Santa-Clara (2015) but adds little value to passive investments in the long-short basis, basis-momentum, hedging pressure or value factor premiums. Variance timing is profitable for all long-only versions of the commodity factors but alphas are marginally statistically significant only for the low basis and high value factors.

We use different approaches to predict commodity factor portfolio returns and find little evidence to suggest that return forecasting adds value once variance timing has been implemented. The failure of return forecasting to add value, consistent with the results reported in Ahmed and Tsvetanov (2016), applies to both long-short and long-only versions of the commodity factor portfolios.

Our findings have important implications for commodity portfolio management. A multifactor commodity portfolio combining the high momentum, the low basis, the high basis-momentum, the value and the high hedging pressure commodity portfolios is significantly better than the widely used S&P GSCI benchmark. The commodity factor portfolio outperforms the S&P GSCI consistently across sub-periods. The difference in performance is statistically significant and unlikely to be the result of chance. The Harvey and Liu (2019) testing methodology suggests that the S&P GSCI is not a risk factor. The implication from this finding is that investors should replace the S&P GSCI with the better diversified and performing portfolio of commodity factors.

The rest of the paper is organized as follows. In Section 2 we describe the data. In Section 3 we discuss the return and risk characteristics of commodities. Section 4 presents the methodologies and results on the question of which commodity factors are priced. Section 5 presents evidence on the optimal commodity portfolio when commodity returns are driven by factors. Section 6 provides evidence on whether commercially available commodity indices are spanned by commodity factor portfolios. Section 7 examines the performance of dynamic tactical commodity allocation based on the predictability of commodity return and variance timing. Section 8 concludes.

2. Data and variables

2.1. Commodity futures data

We base our analysis on monthly data covering the period January 1970 to August 2018. Our sample starts from January 1970 in order to have a common sample period of our commodity factor with the industry-standard benchmark for commodities investing S&P GSCI. The commodity monthly futures returns are constructed from end-of-day settlement prices sourced from Commodity Research Bureau (CRB) and Bloomberg for commodities traded at the four North American Exchanges (NYMEX, NYBOT, CBOT, and CME) and the Tokyo Commodity Exchange (TOCOM), and Bloomberg for commodities on the London Metals Exchange (LME). Our dataset consists of 38 commodities covering five major sectors, namely, energy, grains & oilseeds, livestock, metals and softs**.** Table 1 tabulates the 38 commodities grouped by category, the exchange on which they are traded, the corresponding Bloomberg/CRB ticker symbol, the year of the first recorded observation, the delivery months and the Commodity Futures Trading Commission (CTFC) code. The dataset is comparable with the dataset used by Gorton et al.(2013), Hong and Yogo (2012), Szymanowska et al. (2014), and Bakshi, Gao and Rossi (2019).

Following Gorton et al. (2013) and Yang (2013) we calculate futures monthly excess (of the risk-free rate) returns on a fully collateralized futures position, for each commodity j as $R^{T_n}_{j,t+1} = \frac{F^{T_n}_{j,t+1} - F^{T_n}_{j,t}}{F^{T_n}_{j,t}}$, where $F^{T_n}_{j,t}$ is the futures price at the end of month t for the n^{th}- nearby contract of commodity j with expiration month T_n and $F^{T_n}_{j,t+1}$ is the futures price of the same contract at the end of month $t + 1$. We consider the first nearby (nearest to maturity) futures contracts ($n = 1$) and second nearby (second nearest to maturity) futures contracts ($n = 2$) and exclude future contracts with less than one month to maturity, in which case futures traders need to take a physical delivery of the underlying commodity (Hong and Yogo, 2012). Hence, the monthly futures returns are calculated based on a roll-over strategy where an investor maintains a long position in the first nearby (nearest to maturity) futures contract on commodity j until the beginning of the delivery month and rolls-over to the second nearby (second nearest to maturity) contract with the following delivery month. Note that on the rollover day we close the position in the first nearby futures contract, and at the same time we open a position in the second nearby contract which then becomes the nearest to maturity contract.

Table 2 reports the summary statistics of the 38 commodities over the period January 1970 to August 2018. Table 2 shows that investment in most individual commodities is unattractive; 26 out of 38 commodities have Sharpe ratios below 0.25, consistent with findings by Bakshi et al.(2019, Table Internet-II). The absolute first-order autocorrelation for 29 out of 38 commodities is below 0.1, indicating that most commodity future returns are serially uncorrelated. Most of the commodities have a positive skewness. Finally, 27 of 38 commodities are in contango on average. In general, the magnitudes shown in Table 2 are consistent with the evidence reported in Erb and Harvey (2006, Table 4), Gorton et al. (2013, Table I) and Bakshi et al. (2019, Table Internet-II).

2.2. Commodity factor portfolios

We construct long-only and long-short commodity factor portfolios. We focus on nine commodity sorting characteristics, i.e. (a) *Momentum* (Miffre and Rallis, 2007; Fuertes et al., 2015; Bakshi et al., 2019; Boons and Prado, 2019), (b) *Basis* (Szymanowska et al., 2014; Gorton et al., 2013; Yang, 2013;

Table 1
Commodity futures data.

Category	Commodity futures	Exchange	Ticker	Start	Delivery Months	CFTC Code
Energy	Brent Crude Oil	ICE	CO	1988:07	1: 12	ICE website
	Gasoil Petroleum	ICE	QS	1986:06	1: 12	ICE website
	Gasoline	NYMEX	HU/XB	1984:12	1: 12	111659
	Heating Oil	NYMEX	HO	1978:11	1: 12	22651
	Natural Gas	NYMEX	NG	1990:04	1: 12	23651
	Propane	NYMEX	PN	1987:08	1: 12	066651
	WTI Crude Oil	NYMEX	CL	1983:04	1: 12	67651
Grains & Oilseeds	Canola	WCE	RC	1959:09	1, 3, 5, 6, 7, 9, 11	NA
	Corn	CBOT	C-	1959:07	3, 5, 7, 9, 12	002601, 002602
	Oats	CBOT	O-	1986:08	3, 5, 6, 9, 12	004601
	Rough Rice	CBOT	RR	1959:07	1, 3, 5, 7, 9, 11	039601, 039781
	Soybean Meal	CBOT	SM	1959:07	1, 3, 5, 7, 8, 9, 10, 12	026 603
	Soybean Oil	CBOT	BO	1959:07	1, 3, 5, 7, 8, 9, 10, 12	007601
	Soybeans	CBOT	S-	1959:07	1, 3, 5, 7, 8, 9, 11	005601, 005602
	Wheat	CBOT	W	1959:07	3, 5, 7, 9, 12	001601, 001602
Livestock	Feeder Cattle	CME	FC	1971:12	1, 3, 4, 5, 8, 9, 10, 11	061641
	Lean Hogs	CME	LH	1966:03	2, 4, 6, 7, 8, 10, 12	054641, 054642
	Live Cattle	CME	LC	1964:12	2, 4, 6, 8, 10, 12	057642
	Pork Belly	CME	PB	1961:09	2, 3, 5, 7, 9	056641
Metals	Aluminum	LME	LA	1998:01	1: 12	NA
	Copper	NYMEX	HG	1959:07	3, 5, 7, 9, 12	085691, 085692
	Gold	NYMEX	GC	1975:01	2, 4, 6, 8, 10, 12	088691
	Lead	LME	LL	1998:01	1: 12	NA
	Nickel	LME	LN	1998:01	1: 12	NA
	Palladium	NYMEX	PA	1977:01	3, 6, 9, 12	075651
	Platinum	NYMEX	PL	1968:03	1, 4, 7, 10	076651
	Silver	NYMEX	SI	1963:06	1, 3, 5, 7, 9, 12	084691
	Tin	LME	LT	1998:01	1: 12	NA
	Zinc	LME	LX	1998:01	1: 12	NA
Softs	Cocoa	ICE	CC	1959:07	3, 5, 7, 9, 12	073732
	Coffee	ICE	KC	1972:08	3, 5, 7, 9, 12	083731
	Cotton	ICE	CT	1959:07	3, 5, 7, 10, 12	033661
	Ethanol	CME	DL	2005:05	1: 12	025601
	Lumber	CME	LB	1969:10	1, 3, 5, 7, 9, 11	058641, 058643
	Milk	CME	DE	1996:01	1, 2, 3, 6, 8, 9, 10	052641
	Orange Juice	ICE	JO	1967:02	1, 3, 5, 7, 9, 10,	040701
	Rubber	TOCOM	YR	1992:01	1: 12	NA
	Sugar	ICE	SB	1961:02	3, 5, 7, 10	080732

This Table lists 38 commodities and tabulates the categories they belong, the exchange on which they are traded, the Bloomberg/CRB ticker symbol, the year of the first recorded observation, the delivery months and the code in the Commitment of Traders reports issued by the Commodity Futures Trading Commission (CFTC). The commodity futures contracts are traded on the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CME), the New York Commodities Exchange (COMEX), the Intercontinental Exchange (ICE), the London Metal Exchange (LME), the New York Mercantile Exchange (NYMEX) and the Tokyo Commodity Exchange (TOCOM).

Fuertes et al., 2015; Bakshi et al., 2019; Boons and Prado, 2019), (c) *Basis-Momentum* (Boons and Prado, 2019), (d) *Skewness* (Fernandez-Perez et al., 2018), (e) *Inflation beta* (Bodie and Rosansky, 1980; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Szymanowska et al., 2014), (f) *Volatility* (Dhume, 2011; Gorton et al., 2013; Szymanowska et al., 2014), (g) *Hedging Pressure* (Cootner, 1960; Hirshleifer, 1988; De Roon et al., 2000; Basu and Miffre, 2013; Dewally et al., 2013), (h) *Open Interest* (Hong and Yogo, 2012; Szymanowska et al., 2014) and (i) *Value* (Asness et al., 2013). For a full description of the commodity factors see Section B of the Internet Appendix.[5]

To construct the commodity factor portfolios, we sort commodities based on their shorting characteristics at the beginning of month t and calculate the equally weighted return of the top and bottom 30 percent portfolios of commodities at the end of month t. We also calculate the return of the average commodity (AVG) portfolio as the equally weighted return of the 38 commodity future contracts, rebalanced monthly. Note that at the beginning of our sample (January 1970) 17 commodity futures are available. The complete set of 38 commodity futures is available from January 2006 until the end of our sample.

3. The performance of commodity portfolios

3.1. The return and risk of commodity portfolios

In Panel A of Table 3 we show the performance of the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI), a widely used benchmark in professional asset management and the average commodity portfolio (AVG). In Panels B to J we present descriptive statistics of the performance of high, medium, low and long-short commodity factor portfolios based on momentum, the basis, basis-momentum, skewness, inflation beta, volatility, hedging pressure, open interest and value, over the full sample period January 1970 – August 2018. Mean, standard deviation, skewness and kurtosis are annualised (Cumming et al., 2014). The Goldman Sachs Commodity Index (S&P GSCI) and the average commodity market factor (AVG) had average excess returns of 3.90% and 5.13% per annum, respectively. The volatility of the S&P GSCI (19.64%) is significantly higher than the volatility of the average commodity market factor (13.61%) reflecting the overweighting of energy in the S&P GSCI (the stan-

[5] We exclude from our analysis commodity factors based on the speculative pressure (Cootner, 1960, Hirshleifer, 1988, Basu and Miffre, 2013, Dewally et al., 2013), dollar beta (Erb and Harvey, 2006, Szymanowska et al., 2014) and liquidity (Marshall, Nhut, and Visaltanachoti, 2012, Szymanowska et al., 2014) because data were not available in 1970.

Table 2
Summary statistics of commodities.

Category	Commodity futures	N	Mean	SD	Skewness	Kurtosis	SR	AR(1)	Basis (mean)
Energy	Brent Crude Oil	344	11.44%	32.18%	0.128	3.282	0.355	0.232	−0.001
	Gasoil Petroleum	387	12.44%	32.38%	0.115	3.138	0.384	0.123	−0.001
	Gasoline	405	15.17%	33.56%	0.163	3.258	0.452	0.117	−0.005
	Heating Oil	478	9.12%	31.31%	0.249	3.379	0.291	0.116	0.000
	Natural Gas	341	−8.17%	47.06%	0.172	3.127	−0.174	0.100	0.020
	Propane	266	23.01%	46.57%	1.071	5.972	0.494	−0.010	−0.006
	WTI Crude Oil	425	8.28%	32.45%	0.104	3.228	0.255	0.183	0.000
Grains & Oilseeds	Canola	528	−0.64%	22.79%	0.180	3.372	−0.028	0.015	0.009
	Corn	584	−2.23%	26.19%	0.304	3.443	−0.085	0.000	0.018
	Oats	584	1.04%	33.14%	0.564	4.323	0.031	−0.043	0.015
	Rough Rice	385	−5.23%	27.65%	0.254	3.377	−0.189	0.061	0.021
	Soybean Meal	584	10.50%	33.78%	0.609	4.237	0.311	0.049	−0.001
	Soybean Oil	584	6.31%	31.37%	0.419	3.562	0.201	−0.045	0.002
	Soybeans	584	5.31%	28.03%	0.377	3.727	0.189	0.012	0.004
	Wheat	584	−2.13%	27.66%	0.191	3.205	−0.077	0.038	0.016
Livestock	Feeder Cattle	561	2.92%	16.79%	−0.119	3.197	0.174	−0.015	0.000
	Lean Hogs	584	4.02%	27.07%	0.040	3.085	0.149	−0.033	0.016
	Live Cattle	584	4.31%	17.56%	−0.041	3.123	0.245	0.027	0.000
	Pork Belly	496	1.17%	37.57%	0.158	3.130	0.031	−0.074	0.005
metals	aluminum	248	−1.16%	19.76%	0.069	3.022	−0.059	0.032	0.004
	Copper	584	5.94%	27.03%	0.106	3.252	0.220	0.119	0.000
	Gold	524	1.29%	19.02%	0.133	3.283	0.068	−0.002	0.008
	Lead	248	9.03%	29.30%	0.010	3.083	0.308	0.007	0.001
	Nickel	248	10.43%	35.41%	0.071	3.014	0.295	0.039	0.000
	Palladium	500	9.91%	34.82%	0.090	3.243	0.285	−0.002	0.005
	Platinum	584	3.50%	27.08%	0.136	3.372	0.129	−0.014	0.007
	Silver	584	3.06%	31.94%	0.170	3.434	0.096	0.050	0.012
	Tin	248	9.75%	24.14%	0.128	3.111	0.404	0.082	−0.001
	Zinc	248	3.13%	26.36%	−0.018	3.140	0.119	0.005	0.003
Softs	Cocoa	584	6.53%	31.94%	0.187	3.107	0.204	−0.051	0.003
	Coffee	553	5.18%	37.09%	0.335	3.276	0.140	−0.031	0.007
	Cotton	584	4.52%	26.27%	0.142	3.179	0.172	0.051	0.006
	Ethanol	160	36.62%	38.16%	0.334	3.279	0.960	0.120	−0.022
	Lumber	584	−2.53%	29.53%	0.097	3.107	−0.086	0.043	0.018
	Milk	272	2.02%	19.56%	−0.106	3.551	0.103	0.039	0.001
	Orange Juice	584	4.08%	31.85%	0.435	3.704	0.128	−0.078	0.006
	Rubber	320	2.35%	35.33%	0.083	3.038	0.067	0.081	0.005
	Sugar	584	5.93%	40.27%	0.374	3.382	0.147	0.177	0.010

This Table reports summary statistics of the 38 commodity futures returns in excess of the risk-free rate for the period 1970:01 to 2018:08. N denotes the number of observations, Mean is the average return, SD is the standard deviation, Skew denotes the skewness, Kurt is the kurtosis, SR is the Sharpe Ratio, AR(1) is the autocorrelation of first order. The last column presents the average basis for each commodity. Mean, SD, Skew, Kurt and SR are annualized. For the annualized skewness and kurtosis, we follow Cumming et al. (2014).

dard deviation of the S&P GSCI Light Energy, which invests less in energy is 14% per annum over the same period).

The high basis-momentum commodity portfolio exhibits the highest realized excess return (14.68%) followed by the high momentum (13.13%) and low basis (12.25%) commodity portfolios. The high open interest (4.09%), high inflation beta (6.12%), low skewness (6.29%) and high value (6.41%) commodity portfolios achieved the lowest excess returns. The inflation beta portfolio exhibits the highest volatility (20.45%), followed by the high momentum commodity portfolio (20.09%), high open interest (18.81%) and high hedging pressure (18.16%). The long-short commodity basis-momentum, momentum and basis achieved premia in excess of 10% per annum, 16.36%, 14.93%, and 13.76% respectively. The value (21.15%), momentum (20.80%) and hedging pressure (20.37%) commodity premia have the highest volatilities. Both long and short portfolios contribute to the profitability of most commodity factor premia.

Sharpe ratio comparisons show that the S&P GSCI offers a less attractive return to risk trade-off (0.198) than the average commodity portfolio (0.377). The long components of all commodity factor premia exhibit higher Sharpe ratios than the S&P GSCI. Six out of nine long commodity factor portfolios that make the long-leg of the premia exhibit higher Sharpe ratios than the average commodity portfolio (AVG); the exceptions are the high inflation beta, high hedging pressure and high open interest commodity portfolios. The basis-momentum, basis and momentum commodity premia had the highest return to risk ratios (0.930, 0.811 and 0.718 respectively) and the open interest (-0.027), value (0.136) and inflation beta (0.159) the lowest.[6,7]

3.2. Transaction costs

The excess returns reported in Table 3 assume no transactions costs. The creation and maintenance of commodity factor portfo-

[6] In the Internet Appendix, section A.1, we investigate the performance of the commodity benchmarks and the long-short commodity factors before and after the financialization of commodity futures, i.e. January 1970 to December 2004 and January 2005 to August 2018, respectively. On average, across commodity portfolios returns and risks are higher in the pre-financialization period. We also examine the performance of commodity portfolios for the period spanning from January 1990 to August 2018, a period which coincides with the advent of commercial commodity indices. Performance statistics are similar to the full sample period.

[7] The commodity factor portfolios presented in Table 3 are constructed by equally weighting individual commodities. In the Internet Appendix, section A.2, we employ alternative portfolio construction methodologies (inverse volatility, maximum diversification, minimum variance and mean-variance). Our results suggest that equally weighted commodity portfolios have similar performance to portfolios based on alternative weighting schemes. Hence from this point on we report only results based on the EW weighting scheme.

Table 3
Commodity factor portfolios.

	N	Mean	SD	Skewness	Kurtosis	SR	SR adjusted
Panel A. Commodity Benchmarks							
S&P GSCI	584	3.90%	19.64%	0.007	3.203	0.198	–
AVG	584	5.13%	13.61%	0.020	3.313	0.377	0.300
Panel B. Commodity Momentum							
Low	584	−1.79%	17.29%	0.227	3.447	−0.104	−0.165
Medium	584	4.58%	13.85%	0.075	3.286	0.331	0.255
High	584	13.13%	20.09%	0.042	3.340	0.654	0.601
Long Short (High-Low)	584	14.93%	20.80%	0.076	3.144	0.718	0.616
Panel C. Commodity Basis							
Low	584	12.25%	17.57%	0.108	3.297	0.697	0.637
Medium	584	4.94%	15.70%	−0.049	3.257	0.314	0.247
High	584	−1.52%	15.58%	0.108	3.199	−0.097	−0.165
Long Short (Low-High)	584	13.76%	16.98%	0.029	3.097	0.811	0.686
Panel D. Commodity Basis-Momentum							
Low	584	−1.69%	16.34%	0.303	3.636	−0.103	−0.168
Medium	584	3.22%	15.80%	−0.027	3.262	0.204	0.137
High	584	14.68%	16.92%	0.184	3.289	0.867	0.805
Long Short (High - Low)	584	16.36%	17.60%	0.064	3.371	0.930	0.810
Panel E. Commodity Skewness							
Low	584	6.29%	16.21%	0.064	3.150	0.388	0.323
Medium	584	5.81%	15.21%	0.020	3.246	0.382	0.312
High	584	3.46%	17.63%	0.307	3.625	0.196	0.136
Long Short (Low-High)	584	2.84%	17.56%	−0.047	3.230	0.162	0.041
Panel F. Commodity Inflation beta							
Low	584	2.90%	17.45%	0.259	3.565	0.166	0.106
Medium	584	5.49%	14.20%	0.135	3.241	0.387	0.312
High	584	6.12%	20.45%	0.046	3.318	0.299	0.248
Long Short (High - Low)	584	3.22%	20.19%	0.090	3.154	0.159	0.055
Panel G. Commodity Volatility							
Low	584	1.39%	16.63%	0.033	3.202	0.084	0.020
Medium	584	5.48%	15.86%	0.096	3.342	0.346	0.279
High	584	8.48%	17.17%	0.104	3.454	0.494	0.432
Long Short (High - Low)	584	7.09%	17.10%	0.123	3.215	0.415	0.291
Panel H. Commodity Hedging Pressure							
Low	584	1.67%	19.51%	0.807	4.957	0.085	0.031
Medium	584	3.95%	17.22%	0.214	3.524	0.230	0.168
High	584	6.62%	18.16%	0.039	3.195	0.365	0.306
Long Short (High - Low)	584	4.95%	20.37%	−0.335	3.608	0.243	0.139
Panel I. Commodity Open Interest							
Low	584	4.54%	17.74%	0.214	3.471	0.256	0.196
Medium	584	4.14%	15.98%	0.228	3.550	0.259	0.193
High	584	4.09%	18.81%	0.364	3.696	0.217	0.161
Long Short (High - Low)	584	−0.45%	16.38%	0.097	3.123	−0.027	−0.156
Panel J. Commodity Value							
Low	584	3.54%	21.06%	0.203	3.452	0.168	0.118
Medium	584	4.51%	15.52%	0.134	3.450	0.290	0.222
High	584	6.41%	16.38%	0.277	3.512	0.391	0.327
Long Short (Low-High)	584	2.87%	21.15%	−0.070	3.107	0.136	0.036

This Table presents the descriptive statistics for the period 1970:01 to 2018:08 of the commodity benchmarks i.e. S&P GSCI and the Average commodity market factor based on the individual commodities (AVG) and the commodity factor portfolios of the low, medium, high and long-short commodity momentum (Panel B), basis (Panel C), basis-momentum (Panel D), skewness (Panel E), inflation beta (Panel F), volatility (Panel G), hedging pressure (Panel H), open interest (Panel I) and value (Panel J). The low and high commodity portfolio returns are returns of equally weighted commodity portfolios of the bottom 30 percent and top 30 percent of the 38 commodities we have in our sample. The mean, standard deviation (SD), Skewness, Kurtosis, Sharpe Ratio (SR) and Adjusted Sharpe Ratio (SR Adjusted, assuming half spread of 4.4 basis points) are annualized.

lios generates turnover which depending on the cost of trading will reduce the return of commodity factor portfolios. Investing in commodity factor portfolios implemented using commodity futures generates two kinds of costs: (a) roll-over costs associated with the cost of rolling over the maturing contract to the second nearby futures contract and (b) rebalancing costs associated with the rebalancing of portfolio weights required to maintain factor exposure. The turnover associated with monthly roll-over is $12 \times 2 \times 100\%$ for long-only portfolios and $12 \times 4 \times 100\%$ for long-short portfolios. A monthly roll-over futures strategy does not generate additional rebalancing turnover since the roll-over transactions could be used to implement rebalancing trades. We assume monthly roll-over for all futures contracts[8] and estimate transaction costs by multiplying roll-over generated turnover with the cost of trading.

Marshall et al. (2012) estimate, depending on different dollar value trade size buckets, half spreads between 3.1 to 4.4 basis points.[9] If we conservatively assume that the half-spread is 4.4 basis points, the total annual roll-over transaction cost of a long-only commodity portfolio is $12 \times 2 \times 4.4 = 105.6$ basis points. For a long-short commodity portfolio, transaction costs will be double i.e. 211.2 basis points. In the last column in Table 3 we show Sharpe ratios adjusted for transaction costs. Transaction costs adjusted Sharpe ratios for most commodity factor portfolios and premia are marginally lower than Sharpe ratios that ignore transaction costs and remain economically significant. However, taking into account transaction costs weakens considerably the profitability of the skewness, inflation beta, open interest and value commodity factor premia.

4. Choosing priced commodity factors

The results in Table 3 confirm evidence in the literature suggesting that commodity factor-based portfolios offer a superior risk-return trade-off compared to the widely used in practice S&P GSCI benchmark. Six out of nine long-only factor-based portfolios outperform an equally weighted portfolio of the 38 commodities we examine in this study. The average commodity portfolio[10] has been used in many academic studies as a proxy of the "market" portfolio for commodities and as a superior alternative to the S&P GSCI. In this Section we apply the recent methodologies of Harvey and Liu (2019) and Barillas and Shanken (2017) and Fama and French (2018) to test whether the S&P GSCI, the average commodity portfolio (AVG) and the basis, momentum and basis-momentum, skewness, inflation beta, volatility, hedging pressure, open interest and value commodity factors are priced in the cross-section of commodity returns. In the presence of multiple priced commodity risk premia an investor in addition to the commodity "market" portfolio should also consider exposure to non-market risk premia. If commodity factor premia are uncorrelated, investing in a portfolio of commodity risk premia should provide considerable efficiency gains compared to the benchmark commodity market portfolio.

The methodology developed in Harvey and Liu (2019) identifies from among a number of candidate factors those that are priced, addresses data mining directly, takes into account the cross-correlation between factors and allows for general distributional assumptions and more specifically non-normality. The methodology, applied to either portfolios or individual securities as test assets, has been designed to answer the following question: given a benchmark and an alternative factor model, what is the incremental contribution of the alternative model? Barillas and Shanken (2017) and Fama and French (2018) use an alternative testing methodology to assess the benefits from adding a factor to a factor model. The methodology involves running a spanning regression of a candidate factor on a model's other factors. A non-zero intercept indicates that the factor makes a marginal contribution to the factor model and helps explain average returns. The GRS (Gibbons et al., 1989) test of competing models tests whether a new factor improves the mean-variance efficiency of a portfolio constructed from existing factors.

4.1. The Harvey and Liu (2019) method

Harvey and Liu (2019) utilize multiple hypothesis testing and a bootstrapping technique to identify the factors that can explain the cross-section of expected equity returns. The test consists of estimating two factor models: the baseline model and an augmented model that includes an additional factor relative to the baseline model. According to Harvey and Liu (2019) p. 18 "a risk factor is considered useful if, relative to the baseline model, the inclusion of the risk factor in the baseline model helps reduce the magnitude of the cross section of intercepts under the baseline model". We employ the two test statistics SI_{ew}^{m} and SI_{ew}^{med} in Harvey and Liu (2019) to evaluate the statistical significance in explaining the cross-section of commodity expected returns between the baseline and the augmented regression model. SI_{ew}^{m} and SI_{ew}^{med} measure the difference in equally weighted scaled mean and median absolute regression intercepts between the baseline model and the augmented model, respectively. More details on the two statistics can be found in Harvey and Liu (2019).

Table 4 presents (i) SI_{ew}^{m} and SI_{ew}^{med}, (ii) the bootstrapped 5th percentile on the distribution of SI_{ew}^{m} and SI_{ew}^{med} for each individual commodity risk factor with the corresponding p-values under the null hypothesis that the commodity risk factor individually has no ability to explain the cross-section of test assets returns (single hypothesis testing) and (iii) the bootstrapped 5th percentile on the distribution of the minimum SI_{ew}^{m} and SI_{ew}^{med} amongst the commodity risk factors with the corresponding p-values under the null hypothesis that the commodity risk factor individually has no ability to explain the cross-section of test assets returns (multiple hypothesis testing).

Panel A of Table 4 tabulates the results when the 38 individual commodities of Table 1 are the test assets. We start our analysis by testing whether any of the eleven commodity risk factors, namely the S&P GSCI and the average commodity factor, as well as the long-short momentum, long-short basis, long-short basis-momentum, long-short skewness, long-short inflation beta, long-short volatility, long-short hedging pressure, long-short open interest and long-short value, can explain the cross-section of expected individual commodity returns. We find that the average commodity factor is the best among the factors, since it reduces the mean (median) scaled absolute intercept by 30.7% (35.6%), the highest reduction among the remaining factors. The bootstrapped 5th percentile of SI_{ew}^{m} (SI_{ew}^{med}) for the average commodity factor is -0.216 (-0.285), a reduction in the mean (median) scaled intercept of 21.6% and 28.5% respectively. This factor reduces the mean (median) scaled intercept by more than the 5th percentile with a p-value equal to 0.010 (0.017) (see Panel A.1). For the multiple hypothesis test, the bootstrapped 5th percentile of SI_{ew}^{m} (SI_{ew}^{med}) is -0.226 (-0.296) and statistically significant with a multiple testing p-value equal to 0.010 (0.018).

Overall, the average commodity factor is the most important among the candidate factors and is statistically significant at the 5% or better level of significance. When we include the average commodity factor in the baseline model we find that the second most dominant factor is the long-short basis factor with a multiple testing p-value equal to 0.000 based on SI_{ew}^{m} and SI_{ew}^{med} (Panel

[8] Twenty out of the thirty-eight futures contracts have seven or more roll-over months per year. Assuming a one-month roll-over schedule results in maximum turnover and transaction costs estimates.

[9] Bollerslev et al. (2018) estimate the average bid-ask spread of twenty commodities to be equal to 3.5 basis points (see Table A1, p.2765).

[10] Erb and Harvey (2006) caution against using an equally weighted portfolio of commodities as a proxy for the return of the commodities market, arguing that a monthly rebalanced equally weighted index will be distorted by a rebalancing premium and is not investable in large scale. We calculate the average portfolio using quarterly and annual rebalancing and, like Bhardwaj, Gorton and Rouwenhorst (2015), we find that average returns are marginally higher to returns based on monthly rebalancing (results available upon request). Investability is more of an issue but as observed by Levine et al. (2018) there is little evidence to suggest that including less liquid commodities inflates the return of the average portfolio. When we create an equally weighted portfolio consisting of the futures contracts that make-up the S&P GSCI, we find no difference in performance compared with the 38 equally weighted commodity index (results available upon request).

Table 4
Cross-Sectional tests.

Panel A. Test Assets: Individual Commodities

Panel A.1: Baseline = No Factor

	single test			single test		
Factor	*SI_{ew}^{m} (mean)*	*5-th percentile*	*p-value*	*SI_{ew}^{med} (median)*	*5-th percentile*	*p-value*
AVG	−**0.307**	−0.216	0.010	−**0.356**	−0.285	0.017
Momentum	−0.119	−0.033	0.000	−0.001	−0.079	0.386
Basis	−0.271	−0.045	0.000	−0.218	−0.074	0.002
Basis Momentum	−0.195	−0.028	0.000	−0.293	−0.070	0.000
Skewness	−0.042	−0.066	0.209	0.008	−0.135	0.771
Inflation beta	−0.058	−0.085	0.111	0.071	−0.094	0.795
Volatility	−0.010	−0.021	0.126	0.057	−0.071	0.894
Hedging Pressure	−0.037	−0.064	0.173	−0.146	−0.161	0.068
Open Interest	0.002	−0.033	0.596	0.009	−0.070	0.701
Value	0.043	−0.063	0.903	0.014	−0.108	0.640
SPGSCI	−0.137	−0.166	0.088	−0.173	−0.187	0.069
	multiple test			**multiple test**		
		−0.226	**0.010**		−0.296	**0.018**

Panel A.2: Baseline = AVG

	single test			single test		
Factor	*SI_{ew}^{m} (mean)*	*5-th percentile*	*p-value*	*SI_{ew}^{med} (median)*	*5-th percentile*	*p-value*
AVG						
Momentum	−0.012	−0.022	0.120	0.046	−0.091	0.795
Basis	−**0.215**	−0.038	0.000	−**0.292**	−0.081	0.000
Basis Momentum	−0.172	−0.030	0.000	−0.118	−0.082	0.021
Skewness	−0.052	−0.052	0.048	0.077	−0.120	0.929
Inflation beta	−0.045	−0.097	0.214	0.004	−0.143	0.474
Volatility	−0.016	−0.025	0.106	−0.078	−0.078	0.050
Hedging Pressure	0.130	−0.041	0.992	0.258	−0.118	0.975
Open Interest	0.013	−0.031	0.763	−0.032	−0.084	0.211
Value	−0.008	−0.030	0.307	−0.057	−0.085	0.123
SPGSCI	0.180	−0.121	0.974	0.091	−0.168	0.675
	multiple test			**multiple test**		
		−0.137	**0.003**		−0.208	**0.010**

Panel A.3: Baseline = AVG + Basis

	single test			single test		
Factor	SI_{ew}^{m} (mean)	5-th percentile	p-value	SI_{ew}^{med} (median)	5-th percentile	p-value
AVG						
Momentum	0.039	−0.031	0.971	0.169	−0.109	0.985
Basis						
Basis Momentum	−0.046	−0.038	0.027	0.008	−0.105	0.601
Skewness	−0.008	−0.036	0.309	−0.083	−0.117	0.085
Inflation beta	−0.014	−0.113	0.628	−0.020	−0.195	0.516
Volatility	0.007	−0.032	0.664	0.017	−0.103	0.660
Hedging Pressure	0.186	−0.060	1.000	0.480	−0.144	1.000
Open Interest	0.015	−0.030	0.824	0.045	−0.090	0.829
Value	−0.056	−0.031	0.006	0.014	−0.085	0.644
SPGSCI	0.395	−0.122	1.000	0.531	−0.192	1.000
	multiple test			**multiple test**		
		−0.142	0.405		−0.248	0.605

	multiple test			**multiple test**		

Panel B. Test Assets: Commodity Portfolios

Panel B.1: Baseline = No Factor

	single test			single test		
Factor	SI_{ew}^{m} (mean)	5-th percentile	p-value	SI_{ew}^{med} (median)	5-th percentile	p-value
AVG	−**0.479**	−0.350	0.002	−**0.604**	−0.401	0.000
Momentum	−0.216	−0.101	0.003	−0.230	−0.117	0.006
Basis	−0.272	−0.106	0.000	−0.270	−0.119	0.000
Basis Momentum	−0.123	−0.080	0.014	−0.042	−0.093	0.151
Skewness	0.038	−0.077	0.920	0.083	−0.130	0.941
Inflation beta	−0.050	−0.083	0.139	−0.123	−0.124	0.051
Volatility	−0.054	−0.056	0.052	−0.043	−0.062	0.105
Hedging Pressure	0.022	−0.081	0.938	−0.064	−0.115	0.134
Open Interest	0.003	−0.055	0.665	−0.002	−0.119	0.553
Value	0.070	−0.108	0.857	0.056	−0.139	0.778
SPGSCI	−0.313	−0.289	0.040	−0.312	−0.351	0.082
	multiple test			**multiple test**		
		−0.362	**0.003**		−0.420	**0.000**

Panel B.2: Baseline = AVG

	single test			single test		
Factor	SI_{ew}^{m} (mean)	5-th percentile	p-value	SI_{ew}^{med} (median)	5-th percentile	p-value
AVG						
Momentum	−0.288	−0.100	0.000	−0.168	−0.126	0.028
Basis	−0.287	−0.087	0.000	−**0.279**	−0.105	0.000
Basis Momentum	−**0.360**	−0.091	0.000	−0.109	−0.092	0.030
Skewness	−0.069	−0.075	0.062	−0.047	−0.196	0.279
Inflation beta	−0.007	−0.068	0.392	−0.063	−0.177	0.225
Volatility	−0.111	−0.066	0.004	−0.070	−0.065	0.043
Hedging Pressure	−0.040	−0.048	0.072	−0.132	−0.168	0.090
Open Interest	−0.003	−0.042	0.416	−0.002	−0.160	0.519
Value	0.027	−0.033	0.990	−0.178	−0.164	0.041
SPGSCI	0.013	−0.034	0.902	−0.125	−0.102	0.034
	multiple test			**multiple test**		
		−0.126	**0.000**		−0.265	**0.041**

(continued on next page)

Table 4
(continued)

	Panel B.3: Baseline =AVG + Basis-Momentum			Panel B.3: Baseline = AVG + Basis		
	single test			**single test**		
Factor	SI^{m}_{ew} (mean)	5-th percentile	p-value	SI^{med}_{ew} (median)	5-th percentile	p-value
AVG						
Momentum	−**0.190**	−0.115	0.005	−0.167	−0.101	0.008
Basis	−0.147	−0.086	0.003			
Basis Momentum				−0.102	−0.089	0.036
Skewness	−0.011	−0.076	0.414	−0.078	−0.203	0.197
Inflation beta	0.000	−0.082	0.804	0.005	−0.218	0.672
Volatility	−0.121	−0.086	0.012	−0.112	−0.109	0.047
Hedging Pressure	−0.114	−0.080	0.016	−**0.511**	−0.150	0.000
Open Interest	−0.020	−0.071	0.273	−0.076	−0.160	0.170
Value	0.009	−0.034	0.862	−0.287	−0.073	0.000
SPGSCI	0.015	−0.044	0.884	−0.162	−0.113	0.022
	multiple test			**multiple test**		
		−0.141	**0.008**		−0.281	**0.000**

	Panel B.4: Baseline =AVG + Basis-Momentum +Momentum			Panel B.4: Baseline = AVG + Basis + Hedging Pressure		
	single test					
Factor	SI^{m}_{ew} (mean)	5-th percentile	p-value	SI^{med}_{ew} (median)	5-th percentile	p-value
AVG						
Momentum				0.067	−0.101	0.794
Basis	−0.079	−0.056	0.016			
Basis Momentum				0.235	−0.118	0.989
Skewness	−0.021	−0.085	0.353	0.017	−0.224	0.827
Inflation beta	−0.036	−0.138	0.285	0.057	−0.226	0.818
Volatility	−0.067	−0.084	0.097	0.253	−0.116	0.963
Hedging Pressure	−0.113	−0.086	0.018			
Open Interest	−0.004	−0.075	0.533	−0.025	−0.212	0.374
Value	−**0.207**	−0.077	0.000	0.305	−0.101	0.986
SPGSCI	−0.012	−0.030	0.176	0.228	−0.122	0.977
	multiple test					
		−0.154	**0.009**		−0.317	0.929

	Panel B.5: Baseline =AVG + Basis-Momentum + Mom + Value		
	single test		
Factor	SI^{m}_{ew} (mean)	5-th percentile	p-value
AVG			
Momentum			
Basis	−**0.263**	−0.097	0.000
Basis Momentum			
Skewness	−0.034	−0.093	0.258
Inflation beta	−0.009	−0.117	0.558
Volatility	−0.074	−0.084	0.079
Hedging Pressure	−0.054	−0.088	0.131
Open Interest	0.001	−0.074	0.769
Value			
SPGSCI	0.036	−0.047	0.965
	multiple test		
		−0.146	**0.000**

	Panel B.6: Baseline =AVG + Basis-Momentum + Mom + Value + Basis		
	single test		
Factor	SI^{med}_{ew} (mean)	5-th percentile	p-value
AVG			
Momentum			
Basis			
Basis Momentum			
Skewness	−0.005	−0.103	0.561
Inflation	−0.009	−0.134	0.549
Volatility	−0.061	−0.109	0.147
Hedging Pressure	−0.054	−0.084	0.126
Open Interest	−0.009	−0.089	0.456
Value			
SPGSCI	0.023	−0.048	0.896
	multiple test		
		−0.162	0.558

This Table presents (i) the two metrics SI^{m}_{ew} and SI^{med}_{ew} developed by Harvey and Liu (2019) which measure the difference in equally weighted scaled mean/median absolute regression intercepts between the baseline model and the augmented model, (ii) the bootstrapped 5th percentile on the distribution of SI^{m}_{ew} and SI^{med}_{ew} for each individual commodity risk factor with the corresponding p-values under the null hypothesis that the commodity risk factor individually has no ability to explain the cross-section of test assets returns (single hypothesis testing) and (iii) the bootstrapped 5th percentile on the distribution of the minimum and amongst the commodity risk factors with the corresponding p-values under the null hypothesis that the commodity risk factor individually has no ability to explain the cross-section of test assets returns (multiple hypothesis testing). The candidate factors are the average commodity factor based on individual commodities (AVG), S&P GSCI, long-short momentum, long-short basis, long-short basis-momentum, long-short skewness, long-short inflation beta, long-short volatility, long-short hedging pressure, long-short open interest and long-short value. As for tests assets we consider the 38 individual commodities (Panel A) and the 27 commodity portfolio factors, i.e. low, medium and high portfolios (Panel B). The period spans from January 1970 to August 2018.

A.2). When we include the long-short basis factor into the baseline model (see Panel A.3) we find that none of the remaining candidate commodity factors is significant under the multiple hypothesis testing on SI^{m}_{ew} (p-value=0.405) and SI^{med}_{ew} (p-value=0.605).

Panel B of Table 4 tabulates the results when commodity portfolios are considered as test assets. In particular, we use the 27 low, medium and high commodity factor portfolios. The average commodity factor is the best among the factors, reducing the mean (median) scaled absolute intercept by 47.9% (60.4%), the highest reduction among the remaining factors. The bootstrapped 5th percentile of SI^{m}_{ew} (SI^{med}_{ew}) for the average commodity factor shows that the reduction in the mean (median) scaled intercept is 35.0% (40.1%), at the 5th percentile. This factor reduces the mean (median) scaled intercept by more than the 5th percentile with p-values equal to 0.002 (0.000) (see Panel B.1). With respect to the multiple hypothesis test, the bootstrapped 5th percentile of SI^{m}_{ew} (SI^{med}_{ew}) is -0.362 (-0.420) and statistically significant with a multiple testing p-value equal to 0.003 (0.000). Overall, the average commodity factor is the most important among the candidate factors and is statistically significant at 1% level with respect to the single and multiple hypothesis tests.

We repeat our analysis by including the average commodity factor into the baseline model and we find that the second most dominant factor is the long-short basis-momentum commodity factor with a multiple testing p-value equal to 0.000 based on SI^{m}_{ew} (Panel B.2). When we include the long-short basis-momentum factor into the baseline model we find that the third most dominant factor is the long-short momentum factor with a multiple testing p-value equal to 0.008 based on SI^{m}_{ew} (Panel B.3). When we include the long-short momentum factor into the baseline model we find that the fourth most important factor is the long-short value with a multiple testing p-value equal to 0.009 based on SI^{m}_{ew} (Panel B.4). Thereafter, we include the long-short value factor into the baseline model and find that the fifth most important factor is the long-short basis with a multiple testing p-value equal to 0.000 based on SI^{m}_{ew} (Panel B.5).

Finally, we include the long-short basis into the baseline model and find that none of the remaining candidate factors is not significant under the multiple hypothesis testing on SI^{m}_{ew} (p-value=0.558, see Panel B.6). When employing the test-statistic SI^{med}_{ew}, only the average commodity factor followed by the long-short basis and long-short hedging pressure are able to explain the cross-section of commodities.

Our results are sensitive to the use of individual commodities or commodity portfolios as test assets. There is no consensus in the academic asset pricing literature on equities whether individual stocks or equity portfolios should be used as test assets. A number of academic studies argue that individual stocks are very noisy to be considered as test assets (Jensen et al., 1972; Fama and MacBeth, 1973). Other studies argue that portfolios might create bias and inefficiency when used as test assets (Avramov and Chordia, 2006; Lewellen et al., 2010; Ang et al., 2019). Harvey and Liu (2019) argue that the use of individual stocks as test assets minimise the data snooping bias that arises from portfolio-based asset pricing tests (Lo and MacKinlay, 1990).

In summary, using individual commodities as testing assets we find that the average commodity portfolio is the most dominant commodity risk factor. The two-factor model comprised of the average commodity factor and the long-short basis can explain the cross section of individual commodities. Using commodity portfolios as test assets we find that a six-factor model comprised of the average commodity factor, the long-short momentum, the long-short basis, the long-short basis momentum, long-short hedging pressure and long-short value can explain the cross section of commodity portfolios. The average commodity factor is considered the best among the candidate commodity risk factors in explaining the cross-section of individual commodity returns and commodity portfolios, while on the other hand the commodity benchmark S&P GSCI is found to be an insignificant factor.

4.2. Spanning tests

Barillas and Shanken (2017) and Fama and French (2018) use spanning regressions to find which equity risk factors are significant in explaining the time variation of expected equity returns. A risk factor is considered useful if, when regressed on the other factors, produces intercepts which are non-zero. The GRS statistic of Gibbons et al. (1989) is used to test whether a factor or factors enhance a model's ability to explain expected returns. Table 5 presents results from a time-series regression over the period January 1970 – August 2018 in which the dependent variable is the return of the candidate commodity risk factor and the independent variables are the returns of the competing model commodity risk factors.

To run the spanning regressions, we need a baseline model. In this respect we include in the baseline model those factors for which there is a theoretical motivation and have been found to be priced in the literature on commodity asset pricing. Hence, we restrict the choice of factors, to the factors proposed by Yang (2013, average commodity and basis factors), Szymanowska et al. (2014, basis factor), Bakshi et al.(2019, average commodity, the basis and momentum factors) and Boons and Prado (2019, average commodity and the basis-momentum factors) to describe the baseline model. The commodity basis represents a reward for global equity volatility (Bakshi et al., 2019), commodity momentum represents a reward to innovations in aggregate speculative activity (Bakshi et al., 2019) and the commodity basis-momentum premium represents a reward to commodity market volatility risk (Boons and Prado, 2019).

Panel A of Table 5 shows that the intercept in the spanning regression for the long-short momentum is 0.50% per month (t-stat = 1.979), for the long-short basis is 0.50% (t-stat = 2.383), for the long-short basis-momentum is 0.80% (t-stat = 4.612), for the long-short hedging pressure is 0.60% (t-stat = 2.268) and for the long-short value is 0.90% (t-stat = 4.432). On the contrary, the intercepts for the long-short skewness, inflation beta, volatility and open interest commodity factor portfolios are insignificant even at the 10% significance level.

Overall, we find that (a) the returns of the average commodity, long-short basis and long-short basis-momentum factors do not span the return of the long-short momentum factor, (b) the returns of the average commodity , long-short momentum and long-short basis-momentum factors do not span the return of the long-short basis factor, (c) the returns of the average commodity, long-short momentum and long-short basis factors do not span the long-short basis-momentum factors, (d) the returns of the average commodity, long-short momentum, long-short basis and long-short basis-momentum factors do not span the long-short hedging pressure factor and (e) the returns of the average commodity, long-short momentum, long-short basis and long-short basis-momentum factors do not span the long-short value factor.

In Panel B of Table 5, we repeat the spanning regression tests by considering the commodity factors that have been found to provide significant intercepts in the baseline model of Panel A. We examine whether these factors provide significant alpha (intercept) relative to an augmented model that comprises the average commodity factor and the long-short momentum, basis, basis-momentum, hedging pressure and value commodity factors. Panel B of Table 5 shows that the intercept in the spanning regression for the long-short momentum is now 0.70% per month (t-stat = 3.479), for the long-short basis is 0.70% (t-stat = 3.321), for the long-short basis-momentum is 0.60% (t-stat = 3.439), for the

Table 5
Time series tests.

Panel A. Baseline Model: AVG, Momentum, Basis, Basis-Momentum							
	Int.	AVG	Momentum	Basis	Basis-Momentum	R^2_{adj}	*se*
Momentum	0.005	0.141		0.317	0.253	16.51%	0.055
	(1.979)	(1.368)		(4.116)	(2.627)		
Basis	0.005	0.095	0.204		0.270	19.36%	0.044
	(2.383)	(1.403)	(3.941)		(4.375)		
Basis-Momentum	0.008	−0.019		0.181	0.300	16.69%	0.046
	(4.612)	(−0.242)		(2.643)	(3.896)		
Skewness	0.001	−0.157	−0.052	0.157	0.096	4.10%	0.050
	(0.293)	(−1.465)	(−0.789)	(2.084)	(1.261)		
Inflation beta	−0.002	0.206	0.189	0.064	0.042	7.79%	0.056
	(−0.728)	(2.059)	(2.327)	(0.869)	(0.496)		
Volatility	0.003	0.005	0.211	0.011	−0.002	6.13%	0.048
	(1.469)	(0.061)	(3.313)	(0.209)	(−0.022)		
Hedging Pressure	0.006	−0.043	0.117	−0.097	−0.170	2.76%	0.058
	(2.268)	(−0.287)	(1.567)	(−1.457)	(−1.570)		
Open Interest	0.000	0.088	−0.056	0.008	0.013	0.16%	0.047
	(−0.174)	(1.517)	(−1.234)	(0.155)	(0.221)		
Value	0.009	−0.217	−0.465	−0.286	0.218	32.34%	0.050
	(4.432)	(−2.787)	(−7.026)	(−4.145)	(2.996)		

Panel B. Augmented Model: AVG, Momentum, Basis, Basis-Momentum, Hedging Pressure, Value									
	Int.	AVG	Momentum	Basis	Basis-Momentum	Hedging Pressure	Value	R^2_{adj}	*se*
Momentum	0.007	0.018		0.130	0.315	0.118	−0.446	34.77%	0.048
	(3.479)	(0.222)		(1.912)	(3.999)	(2.270)	(−7.498)		
Basis	0.007	0.043	0.101		0.292	−0.036	−0.203	24.05%	0.043
	(3.321)	(0.671)	(1.874)		(4.968)	(−0.949)	(−4.360)		
Basis−Momentum	0.006	0.018	0.271	0.324		−0.118	0.188	21.51%	0.045
	(3.439)	(0.213)	(4.492)	(4.478)		(−1.672)	(3.455)		
Hedging Pressure	0.005	−0.019	0.168	−0.066	−0.194		0.109	3.46%	0.058
	(1.950)	(−0.133)	(2.170)	(−0.967)	(−1.626)		(1.063)		
Value	0.009	−0.213	−0.475	−0.278	0.232	0.082		32.83%	0.050
	(4.433)	(−2.811)	(−6.805)	(−3.930)	(3.413)	(1.169)			

Panel C. Multi-factor Tests			
RHS returns (Baseline model)	LHS returns	GRS	p-value
AVG	Basis, Momentum	22.666	0.000
AVG	Basis, Momentum, Basis-Momentum	18.286	0.000
AVG	Basis, Momentum, Basis-Momentum, Hedging Pressure, Value	11.072	0.000
Basis (Szymanowska et al., 2014)	Average, Momentum	6.229	0.002
Basis (Szymanowska et al., 2014)	Average, Momentum, Basis-Momentum	9.663	0.000
Basis (Szymanowska et al., 2014)	Average, Momentum, Basis-Momentum, Hedging Pressure, Value	5.910	0.000
AVG and Basis (Yang, 2013)	Momentum, Basis-Momentum	12.631	0.000
AVG and Basis (Yang, 2013)	Momentum, Basis-Momentum, Hedging Pressure, Value	6.458	0.000
AVG and Basis-Momentum (Boons and Prado, 2019)	Basis, Momentum	7.052	0.001
AVG and Basis-Momentum (Boons and Prado, 2019)	Basis, Momentum, Hedging Pressure, Value	3.675	0.006
AVG, Basis and Momentum (Bakshi, Gao and Rossi, 2019)	Basis-Momentum, Hedging Pressure, Value	5.421	0.001

This Table presents the spanning regressions for the baseline model (Panel A), the augmented model (Panel B) and the GRS statistic of Gibbons, Ross, and Shanken (1989) (Panel C) over the sample period from January 1970 to August 2018. In Panel C the first column is the baseline model, the second column is the sets of additional factors. We consider five baseline models; (a) a model that includes only the average commodity market factor (AVG), (b) the one factor model which includes the basis commodity factor (Szymanowska et al., 2014), (c) the two-factor model, which includes the average commodity (AVG) and the basis factors proposed (Yang, 2013), (d) the two-factor model, which includes the average commodity (AVG) and the basis-momentum factors (Boons and Prado, 2019) and (e) the three-factor model, which includes the average commodity (AVG), the basis and the momentum factors (Bakshi, Gao and Rossi, 2017). Momentum, Basis, Basis-Momentum, Skewness, Inflation beta, Volatility, Hedging Pressure, Open Interest and Value are long-short commodity factors. *Int*. denotes the intercept of the time series regression, R^2_{adj} denotes the adjusted R^2 of the regression, and *se* denotes the standard error of the time series regressions. Newey-West (1987) t-statistics are in parenthesis.

long-short hedging pressure is 0.50% (t-stat = 1.950) and for the long-short value is 0.90% (t-stat = 4.433).

Panel C of Table 5 tabulates the GRS statistic (Gibbons et al., 1989) which tests whether multiple factors jointly provide additional explanation to a baseline model. We choose between the following models:

(a) The three (AVG, basis and momentum), four (AVG, basis, momentum and basis-momentum) and six (AVG, basis, momentum, basis-momentum, hedging pressure and value) factor models against the single market factor (the AVG) model,
(b) The three (AVG, basis and momentum), four (AVG, basis, momentum and basis-momentum) and six (AVG, basis, momentum, basis-momentum, hedging pressure and value) factor models against the single basis factor model of Szymanowska et al. (2014),
(c) The four (AVG, basis, momentum, basis-momentum) and six (AVG, basis, momentum, basis-momentum, hedging pressure and value) factor models against the two (AVG and basis) factor model of Yang (2013),
(d) The four (AVG, basis, momentum and basis-momentum) and six (AVG, basis, momentum, basis-momentum, hedging pressure and value) factor models against the two (AVG and basis-momentum) factor models of Boons and Prado (2019) and

(e) The four (AVG, basis, momentum and basis-momentum) and six (AVG, basis, momentum, basis-momentum, hedging pressure and value) factor models against the three (AVG, basis and momentum) factor model of Bakshi et al.(2019).

The GRS test on the intercepts from the spanning regressions of long-short basis and long-short momentum on the average commodity factor rejects the null hypothesis that the intercepts are jointly zero with a p-value equal to zero (p-value=0.000). We find similar results when we jointly test the intercepts from the spanning regressions of long-short basis, long-short momentum and long-short basis-momentum on the average commodity factor and from the spanning regressions that include also the long-short hedging pressure and long-short value. GRS tests of a three, four and six factor models against the basis model of Szymanowska et al. (2014) suggest that the addition of the average commodity, momentum, basis-momentum, hedging pressure and value factors adds to the explanation of the baseline model. Based on the estimated GRS statistics the two factor models of Yang (2013) and Boons and Prado (2019) are inferior to models that add the momentum and basis-momentum and the basis and momentum factors respectively. These two factor models remain inferior to models that also include hedging pressure and value factors. Finally, the GRS tests of four and six factor models against the three-factor model of Bakshi et al.(2019) suggest that the addition of the basis-momentum, hedging pressure and value factors adds to the explanation of the base model.

In short, we find evidence that a six-factor model, comprised of the average commodity factor and the long-short momentum, basis, basis-momentum, hedging pressure and value commodity factors, contains all economically relevant pricing information.

5. Multifactor commodity portfolios: the benefits from diversification

Evidence of the cross-sectional and time series tests in Section 4 suggests that the five non-market commodity premia (i.e. momentum, basis, basis-momentum, hedging pressure and value) represent independent and non-redundant sources of return available to commodity investors. The correlation matrix of the commodity factors in Table IA4 in the Internet Appendix shows correlations between the commodity factor premia close to zero suggesting potential diversification benefits from creating a multifactor commodity portfolio. To create the combined factor commodity portfolio, we use mean-variance optimization with expected return and variance-covariance based on historical data. To assess the robustness of the mean-variance based portfolios to estimation error we also use equal (EW), inverse variance (IV), minimum variance (MinVar) and maximum diversification portfolio (MDP) weights. These portfolio construction methodologies combine stand-alone factor portfolios (top-down approach) and are widely used in equity multifactor portfolio construction. Top-down approaches involve a two-step portfolio construction process; first, individual factor portfolios are constructed and second the stand-alone factors are combined to create a multifactor portfolio.

An alternative portfolio construction methodology, used by Lewellen (2015) to create a multifactor equity portfolio, combines different commodity characteristics to estimate a commodity's expected return, based on Fama-MacBeth (FM) cross-sectional (CS[11]) regressions and provides an alternative way to combine many characteristics into a composite trading strategy (bottom-up approach). A major advantage of Lewellen's (2015) methodology is that it takes into account all commodity characteristics simultaneously enabling netting out of trades in individual commodities and results in a substantial reduction in the turnover generated when rebalancing compared to combining standalone commodity factor portfolios. DeMiguel et al. (2019) discuss the trading-diversification benefits obtained by combining characteristics in the context of stock portfolios. The slopes of FM regression are estimates of commodity factor returns and are therefore an alternative to the time series approach (Fama, 1976; Fama and French, 2019) to create a multi-factor commodity portfolio. A detailed description of the portfolio construction (top-down and bottom up) methodologies can be found in the Internet Appendix, Section D.

Table 6, Panel A, presents the performance of the average commodity factor. Panels B and C show the performance of multifactor commodity portfolios based on long-only (Panel B) and long-short commodity factor portfolios based on the momentum, basis, basis-momentum, hedging pressure and value factors (Panel C). The multifactor commodity portfolios are created using the six alternative portfolio construction rules. Average return (Mean), standard deviation (SD), Sharpe Ratio (SR), alpha, standard error (se), Appraisal ratio and Certainty Equivalent Return (CER) are annualised. Alpha and standard error (se) estimates are based on the time-series regression of the combined commodity portfolio R_t^{comb} on the average commodity factor (AVG), i.e. $R_t^{comb} = \alpha + \beta AVG_t + \varepsilon_t$.

Panel B of Table 6 shows that over the January 1970 - August 2018 period, a mean-variance based long-only factor portfolio achieved an annual excess return of 11.75% with a standard deviation of 17.20%. Over the same period the average commodity portfolio had an annual excess return of 5.13% with 13.61% standard deviation. The Sharpe ratio of a mean-variance based commodity factor portfolio is almost double the return to risk offered by the average commodity portfolio (0.683 versus 0.377). The difference in Sharpe ratios is statistically significant at the 1% level of significance. The mean-variance-based commodity factor portfolio has an annual alpha of 6.24% that is statistically different from zero and an appraisal ratio of 0.686.

Alternative portfolio construction rules produce commodity factor portfolios with very similar or even higher performance. The Sharpe ratios range between 0.604 (minimum variance) and 0.716 (equally weighted) and are statistically significantly different from the Sharpe ratio of the average commodity portfolio. Alphas using the average commodity portfolio as the benchmark range between 3.84% (MDP) and 5.34% (EW) per year and are statistically significant. Appraisal ratios using the average commodity portfolio as the benchmark range between 0.572 (CS) and 1.083 (EW). Finally, the *CER* for a moderate risk average investor who invests in the EW, IV, MinVar, MDP and CS is equal to 5.23%, 5.08%, 3.68%, 3.71% and 3.06% per annum, respectively, whilst the CER for the same investor who invests in average commodity factor portfolio is equal to 0.43% per annum; the difference of the CERs between the combined portfolios and the average commodity portfolio is statistically significant (except for the MV and CS based portfolios).

Panel C of Table 6 shows that the mean-variance combined portfolio of the non-market long-short commodity portfolios of momentum, basis, basis-momentum, hedging pressure and value, over the January 1970 - August 2018 period exhibit a Sharpe ratio equal to 0.797 much higher than the corresponding of the average commodity portfolio (0.377); the difference in Sharpe ratios is statistically significant at the 5% level of significance. The mean-variance-based commodity factor portfolio has an annual alpha of 10.67% that is statistically different from zero and an appraisal ratio of 0.751. Our empirical evidence is robust to alternative weighting schemes. For instance, the Sharpe ratios range between 0.709 for the CS portfolio and 1.253 for the EW portfolio. The *CERs* range between 7.22% for the MDP and 9.25% for the IV

[11] We thank the referee for suggesting Lewellen's (2015) methodology to create the multifactor commodity portfolio. We provide details of the cross-sectional (CS) methodology of Lewellen (2015) as applied to commodities in the Internet Appendix.

Table 6
Commodity portfolios under different weighting schemes.

	N	Mean	SD	Skew	Kurt	SR	alpha	se	Appraisal Ratio	*CER*	p-value (ΔCER)
					Panel A. Average commodity factor						
AVG	584	5.13%	13.61%	0.020	3.313	0.377	–	–	–	0.43%	–
					Panel B. Combined Long-only factor portfolios						
EW	584	10.62%	14.82%	0.047	3.268	0.716***	5.34%***	0.049	1.083	5.23%	0.000
IV	584	10.24%	14.57%	0.073	3.271	0.703***	5.08%***	0.050	1.009	5.08%	0.000
MinVar	584	8.77%	14.53%	0.161	3.339	0.604***	3.95%***	0.069	0.572	3.68%	0.002
MDP	584	8.94%	14.62%	0.075	3.299	0.612***	3.84%***	0.056	0.691	3.71%	0.009
MV	584	11.75%	17.20%	0.019	3.385	0.683***	6.24%***	0.091	0.686	4.14%	0.942
CS	584	11.59%	18.40%	0.089	3.388	0.630***	5.86%***	0.104	0.564	3.06%	0.586
					Panel C. Combined Long-short factor portfolios						
EW	584	10.58%	8.44%	0.057	3.205	1.253***	9.70%***	0.089	1.087	9.18%	0.001
IV	584	10.76%	8.75%	0.067	3.198	1.230***	10.68%***	0.088	1.220	9.25%	0.001
MinVar	584	8.69%	8.23%	-0.018	3.308	1.056***	8.98%***	0.082	1.096	7.23%	0.007
MDP	584	8.69%	8.22%	-0.019	3.295	1.057***	9.01%***	0.082	1.102	7.22%	0.007
MV	584	11.44%	14.35%	0.117	3.318	0.797**	10.67%***	0.142	0.751	6.56%	0.078
CS	584	12.96%	18.29%	0.087	3.158	0.709**	11.77%***	0.180	0.653	4.92%	0.644

This Table tabulates the results for the equally weighted portfolio of the individual commodities (average commodity factor (i.e. AVG) (Panel A), the combined long-only commodity factor portfolios (Panel B) and the combined long-short commodity factor portfolios (Panel C). We consider different portfolio construction techniques, i.e. equal (EW), inverse variance (IV), minimum variance (MinVar), maximum diversification portfolio (MDP), Mean-Variance (MV,$\gamma = 5$) weighting schemes and the cross-sectional strategy (CS) following Lewellen (2015). Average return (Mean), standard deviation (SD), Skewness (Skew), Kurtosis (Kurt), Sharpe Ratio (SR), alpha (against the average commodity factor (AVG)), standard error (se), Appraisal Ratio ($\frac{alpha}{se}$)and Certainty Equivalent Return (CER, assuming power utility and $\gamma = 5$) is annualized. Alpha and se estimates are based on the time-series regression of the combined commodity portfolio R_t^{comb} on the average commodity factor (AVG), i.e. $R_t^{comb} = \alpha + \beta AVG_t + \varepsilon_t$. The last column denotes the p-value of the difference in the CERs of the commodity portfolio and the AVG commodity factor using the Diebold and Mariano (1995) test). The covariance matrix of average realized utility is estimated using Newey and West (1987) HAC standard errors. We test the hypothesis that the Sharpe ratios of the combined portfolio and the average commodity factor are equal using the methodology of Ledoit and Wolf (2008) with 5000 bootstrap resamples and a block size equal to $b = 5$. The forecast evaluation period spans January 1970 to August 2018. We generate forecasts using a rolling window approach of 60 months. We use Newey-West (1987) standard errors for the statistical significance of alpha.

* denotes significance at 10% level
** denotes significance at 5% level
*** denotes significance at 1% level

per annum, compared to the annualised *CER* of the average commodity factor (0.43%); the differences of the Sharpe ratio and CER between the combined long-short portfolios and the average commodity portfolio are statistically significant at 1% significance level.

Overall, our empirical evidence suggests that the combination of the basis, momentum, basis-momentum, hedging pressure and value factor portfolios is clearly better than the equally weighted portfolio of individual commodities (average commodity factor).[12]

6. Are commercial commodity indices spanned by commodity factor portfolios?

Miffre (2012) classifies commodity indices into three categories. First generation commodity indices are long-only commodity indices which capture broad commodity market movements but ignore the shape of term structure of commodity futures prices. Second generation commodity indices are constructed to avoid the harmful effects of contango and benefit from backwardation. The development of third generation commodity indices are based on commodity characteristics such as the basis or momentum while allowing for long and short positions.

In this Section we test whether commercially available first, second and third generation commodity indices are redundant in the presence of priced commodity factors discussed in Section 4. Following Daskalaki et al.(2017) we consider the S&P Goldman Sachs Commodity Index (S&P GSCI), the Dow Jones-UBS Commodity Index (DJ UBSCI) and the Deutsche Bank Liquid Commodity Index (DBLCI) as first generation indices.[13] For second generation indices we consider the Deutsche Bank Liquid Commodity Index-Optimum Yield (DBLCI-OY), the Morningstar Long-Only Commodity Index (MSDIL) and the Morningstar Long/Flat Commodity Index (MSDILF). Finally, third generation indices are represented by the Morningstar Short/Flat Commodity Index (MSDISF), the Morningstar Short-Only Commodity Index (MSDIS) and the Morningstar Long/Short Commodity Index (MSDILS). Commodities investment strategies based on the MSDILS and MSDISF are essentially similar to traditional trend strategies. Using the MSDILS the investor uses a momentum rule based on the 12-month moving average of a commodity's linked price to determine if a commodity will be held long or short. Using the MSDISF the investor takes only short positions and cash. A detailed description of the first, second and third generation indices can be found in Daskalaki et al.(2017) and the Internet Appendix. We source monthly data of these indices from Bloomberg.

12 Daskalaki, Skiadopoulos and Topaloglou (2017), using an SDE approach, find clear evidence of diversification benefits from the inclusion of second and third generation indices to traditional equity-bond portfolios. In contrast, Fethke and Prokopczuk (2018), using mean-variance spanning and out-of-sample portfolio analysis, find less clear-cut diversification benefits. A comprehensive study of the benefits of including the combined commodity portfolio in the traditional bond-equity asset mix is beyond the scope of this paper. In the Internet Appendix we test whether the combined commodity portfolio enhances the traditional equity-bond efficient frontier. The evidence suggests that the adding the combined commodity portfolio to the traditional equity and bond portfolios does improve the investment efficient frontier.

13 Note that the S&P GSCI is the industry-standard benchmark for commodities investing. The index has been "designed to reflect the relative significance of each of the constituent commodities to the world economy, while preserving the tradability of the index by limiting eligible contracts to those with adequate liquidity". While a capitalization weighted portfolio of all equities is consistent with the equilibrium world of the CAPM, the production weights used for the S&P GSCI cannot be justified similarly. That leaves open the question of what is an appropriate proxy for the commodities "market" portfolio.

Table 7
Spanning regressions of 1st, 2nd and 3rd generation commodity indices.

Panel A. 1st generation commodity indices

	Int.	AVG	Momentum	Basis	Basis-Momentum	Hedging Pressure	Value	R^2_{adj}	*se*
SPGSCI	−0.002	1.117	0.012	0.120	−0.036	−0.047	−0.042	65.23%	0.033
	(−1.522)	(21.602)	(0.183)	(2.695)	(−0.788)	(−1.042)	(−0.740)		
DJUBS	−0.003	1.107	0.020	−0.011	−0.026	−0.050	−0.076	86.75%	0.015
	(−3.005)	(36.087)	(0.764)	(−0.357)	(−0.745)	(−2.462)	(−3.046)		
DBLCI	0.001	0.594	0.170	0.024	0.057	−0.087	0.039	45.83%	0.026
	(0.737)	(10.275)	(4.996)	(0.524)	(1.182)	(−2.558)	(0.871)		

Panel B. 2nd generation commodity indices

	Int.	AVG	Momentum	Basis	Basis-Momentum	Hedging Pressure	Value	R^2_{adj}	*se*
DBLCI-OY	0.001	1.175	0.068	0.007	−0.018	−0.114	−0.046	71.71%	0.026
	(0.649)	(19.218)	(1.111)	(0.134)	(−0.358)	(−2.846)	(−0.878)		
MSDIL	0.000	1.109	0.018	−0.003	−0.016	−0.048	−0.062	83.12%	0.018
	(−0.315)	(35.527)	(0.688)	(−0.113)	(−0.504)	(−2.416)	(−2.264)		
MSDILF	0.001	0.483	0.166	−0.007	−0.025	−0.001	−0.050	63.26%	0.016
	(1.220)	(10.500)	(9.642)	(−0.354)	(−1.055)	(−0.046)	(−1.997)		

Panel C. 3rd generation commodity indices

	Int.	AVG	Momentum	Basis	Basis-Momentum	Hedging Pressure	Value	AVG^2	R^2_{adj}	*se*
MSDIS	0.000	−1.097	0.050	0.000	0.037	0.057	0.027	–	81.49%	0.018
	(-0.101)	(−37.593)	(1.908)	(−0.005)	(1.147)	(3.113)	(1.114)	–		
MSDILS	0.000	0.144	0.244	−0.001	−0.054	0.003	−0.082	2.223	36.52%	0.023
	(0.266)	(2.439)	(9.062)	(−0.019)	(−1.795)	(0.094)	(−2.693)	(3.011)		
MSDISF	0.001	−0.368	0.075	0.003	−0.023	0.002	−0.030	1.115	54.18%	0.013
	(1.176)	(−10.952)	(4.232)	(0.172)	(−1.327)	(0.129)	(−1.597)	(3.891)		

Panels A, B and C of Table 7 present the spanning regressions of the first, second and third generation commodity indices, respectively. The baseline model includes the average commodity factor (AVG) and the long short commodity factors, i.e. Momentum, Basis, Basis-Momentum, Hedging Pressure and Value. The sample period spans from January 1970 to August 2018. *Int*. denotes the intercept of the time series regression,R^2_{adj} denotes the adjusted $R^2$of the regression, and *se* denotes the standard error of the time series regressions. Newey-West (1987) t-statistics are in parenthesis. For first generation commodity indices we consider the S&P Goldman Sachs Commodity Index (SPGSCI), Dow-Jones-UBS Commodity Index (DJUBS) and the Deutsche Bank Liquid Commodity Index (DBLCI). For second generation commodity indices we consider DBLCI-Optimum Yield (DBLCI-OY), Morningstar Long-Only Commodity Index (MSDIL) and the Morningstar Long/Flat Commodity Index (MSDILF). For the third generation commodity indices we consider the Morningstar Short-Only Commodity Index (MSDIS), Morningstar Long/Short Commodity Index (MSDILS) and Morningstar Short/Flat Commodity Index (MSDISF). Note that MSDIL, MSDILF, MSDIS, MSDILS and MSDISF start from January 1980, DJUBS from February 1991, DBLCI from February 1990 and DBLCI-OY from February 1989. The end date is August 2018.

Table IA4 in the Internet Appendix tabulates the correlation matrix of the three generation indices and the commodity factor portfolios. We document high and positive correlation between first and second generation indices and the long-only factor portfolios, whilst the correlation between the third generation indices and the long-short commodity portfolios are close to zero in most cases (see also the discussion in Section A.3 of the Internet Appendix).

Are commercial commodity indices redundant if the investor had access to the commodity factor portfolios? To answer this question we run spanning regressions for the first, second and third generation commercial commodity indices and present the estimation results in Table 7. The baseline model includes the average commodity factor (AVG) and the long-short commodity momentum, basis, basis-momentum, hedging pressure and value factors. Panel A of Table 7 shows that the intercept in the spanning regression for the commodity benchmark S&P GSCI and the DBLCI is statistical insignificant, i.e. -0.20% (t-stat =- 1.522) and 0.10% (t-stat= 0.737) per month, respectively.[14] The intercept in the spanning regression for the broadly diversified index DJ UBSCI is negative and statistically significant. The intercepts and their t-statistics in the spanning regression of the second generation commodity indices DBLCI-OY, MSDIL and the MSDILF do not add to our six factor commodity model's explanation of expected returns over the January 1970 – August 2018 period (see Panel B of Table 7).

Similarly, the intercept in the spanning regression using the six commodity factor model for the third generation short-only commodity Index MSDIS is statistically insignificant. As mentioned earlier the MSDILS and MSDISF indices represent momentum based timing strategies. It is therefore important to include, in addition to the six commodity factors, a variable that will capture a possible commodity market timing premium. Following the approach of Treynor and Mazuy (1966) we add the squared of the average commodity portfolio return to the six commodity factor premia. For both portfolios, the intercepts from the spanning regression are statistically insignificantly different from zero. The spanning regression results suggest that the MSDILS index can be replicated by combining the average commodity portfolio, the momentum commodity premium, the value commodity premium and a market timing factor. Similarly, the MSDISF index can be replicated by a short position in the average commodity portfolio, a positive position in the momentum commodity premium and a market commodity factor.

7. Timing commodity factor portfolios

An investor can capture the average premia offered by commodity factors through a passive investment strategy in commodity factor portfolios. The passive investment strategy rebalances periodically the commodity factor portfolios in accordance with the chosen portfolio construction methodology and will be optimal if return and risk are constant or unpredictable. Successful commod-

[14] The evidence that the intercept in the spanning regression for the S&P GSCI is insignificant together with the evidence shown in subsection 4.1 that the S&P SCI is an insignificant commodity factor in explaining the cross section of commodity returns, suggests that the widely used commodity benchmark S&P GSCI is unlikely to be a portfolio on the efficient frontier.

ity timing strategies on the other hand, requires ability to forecast commodity returns, risks or both.

Evidence on the predictability of commodity returns is controversial. Bessembinder and Chan (1992) find weak evidence of predictability in agricultural, metal and currency future prices while Hong and Yogo (2012) find in-sample evidence of predictability of an equally weighted portfolio of four commodity sectors. Gargano and Timmermann (2014) use both financial and macroeconomic predictors to forecast returns of seven commodity spot indices. They find some evidence of out-of-sample predictability for monthly horizons for some of the commodity indices (industrials, metals and the total commodity index) but little or no predictability for fats/oils, foods, livestock and textiles indices. Ahmed and Tsvetanov (2016) use forecasts from a two-factor model based on an equally weighted index of commodity futures and the basis portfolios to predict the return of fifteen commodity futures. They find no evidence of either statistical or economic value added. Daskalaki et al. (2017) test the predictive ability of macroeconomic and financial variables for equities, bonds and commodity indices. They find that equities and bonds can be predicted by some of the predictors but no evidence of commodity index return predictability. In contrast, Gao and Nardari (2018) report significant benefits from including commodities in a traditional mix of stocks and bonds when they use predictions for the expected return and risks of commodity futures.

Building on evidence suggesting that the value spread (the difference in value indicators in the long/short legs of the value premium) for US stocks predicts returns to the standard equity value strategy (Asness et al., 2000; Cohen, Polk et al., 2003), Baba Yara et al. (2019) report predictive power for the value commodity premium at horizons longer than three months but not for shorter horizons. Koijen et al. (2018) examine the predictability of individual commodities (among other assets) and the profitability of investment strategies that time individual commodities using the basis. They find no statistical relation between individual commodity returns and commodity basis but some support for trading strategies based on carry.

Finally, Boons and Prado (2019) find a positive and statistically significant relation between commodity variance and the returns of the basis-momentum factor portfolio but no predictability for the momentum and basis portfolios. Taken together with evidence from volatility timing strategies applied to equity factor premia (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017) suggests the possibility of timing commodity factor premia using predictors of future commodity volatility.

7.1. Predictor variables and return prediction models

Following previous research on the predictability of commodity returns we consider (a) *macroeconomic predictor variables* (T-bill 1 month, yield spread, default spread, unemployment rate, money supply growth industrial production growth and the Kilian real economic activity index), (b) *commodity-specific predictor variables* (aggregate commodity basis, commodity market interest, the growth in “commodity currency” exchange rates (i.e. AUD-USD, NZD-USD, SA RAND- USD) and the 1-month lagged commodity return), (c) *factor valuation spreads,* defined as the difference in the value signal in the high and low commodity factor exposure portfolios and (d) *factor exposure spreads* defined as the difference in the factor exposure of the high and low commodity factor portfolios. A full description of the predictor variables[15] can be found in Gargano and Timmermann (2014), Gao and Nardari (2018) and the Internet Appendix.

We employ four forecasting models: (a) *the historical average*, (b) *the forecast combination (pooled average) model* (Rapach et al., 2010), (c) *the diffusion index model* (Ludvigson and Ng, 2007) and (d) *the multiple regression model.* A detailed description of the forecasting models we use can be found in Rapach and Zhou (2013) and the Internet Appendix. We use ten years of data as the initial in-sample period and a recursive (i.e. expanding) window[16] to generate monthly out-of-sample forecasts for the period January 1980 to August 2018. The out of sample forecasting statistics for the statistical evaluation of the predictor variables and forecasting models reported in Table IA7 and the discussion in Section A5 of the Internet Appendix suggest weak or non-existent predictive ability for most variables and forecasting models. In the next section we investigate the economic benefits from forecasts based on the various prediction models. Kandel and Stambaugh (1996) have shown that even statistically weak prediction models can produce non-trivial economic gains.

7.2. Performance of commodity timing factor strategies

In this subsection we report the performance of a dynamic strategy that adjusts the weight allocated to a commodity factor premium using the forecasts of risk and return described in Section 7.1. The portfolio construction rule follows Daniel and Moskowitz (2016) who show that for an investor whose objective is to maximize the T periods from $1,\ldots,T$ Sharpe ratio, the optimal weight in the commodity factor premium at time t is $w_t = \frac{1}{\gamma}\frac{\mu_t}{\sigma_t^2}$, where γ is the coefficient of risk aversion, μ_t is the expected commodity factor premium and σ_t^2 is the expected variance over time t. The weight is proportional to the expected commodity premium and inversely proportional to the conditional variance of the commodity premium.

The weight, w_t, allocated to the commodity premium will be constant if the return to risk (variance) ratio is constant. If the return to volatility (Sharpe) ratio is constant or returns are negatively correlated with volatility, the weight on the commodity factor premium will be inversely proportional to forecasts of commodity premium volatility. This is the basis for the volatility targeting strategies of Fleming et al. (2001, 2003), Barroso and Santa-Clara (2015) and Moreira and Muir (2017). To exploit the predictive ability of past variance we assume that the investor cannot forecast the mean but can forecast future variance. In that case the optimal weight in the commodity factor premium is given by $w_t = \frac{c}{\sigma_t^2}$ where c is a constant, chosen so that the managed commodity portfolio has the same unconditional volatility as the unmanaged commodity portfolio (Moreira and Muir, 2017). The choice of a particular volatility target will affect the return, variance and alpha of the variance managed portfolio but will not affect portfolio performance measures such as the Sharpe ratio or the Appraisal ratio. The return of the variance timing strategy is then calculated as $w_t f_{t+1}$ where f_{t+1} denotes the excess return of the unmanaged commodity portfolio. We investigate the predictive ability of lagged variance (based on one-month daily commodity factor premia) for next month’s return, variance and Sharpe ratio (calculated monthly as the ratio of average portfolio return over the volatility of the portfolio based on daily observations in the month). The results reported in the Table IA8 of Internet Appendix suggest that past variance is a good predictor of future variance but largely un-

[15] In the Table IA6 of the Internet Appendix we report the descriptive statistics for the predictor variables for the January 1970 to August 2018 period.

[16] See Neely et al (2012), Gao and Nardari (2018), Rapach and Zhou (2013), among others. Hansen and Timmermann (2012) show that out-of-sample tests of predictive ability have had better size properties when the forecast evaluation period is a relatively large proportion of the available sample.

related to future commodity factor premia and Sharpe ratios, except for the commodity momentum premium where the relation is negative and significant. To exploit, in addition to the variance, the predictive ability of the commodity factor prediction models presented in Section 7.1 we use $w_t = \frac{1}{\gamma}\frac{\mu_t}{\sigma_t^2}$ to calculate monthly optimal weights using as forecast of the future commodity premium the one month ahead forecast generated by the four prediction models: the historical average (histavg), the pooled average model (poolavg), the diffusion index model (DI) and the multiple regression model (MULT).

Table 8 tabulates the annualised alpha and appraisal ratio for the variance-managed and the dynamic commodity portfolios that use forecasts of both return and variance. In Panel A we show results for the variance managed portfolios. In Panel B we present alpha and appraisal ratios for dynamic strategies that use the historical average as predictors of future commodity premia. In Panels C-F we show performance statistics of dynamic strategies that use as predictors commodity specific and macroeconomic variables (Panel C), factor valuation spreads (Panel D), factor exposure spreads (Panel E) and their combination (Panel F). *Alpha* is estimated based on the time-series regression of the managed commodity portfolio on the unmanaged commodity portfolio controlling also for the long-short commodity factors. A positive alpha suggests that the managed commodity portfolios expands the mean-variance efficient frontier and increase the Sharpe Ratio compared to the passive (unmanaged) commodity portfolios.[17]

We find no evidence that variance timing will be beneficial to investors who hold the commodity average market factor[18] over the January 1980 to August 2018 period. Over the same period, we find little evidence that variance timing will be beneficial to timing the basis, basis-momentum, hedging pressure or value commodity premia. The only exception is the variance timing strategy applied to the commodity momentum premium which generates a statistically significant alpha of 7.62% per annum and an appraisal ratio of 0.634.

As Table 8 shows, employing commodity premia prediction models does not improve the excess return generated by the variance managed strategies. The alphas that combine risk and return forecasts are statistically insignificant for all timing commodity factor premia strategies, with the exception of the commodity momentum-based strategy. However, the timing alpha of the variance managed momentum factor is higher than most of the alphas of timing strategies that use in addition predictions of future commodity premia. The evidence suggests that when return forecasts are also used in the timing strategy, there is no improvement to the performance generated by variance timing alone.[19]

7.3. Understanding the profitability of variance managed commodity momentum

The profitability of a variance timing strategy of the long/short commodity momentum portfolio is consistent with the evidence on the success of variance timing of equity momentum reported in Barroso and Santa Clara (2015), Daniel and Moskowitz (2016) and Moreira and Muir (2017), and deserves further investigation. The positive alpha of the variance timing strategy means that the strategy is not simply compensation to commodity factor risk. It is however possible that the commodity momentum variance timing strategy is exposed to other risk factors beyond the commodity factors. In this Section we examine the exposure of the commodity momentum premium variance timing strategy to a set of macroeconomic, liquidity and market risk factors used in the study of Asness, Moskowitz and Pedersen (2013) to investigate the drivers of the returns of global value and momentum factors across markets and asset classes.

We use the business cycle, liquidity, volatility, the global equity market and the global value and momentum premiums as proxies for time-variation in the commodity momentum variance timing strategy. The business cycle is a standard indicator of bad times (measured by a dummy variable that takes the value of 1 when the economy is in recession and 0 otherwise). Asness et al. (2013) find that funding liquidity, measured by innovations in the TED spread, and the market liquidity measure of Pastor and Stambaugh (2003), are significantly positively related to the global momentum factor constructed using equal volatility weights across markets and asset classes (equities, bonds, currencies and commodities). Volatility risk is used as a proxy for changes in the investment opportunity set. Investors require compensation for holding assets that pay poorly during periods of increasing volatility (Ang et al. 2006). Barosso and Santa-Clara (2015), Wang and Xu (2015) and Daniel and Moskowitz (2016) find that equity momentum tends to do badly in periods of high volatility. We use both global equity and commodity volatility to proxy for volatility risk. Finally, we use the three global factors of Asness et al. (2013). The three factors include the return of global equity market and the return of global value and momentum premiums constructed across markets and asset classes.

To find the exposure of the variance managed long-short commodity momentum portfolio, we regress the strategy's return on the set of risk factors. Table 9 shows the estimation results. Specification 1 shows the strategy's exposure to the world equity market portfolio and the global value and momentum factors. Exposure to the market and value factors is insignificant while the timing strategy has a beta of 1.019 with respect to the global momentum factor. Given that the global momentum factor includes commodity momentum the positive coefficient estimate is not surprising. When we include commodity momentum in the regression, the coefficient of the global momentum factor becomes insignificant (results available upon request). Exposure to the business cycle and the funding and market liquidity proxies is not significantly different form zero. The variance timing strategy's return is negatively correlated with innovations in world equity and commodity volatility but the coefficient is statistically significant only for world equity volatility.[20] The negative exposure of the managed variance strategy to volatility suggests that the strategy does poorly when volatility is rising provides evidence in support of the hypothesis that the excess return might be partially compensation for volatility risk. However, given the low explanatory power of volatility for the strategy's returns, the profitability of the variance timing momentum strategy might also be indicative of market inefficiencies rather than systematic risk.

[17] We report in Table IA9 in the Internet Appendix detailed performance statistics for the variance-managed and the combined return-forecast and variance-managed commodity portfolios (i.e. average commodity factor and the long-short commodity momentum, long-short basis, long-short basis-momentum, long-short hedging pressure and long-short value).

[18] Similar results are reported in Harvey et al. (2018). They find negligible effects from volatility timing to the Sharpe ratios of six agricultural, six energy and seven metal futures contracts.

[19] We also considered the timing benefits for long-only commodity portfolios. The results reported in Table IA10 in Internet Appendix, suggest positive, albeit marginally statistically significant, benefits only for the low basis and high value commodity portfolios. As in the case of long/short commodity portfolios, there is no value added from using commodity factor return prediction models.

[20] The weak relation between commodity volatility and the variance timing strategy might reflect the idiosyncrasies of the commodity market which could make commodity volatility a weak proxy for market wide risk.

Table 8
Variance managed and return-forecast commodity portfolios.

	$f \equiv AVG$		$f \equiv L/S\,MOM$		$f \equiv L/S\,BASIS$		$f \equiv L/S\ BASIS-MOM$		$f \equiv L/S\,HP$		$f \equiv L/S\,VALUE$	
	alpha	Appraisal Ratio	alpha	Appraisal Ratio	alpha	Appraisal Ratio	alpha	Appraisal Ratio	alpha	Appraisal Ratio	alpha	Appraisal Ratio
Panel A. Variance Managed Portfolios												
f^{σ^2}	−0.18%	−0.020	7.62%***	0.634	−0.37%	−0.044	2.49%	0.198	1.17%	0.139	0.15%	0.013
Panel B. Return-forecast and Variance Managed commodity portfolios using historical average												
$f^{\sigma^2,r}_{histavg}$	−1.65%	−0.198	7.35%***	0.634	−0.72%	−0.084	2.53%	0.198	−1.85%	−0.136	−2.44%	−0.177
Panel C. Variance Managed and Return-forecast commodity portfolios using commodity specific & macroeconomic variables												
$f^{\sigma^2,r}_{poolavg}$	−1.34%	−0.157	6.97%***	0.627	−0.74%	−0.083	2.41%	0.188	1.09%	0.087	−3.11%	−0.205
$f^{\sigma^2,r}_{DI}$	1.32%	0.124	5.59%***	0.450	−2.89%	−0.277	1.27%	0.099	1.31%	0.088	−6.47%	−0.367
$f^{\sigma^2,r}_{MULT}$	−0.85%	−0.078	1.31%	0.076	3.55%	0.248	2.69%	0.188	−0.67%	−0.043	−2.65%	−0.138
Panel D. Variance Managed and Return-forecast commodity portfolios using factor valuation spreads												
$f^{\sigma^2,r}_{MULT}$	–	–	8.07%***	0.644	−0.94%	−0.106	1.69%	0.143	−0.40%	−0.028	2.48%	0.128
Panel E. Variance Managed and Return−forecast commodity portfolios using factor exposure spreads												
$f^{\sigma^2,r}_{MULT}$	–	–	7.03%***	0.628	−0.23%	−0.022	1.70%	0.130	−2.40%	−0.156	2.48%	0.128
Panel F. Variance Managed and Return-forecast commodity portfolios using commodity specific & macroeconomic variables, factor valuation spreads and factor exposure spreads												
$f^{\sigma^2,r}_{poolavg}$	–	–	7.06%***	0.632	−0.73%	−0.082	2.33%	0.183	0.80%	0.064	−2.87%	−0.193
$f^{\sigma^2,r}_{DI}$	–	–	5.31%***	0.453	−2.91%	−0.262	1.05%	0.081	1.31%	0.090	−6.03%	−0.334
$f^{\sigma^2,r}_{MULT}$	–	–	3.30%*	0.192	3.85%	0.270	1.11%	0.081	−1.94%	−0.122	−2.16%	−0.111

This Table tabulates the results for the return-forecast and variance managed for the average commodity factor (AVG) and long-short commodity portfolios. Panel A presents the 1-month variance-managed commodity portfolio f^{σ^2}. Panels B, C, D and E present the combined return-forecast and 1-month variance-managed portfolio $f_j^{\sigma^2,r}$. In Panel B the return forecasts are based on the historical average. In Panel C the return forecasts are based on commodity specific & macroeconomic variables. In Panel D the return forecasts are based on the factor valuation spreads. . In Panel E the return forecasts are based on the factor exposure spreads. In Panel F the return forecasts are based on commodity specific & macroeconomic variables, factor valuation spreads and factor exposure spreads. $j = histavg$ stands for the historical average. $j = poolavg$ stands for the pooled average method; $j = DI$ stands for the diffusion index method and $j = MULT$ stands for the multiple regression method. We consider the unmanaged AVG and the unmanaged commodity long/short (L/S) portfolios *MOM* (i.e. Momentum), *BASIS* (i.e. Basis), *BASIS-MOM* (i.e. Basis-Momentum), *HP* (i.e. Hedging Pressure) and *Value* (i.e. Value). The alpha (against the multifactor model) and Appraisal ratio are annualised. The forecast evaluation period spans January 1980 to August 2018. We generate forecasts using an expanding window approach with an initial time window of 10 years. We use Newey-West (1987) standard errors for the statistical significance of alpha.

* denotes significance at 10% level

** denotes significance at 5% level

*** denotes significance at 1% level

Table 9
Risk exposures of variance managed long-short commodity momentum.

	1	2	3	4	5	6
Constant	0.009***	0.015***	0.014***	0.014***	0.014***	0.014***
Global equity	0.062					
Value "everywhere"	0.234*					
Momentum "everywhere"	1.019***					
Business cycle		−0.006				
Innovations in world equity volatility			−1.180***			
Innovations in commodity volatility				-0.108		
Innovations in TED					−0.006	
Innovation in market liquidity						0.013
R^2_{adj}	0.10	−0.001	0.003	−0.002	−0.002	−0.002

Table 9 presents the risk exposures of the variance managed long-short commodity momentum portfolio. We run 6 regressions, where we regress the variance managed long-short commodity momentum portfolio on the following risk factors: (a) the returns of the global equity index and the value and momentum "everywhere" factors of Asness, Moskowitz, and Pedersen (2013), (b) the business cycle, a dummy variables that takes the value of 1 when the US economy is in recession and 0 when in expansion), (c) the innovations in the global equity volatility, measured as the change in the monthly global equity volatility based on the daily returns of the global equity index, (d) the innovations in the commodity volatility, measured as the change in monthly commodity volatility based on the daily returns of the average commodity factor, (e) innovations of the TED spread, and (f) innovations in the market liquidity measure of Pastor and Stambaugh (2003). R^2_{adj} is the adjusted R^2 of the regression.
* denotes significance at 10% level
** denotes significance at 5% level
*** denotes significance at 1% level

8. Conclusions

We use a factor-based approach to combine commodity factor portfolios with exposure to commodity factor momentum, the basis, the basis-momentum, hedging pressure and value. These factors were found to jointly explain best the cross-section of commodity returns. Irrespective of the portfolio construction methodology used to create the multifactor commodity portfolio, we find significant improvements in the return to risk trade-off offered by commodity portfolios benchmarked on the S&P GSCI, the average commodity portfolio and other commercially available indices.

We find strong evidence in favour of variance timing the momentum commodity premium but no evidence that variance timing is beneficial to the other commodity factors. We predict commodity factor portfolio returns using state-of-the art forecasting methodologies and construct dynamic commodity allocation strategies combining expected returns with variance timing. Dynamic commodities strategies based on commodity factor return prediction models provide little value added.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2020.105807.

CRediT authorship contribution statement

Athanasios Sakkas: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft. **Nikolaos Tessaromatis:** Conceptualization, Methodology, Formal analysis, Writing - review & editing.

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