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Anomalies in Commodity Futures Markets*

Fabian Hollstein[†], Marcel Prokopczuk[†,‡], and Björn Tharann[†]

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Abstract

In recent years, commodity markets have become increasingly popular among financial investors. While previous studies document a factor structure, not much is known about how prominent anomalies are priced in commodity futures markets. We examine a large set of such anomaly variables. We identify sizable premia for jump risk, momentum, skewness, and volatility-of-volatility. Other prominent variables, such as downside beta, idiosyncratic volatility, and MAX, are not priced in commodity futures markets. Commodity investors should rebalance their portfolios regularly. Returns for annual holding periods are substantially weaker than for monthly rebalancing.

JEL classification: G10, G11, G17

Keywords: Anomalies, commodity futures markets

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†Leibniz University Hannover, Koenigsworther Platz 1, D-30167 Hannover, Germany.

‡ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, U.K.

I Introduction

Several recent papers find evidence for a factor structure in commodity futures returns (Szymanowska et al., 2014; Bakshi et al., 2019; Boons & Prado, 2019). A natural question is thus whether there are further factors and anomalies besides those documented in these papers that are also priced in commodity futures markets. Theoretically there should be one stochastic discount factor (SDF) that prices all assets. Hence, if they are proxies for risk, anomalies and factors should be priced across markets.

This paper takes a large set of anomalies previously studied in equity markets and examines whether they are also priced in commodity futures markets. Our main contribution is thus to provide the first study to test for the existence of a large set of anomalies in commodity markets. Commodity futures markets have increasingly become important, also for financial investors (e.g., Cheng & Xiong, 2014; Adams & Glück, 2015; Basak & Pavlova, 2016). For example, in 2015, according to the World Federation of Exchanges (WFE), more than 5 billion commodity futures contracts have been traded in total. Therefore, understanding risk premia and return anomalies in these markets is of vital interest to financial investors and firms with a commercial interest in these markets.

We use simple portfolio sorts with a holding period of one month to test for anomalies in commodity markets. We detect distinct patterns in the anomalies we study. For many anomalies documented in the equity literature, we do not obtain significant return premia in commodity futures markets. The main anomalies for which this is the case are downside beta, idiosyncratic volatility, and the MAX measure. On the other hand, we obtain anomaly returns of similar magnitude as in equity markets for jump risk, momentum, skewness, and volatility-of-volatility.

The jump risk, momentum, skewness, and volatility-of-volatility anomalies in commodity futures markets are distinct from one another. Augmenting existing factor models with either of these leaves the alphas of the other anomalies largely unchanged. Thus, the risk factors (or behavioral biases) that underlie them appear to differ across the significant anomalies.

We test the robustness of our results in several dimensions. Using cross-sectional Fama

& MacBeth (1973) regressions, we reach very similar conclusions. We also obtain largely similar results when building different numbers of portfolios (2, 3, 4, or 5) and for several subsample periods. Interestingly, for the post-financialization period, it seems that the MAX measure is much more strongly priced than before, while the momentum anomaly gets weaker.[1] Finally, we examine a longer holding period of 1 year. All anomalies tend to get weaker for this holding period. In particular, the profits to momentum investing decline substantially. Thus, portfolios that exploit anomaly strategies in commodity futures market should be rebalanced regularly.

Admittedly, there are several institutional differences between commodity futures and stock markets. Most notably, commodity futures are derivatives and are arguably easier to short than stocks. They are traded by a different set of market participants, with a substantially smaller fraction of retail traders. Furthermore, commodity futures markets are smaller and have historically been segmented from the stock market.[2] These differences may help inform the debate about whether we should think of these factors are driven by rational or behavioral theories.

Based on these institutional differences, one may argue that prices and returns in commodity futures markets could be less affected by behavioral biases than are equity markets.[3] Following this conjecture, downside beta, idiosyncratic volatility, and the MAX measure may be priced in equity markets because of investors' behavioral biases.[4] Based on the presumption that commodity futures prices are more rational, those anomalies that are priced across markets likely reflect systematic risk. Thus, jump risk, momentum, skewness,

[1]The post-financialization period starts with the introduction of the Commodity Futures Modernization Act (CFMA) in December 2000.

[2]Note that the factor construction differs somewhat between the two markets. E.g., there is no accounting data in commodities, which makes the construction of anomalies like profitability or investment infeasible. Finally, investors in commodity markets may face margin constraints.

[3]Admittedly, there are also further issues that may confound the following interpretation. For example, the equity and commodity markets are likely segregated to some extent. Furthermore, there may be frictions and true risk factors may be weaker in commodity markets (Giglio et al., 2021), which could lead us to falsely flag them as behavioral. Finally, traders on commodity markets may also collectively be subject to behavioral biases.

[4]On the other hand, the finding that the MAX measure is more strongly priced in the post-financialization period indicates that it might not be due to behavioral biases. In the post-financialization period investors are likely more sophisticated and limits to arbitrage are lower. Thus, behavioral anomalies should be weaker. We thank an anonymous referee for suggesting this and other mechanisms.

and volatility-of-volatility may have a risk-based explanation.[5]

Our paper adds to the literature that tests whether return premia associated with a variable originally documented in the U.S. equity market extend to other markets. For example, Titman et al. (2013), Watanabe et al. (2013), Sun et al. (2014), Eisdorfer et al. (2018), Lu et al. (2018), Hollstein (2020), and Hollstein & Sejdiu (2021) study such variables in international equity markets. These studies aim to examine whether the U.S. findings are due to data mining and to what extent anomalies are stronger in more or less developed or open markets, which helps gauge whether behavioral or risk-based explanations are more likely. With our analysis of commodity futures markets, we contribute to this literature from a different angle.

Our study also relates to the literature on anomalies and risk premia in commodity futures markets. Previous studies document that commodity-specific variables can predict cross-sectional variation in returns. These variables include the commodity market return (e.g., Yang, 2013), the shape of the term structures, hedging pressure (e.g., De Roon et al., 2000; Basu & Miffre, 2013), or a combination of these (e.g., Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Szymanowska et al., 2014; Fernandez-Perez et al., 2018; Bakshi et al., 2019).[6]

Some previous studies also examine the performance of strategies developed in equity markets on commodity markets (e.g., Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Asness et al., 2013; Szymanowska et al., 2014; Fernandez-Perez et al., 2016). Bakshi et al. (2019) develop a model for the cross-section of commodity markets, which, among others, also includes a momentum factor. We contribute to this literature by studying a substantially larger set of anomalies in the cross-section of commodity futures. In total, these previous studies consider only few of the most important anomalies detected in equity markets. We study a comprehensive set of different variables documented for equity markets in a systematic way. For all actors on commodity markets (commercial and financial), this

[5]Again, in the case of momentum, the results could also be interpreted differently. The fact that the equity momentum factor cannot explain commodity momentum shows that both are not driven by the same risk factor. Thus, it could be that momentum in equity and commodity markets is driven by different behavioral biases in different markets.

[6]Part of these studies argues that equity risk factors may not be perfectly suited for pricing commodities. As a consequence of this, we are careful to examine the abnormal returns of strategies in commodity futures markets, with respect not only to equity but also to commodity factors models.

knowledge about the risk premia and return patterns in these markets is very important. For example, we show that the model of Bakshi et al. (2019) that works well for carry, momentum, and commodity category portfolios performs far less well when confronted with many other anomalies.

The remainder of this paper proceeds as follows. Section II introduces the data, factor models, and variables. Section III presents our main empirical results. In Section IV, we present further analyses and test the robustness of our main results. Finally, we draw conclusions in Section V.

II Data & Methodology

A Data

We retrieve futures and options data for 26 commodities from the Commodity Research Bureau (CRB). All time series are denoted in U.S. Dollar (USD). Our sample period spans from August 1959 until December 2015. Table 1 provides an overview of the commodities and the corresponding numbers of observations.

To avoid irregular pricing patterns in a futures contract maturity, we roll the futures returns following Szymanowska et al. (2014) and Bakshi et al. (2019). We consider the nearest to maturity contract as the spot contract and roll over the contracts during the month that is two months prior to maturity. It is important to note that we sort the commodities and hold commodity futures with fixed maturity. That is, we regularly roll the commodity futures and our strategy earns only commodity futures spot, not term premia (Szymanowska et al., 2014).

The CRB does not provide unique strike prices for commodity options. We therefore use an algorithm to determine the exact strike price.[7] We also check for standard no-arbitrage

[7]The CRB fills the actual strike price with zeros to obtain a 4-digit number. Therefore, to find the exact strike price, we first divide the reported strike price by 1000, 100, 10, and 1, and then we minimize the distance between the early exercise payoff and the option price, i.e., we compute $\epsilon_{C,K_i} = |C - max\ (S - K_i, 0)|$ and $\epsilon_{P,K_i} = |P - max\ (K_i - S, 0)|$ in the case of calls and puts, respectively. C and P denote the call and put price, respectively. S and K_i are the stock and strike price, respectively. We then take the strike price with the smallest pricing error. Finally, repeating this procedure for every day, we compute the mode of the strike price per contract.

conditions and discard observations not fulfilling these.[8] We then compute the implied volatility following Barone-Adesi & Whaley (1987), accounting for the early exercise premium in American options. Finally, we impose a monotonicity condition so that call (put) option prices of the same maturity decrease (increase) with the strike price. Finally, to limit the effect of recording errors, we impose the condition that deletes all options with implied volatility greater than three times the median implied volatility.

We obtain the monthly time series of the S&P 500 total return index from the Center for Research in Security Prices (CRSP) database. In addition, we take the non-standardized S&P 500 index option data with different maturities from OptionMetrics. We obtain the factors for the Fama & French (1996) 3-factor model, the Carhart (1997) 4-factor model, as well as the Fama & French (2015) 5-factor model from Kenneth French's website. As risk-free rate, we use the 1-month Treasury Bill rate provided by Kenneth French.

B Factor Models

To test whether several variables are priced in the cross-section of commodity futures returns, we examine the abnormal performance of the strategies relative to both equity and commodity factor models. As equity factor models, we use the Capital Asset Pricing Model (CAPM), the Fama & French (1996) 3-factor model, comprising a market factor (MRP), a size factor (SMB), and a value factor (HML). We also use the Carhart (1997) 4-factor model, which augments the 3-factor model by a momentum factor (UMD). Finally, we take the Fama & French (2015) 5-factor model, incorporating the market, the size, the value, as well as a profitability (RMW) and an investment factor (CMA).

Under the law of one price and free portfolio formation, there exists a unique stochastic discount factor that prices all assets (Cochrane, 2005a). Given that theorem, asset pricing models for stocks should also have explanatory power for the cross-section of commodity futures. However, to account for the possibility that commodity futures may be driven by commodity-specific risks, we also consider the commodity factor models of Bakshi et al. (2019) and Fernandez-Perez et al. (2018). Bakshi et al. (2019) (BGR) introduce a 3-factor

[8] No-arbitrage states for calls and puts that $max\ (K - S_t, 0) \leq P_t \leq K$ and $max\ (S_t - K, 0) \leq C_t \leq S_t$, respectively, where K is the option's strike price, and S_t, P_t, and C_t are the time-t stock, put, and call prices, respectively.

model, which includes a long-only commodity factor (EW), a term structure factor (TS), and a commodity momentum factor (MOM). Fernandez-Perez et al. (2018) ($FFFM$) augment that model by a hedging pressure factor (HP). Section A of the Appendix describes the construction of the factors in more detail.

C Returns and Variables

Commodity Futures Excess Returns Following Gorton et al. (2013) and Bakshi et al. (2019), we compute the simple return on a fully-collateralized futures position as

$$r_{t+1} = \frac{F_{t+1,T} - F_{t,T}}{F_{t,T}} + r_t^f, \tag{1}$$

where $F_{t+1,T}$ and $F_{t,T}$ are the futures prices on the nearby contract with expiration at T at the end of month $t+1$ and t, respectively. r_t^f represents the interest on a fully-collateralized futures position. We therefore define the corresponding excess return on a fully-collateralized futures position as

$$er_{t+1} = r_{t+1} - r_t^f, \tag{2}$$

where er_{t+1} denotes the excess return. Finally, we are cautious not to mix information from different futures contracts in the return computation in that we always compute the returns comparing prices from one contract at different points in time (Singleton, 2013).

Variables We analyze several variables that have been introduced and discussed in the literature. Our focus is mainly (with some exceptions) on "anomaly" variables which have not been used to create a major factor model, neither for the stock market, nor for the commodity market.

We study aggregate volatility (Ang et al., 2006b; Cremers et al., 2015), aggregate jump risk (Cremers et al., 2015), downside beta (Ang et al., 2006a), idiosyncratic volatility (Ang et al., 2006b; Ang et al., 2009), past performance measures (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993), a maximum return measure (Bali et al., 2011), as well as value (Asness et al., 2013), and volatility-of-volatility (Baltussen et al., 2018). In addition, we consider illiquidity (Amihud, 2002), co-skewness (Harvey & Siddique, 2000), co-kurtosis (Dittmar, 2002), historical moment measures (Amaya et al., 2015), and risk-neutral moments

(Bakshi et al., 2003). Table 2 provides an overview of the variables, and Section B of the Appendix describes the construction of the variables in further detail. To guard against any seasonalities in the variables, we use an estimation window of 1 year (or multiples of 1 year) whenever possible.

III Main Empirical Results

A Summary Statistics

Table 1 reports summary statistics on the different monthly commodity futures excess returns. Examining the performance of the commodities, we observe two-fold patterns. On the one hand, most commodity futures perform exceptionally well as an investment over the time period under investigation. Notable annualized mean excess returns are observable in the case of brent crude oil (10.86 %), copper (10.48 %), palladium (10.94 %), soybean meal (9.54 %), and WTI crude oil (7.72 %). On the other hand, some commodities show a very poor performance, indicated by negative annualized mean returns. Examples are corn (–1.85 %), lumber (–4.65 %), natural gas (–8.24 %), oats (–0.76 %), rough rice (–4.42 %), and wheat (–1.27 %).[9] Overall, the patterns of our summary statistics are similar to those of Gorton & Rouwenhorst (2006) and Bakshi et al. (2019).

Table 2 presents summary statistics on the factors and variables under study. MOM and UMD exhibit a similar magnitude in annualized average returns (7.44 % and 8.49 %, respectively), but have different standard deviations (32.95 % and 50.79 %, respectively). Thus, it seems that even though the risk premia appear similar on average, in equity markets the momentum strategy is more volatile than that in commodity markets.

We also observe that the idiosyncratic volatility derived from the BGR model is lower than that derived from the Fama & French (1996) 3-factor model, indicated by annualized averages of 20.82 % and 25.20 %, respectively. The BGR model thus appears to explain, on average, a larger fraction of the variation in commodity returns than the 3-factor model. However, since the main purpose of factor models is to explain differences in average returns

[9] Note that because we annualize the monthly returns, some 10 %-quantiles exhibit values smaller than –1.

rather than the variation in returns, this preliminary evidence does not necessarily imply that the BGR model is better suited for explaining commodity returns than the 3-factor model.[10]

Table 3 reports average correlations among the variables under investigation. $AggJump$ and $AggVol$ exhibit a correlation of –0.71. Thus, there seems to be a negative relation between the smooth volatility and jump risk sensitivities of commodities. Further, we notice moderate correlations between $Momentum$ and $3YReversal$, as well as $5YReversal$ of 0.47 and 0.41, respectively, which is not surprising, because all these measures cover the past performance of commodities. The relatively high negative correlations between $Value$ and $3YReversal$ as well as $5YReversal$ of –0.54 and –0.67, respectively, are likewise not surprising given the definition of $Value$ as a ratio of past to current futures prices.

The correlations between $HistVar$ and $IdioVol^{FF3}$ (0.91), and $IdioVol^{BGR}$ (0.81) indicate that both factor models have difficulty in explaining the variation in returns. Interestingly, we find a high correlation between MAX and $HistVar$ of 0.75, MAX and $IdioVol^{FF3}$ of 0.76, and MAX and $IdioVol^{BGR}$ of 0.67.[11] Interestingly, even though MAX is sometimes interpreted as a measure of skewness, its correlation to $HistSkew$ is only moderate, amounting to 0.37.

B Portfolio Sorts

At the end of each month, we sort the commodities into 3 portfolios according to the specific variable under study.[12] Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitudes of the sorting variable.[13] We refer to portfolio 3–1 as the hedge portfolio that simultaneously goes long in portfolio P3 and short in portfolio P1. Since we base our analysis on the most conservative position by using fully-collateralized futures positions, the return of the 3–1 portfolio is defined as the difference between the half of the return on portfolio 3 and the half of the return on portfolio 1. The remaining half of the investment

[10]We discuss the suitability of the different factor models for commodity markets further, in Section IV.A.

[11]The high correlations between MAX and idiosyncratic volatility are consistent with those reported by Hou & Loh (2016), who find a correlation of 0.90 for equity markets.

[12]We split the commodities into terzile portfolios to deal with a limited number of commodities available, particularly at the beginning of our sample period. We examine the robustness of our results to building 2, 4, and 5 portfolios in Section IV.D. These are very similar to those for 3 portfolios reported in this section.

[13]We impose the restriction that each month at least 6 commodities must be available.

serves as collateral and earns the risk-free interest rate.[14] We rebalance the portfolios every month.

Table 4 presents the results. In parentheses, we report robust Newey & West (1987) standard errors with 6 lags. Stars indicate the statistical significance of the results. In addition, we also perform the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001).[15] The superscript "m" indicates statistical significance after the multiple-testing adjustment.

(i) Risk or Mispricing Variables

We begin the discussion by examining variables that are unambiguously flagged as risk-based in the previous literature: aggregate volatility and jump risk. In the following, we turn the focus on variables that are motivated (at least in part) by behavioral biases of investors: downside beta, idiosyncratic volatility, momentum, reversal, MAX, value, and volatility-of-volatility.

Aggregate Volatility Risk Sorting the commodities according to their sensitivities to aggregate volatility we find an insignificant negative mean return of the hedge portfolio of –1.63 % p.a. (Panel A of Table 4). The factor alphas are of similar magnitude and none of them is significantly different from zero.

Our findings are much smaller in magnitude and insignificant compared with those reported in Ang et al. (2006b), who obtain –1 % per month for the equity market. The authors argue that the price of aggregate volatility has to be negative because an increasing market volatility is associated with a worsening of investment opportunities.

However, when separating aggregate volatility and jump risk, following Cremers et al. (2015), we find a significant positive mean return of a long–short portfolio of 3.56 % p.a. The

[14]For robustness, we follow Locke & Venkatesh (1997) and also impose monthly transaction costs of two times 0.033 %. Although we take a conservative viewpoint and assume a complete turnover of the commodities, we find that the results are largely unaffected by transaction costs. The results including transaction costs are qualitatively similar and are available upon request.

[15]For the multiple-testing approach, one first sorts the p-values of the M anomalies in ascending order. Those values are defined as statistically significant, for which it holds that $p_{(b)} \leq \frac{b}{Mc(M)}\alpha_d$, where b is the rank of the p-value (1 for the lowest, M for the highest), M is the number of overall p-values. We set $c(M) = 1$ as in Harvey et al. (2016). α_d is the false discovery rate, i.e., the expected proportion of null hypotheses that are falsely rejected, set to be 10%. For example, for 5 anomalies to be significant in the main setup (with 21 tested anomalies), they must all have p-values below 2.38%. For 10 anomalies to be significant, they must all have p-values below 4.76%.

alphas relative to all factor models are statistically significant, although not with respect to the multiple-testing threshold. Thus, there is some indication that smooth aggregate volatility is priced in the cross-section of commodity returns. Our findings are in contrast to Cremers et al. (2015), who observe a negative contemporaneous relationship between stock returns and smooth aggregate volatility with a significant alpha of –2.7 % p.a. of a 5–1 portfolio, relative to the Fama & French (1996) 3-factor model. They motivate the negative risk premium also with hedging opportunities against market risk. Assets that exhibit a positive correlation with market volatility risk provide a natural hedge and, thus, investors require lower expected returns.

There is one important potential reason why our results for commodity futures differ from theirs for equity returns. Commodity futures returns typically perform well in the early stages of recessions (Gorton & Rouwenhorst, 2006) when (continuous) aggregate volatility typically spikes most strongly. Thus, aggregate volatility risk may be well-hedgeable with all commodities. Even stronger reactions to innovations to continuous aggregate volatility may simply indicate higher variability of the commodity returns.

Aggregate Jump Risk We also sort according to the sensitivities to the jump part of aggregate return variation. Going short a portfolio with low aggregate jump risk sensitivities and long one with high such sensitivities generates a significant mean return of –4.63 % p.a. (Panel A of Table 4). We find significant alphas relative to all factor models. In 4 out of 7 cases, the results are also significant with respect to the multiple-testing threshold. Thus, jump risk appears to be significantly priced in the cross-section of commodity returns.

Our findings are consistent with those in Cremers et al. (2015) for equity returns, who find a significant contemporaneous alpha of –9.4 % p.a. relative to the 3-factor model. The authors relate the negative pricing to investors who seek a hedge against crises. This intuition is consistent with our findings. Commodities that are more positively correlated with innovations in aggregate jump risk earn lower average returns. The smaller magnitude of the average returns we find is natural, since contemporaneously the impact of variables will always be stronger than in the predictive setting used in our study as long as factor sensitivities are time-varying. Note also that the results across aggregate volatility and jump risk are consistent in total. Aggregate unseparated volatility risk is unpriced in commodity markets. When separating into continuous and jump parts, the continuous part is priced positively and the jump part is priced negatively.

Downside Beta Sorting the commodities according to their downside betas, we find an insignificant mean return of the hedge portfolio of –1.37 % p.a. (Panel B of Table 4). Relative to all the factor models, the alphas of the 3–1 portfolio are not statistically significant either. Thus, downside beta risk appears to be not priced in the cross-section of commodity returns.

Our results are in contrast to those in Ang et al. (2006a), who find that downside beta is positively priced in the cross-section of stock returns. Using contemporaneous portfolio sorts, they obtain a 5–1 return of 11.8 % p.a. Examining the joint cross-section of different asset classes, Lettau et al. (2014) find that downside risk is positively priced with a 6–1 return of 9.66 % p.a. Ang et al. (2006a) theoretically justify their findings with a behavioral property of investors: disappointment-aversion.

Idiosyncratic Volatility When sorting the commodities according to their idiosyncratic volatilities based on the Fama & French (1996) 3-factor model (BGR model), we find an insignificant mean spread return of 0.23 % p.a. (0.85 % p.a.), as presented in Panel B of Table 4. The alphas relative to all factor models are not statistically significant. It seems that in commodity markets, investors are not compensated for bearing idiosyncratic risk.[16]

These results are in contrast to those in Ang et al. (2006b) for the equity market. The authors find a significant negative relationship between idiosyncratic volatility and stock returns, indicated by a significant monthly mean spread return (alpha) of –1.04 % (–0.83 %).

Many studies deliver potential explanations for the idiosyncratic volatility puzzle. Merton (1987) extends the classic CAPM framework to include market frictions and shows that investors do not hold optimally diversified portfolios and, thus, might require positive compensation for bearing idiosyncratic risk. Explicitly modeling commodity markets, Hirshleifer (1988) obtains similar predictions.

On the other hand, Miller (1977) argues that short-sale constraints can lead to an overvaluation of assets, because asset prices might then only reflect the view of the optimistic market participants. The result could be a negative relationship between expected stock

[16] Our findings are consistent with those in Miffre et al. (2012), who find an insignificant monthly alpha of 0.12 % relative to a modified commodity factor model.

returns and idiosyncratic risk. Shleifer & Vishny (1997) argue that the overpricing cannot be arbitraged away, because shorting these stocks is particularly risky. Thus, idiosyncratic volatility limits arbitrage. Further studies arguing along these lines are Boehme et al. (2009), Lamont (2012), and Stambaugh et al. (2015).

Thus, the literature generally associates its negative pricing with the behavioral biases of investors along with binding short-sale restrictions. In commodity markets, where limits to arbitrage are lower and behavioral biases may be weaker, we do not detect an idiosyncratic volatility puzzle.

Momentum Going short a commodity portfolio with the worst past 1-year performance and simultaneously going long a commodity portfolio with the best past 1-year performance yields a highly significant mean return of 7.44 % p.a. (Panel C of Table 4). We find that the alphas relative to all factor models are statistically significant.[17] Momentum alphas also clear the multiple-testing threshold in 6 out of 7 cases. Thus, our findings indicate that 1-year momentum is priced in the cross-section of commodity returns.

Consistent with our results, analyzing the cross-section of commodity futures returns, Erb & Harvey (2006) and Gorton et al. (2013) document a significant mean return of 10.80 % p.a. and 5.97 % p.a., respectively, of a long–short portfolio, using half of the commodities in the long (short) portfolio, with a holding period of one month and sorting the commodities according to the 12-months' past performance. Similarly, Asness et al. (2013) provide evidence of a substantial mean return of 12.40 % p.a. of a non-collateralized 3–1 portfolio. Szymanowska et al. (2014) document a significant mean return of 9.00 % p.a. of a 4–1 portfolio.

Our findings are consistent with those in Jegadeesh & Titman (1993), who examine the cross-section of stock returns and show that a strategy based on 12-months' past performance (and 3-month holding period) generates a significant monthly average return of 1.31 %. They motivate the success of that strategy by delayed price reactions based on idiosyncratic firm information.

Many behavioral theories have tried to explain the momentum effect. The key behavioral

[17] In the case of the BGR and FFFM model, we skip the momentum factor. It is trivial to note that a factor model with a commodity momentum factor on the right hand side can perfectly explain the long–short return of just that factor.

biases that could cause momentum are conservatism and anchoring biases (Barberis et al., 1998), biased self-attribution (Daniel et al., 1998), and the disposition effect (Grinblatt & Han, 2005; Frazzini, 2006). These issues lead to underreaction of the firm price to new information, which could be further strengthened by informational frictions (Hong & Stein, 1999).

On the other hand, rational asset pricing theories have been developed to explain the momentum effect. These range from firms' investment decisions (Berk et al., 1999), stochastic dividend growth rates (Johnson, 2002), risk (Ahn et al., 2003; Daniel & Moskowitz, 2016), revenues, costs, and growth options (Sagi & Seasholes, 2007), to macroeconomic risk (Liu & Zhang, 2008).

It is also interesting to note that the stock market momentum factor in the Carhart (1997) 4-factor model is not able to explain the returns of the commodity momentum strategy. On the one hand, Cochrane (2005b) argues that since in equity markets momentum can be explained by a momentum factor, it is not possible to form an arbitrage portfolio based on the momentum strategy: by following the strategy, one exposes oneself to systematic factor risk. On the other hand, given that equity momentum cannot explain commodity momentum, momentum investors can diversify their strategies and enhance their portfolio performance by also considering the commodity market.

3- and 5-Year Reversal A portfolio going short the commodities showing the worst 36-month (60-month) past performance and long the commodities with the best 36-month (60-month) past performance generates a positive mean return of 2.36 % p.a. (2.26 % p.a.), as presented in Panel C of Table 4. This mean return is weakly significant for the 36-month period. However, we find that the 4-factor model can explain both the 3-year and the 5-year reversal effect. Interestingly, the slightly positive excess return on 3- and 5-year reversal translates into a strongly statistically significant negative BGR alpha (even after the multiple-testing adjustment).

Our findings are inconsistent with those in De Bondt & Thaler (1985) for the equity market, who obtain a return of –25 % after a holding period of 3 years. Fama & French (1996) find that the "low" portfolio outperforms the "high" portfolio by 0.6 % per month. De Bondt & Thaler (1985) motivate their findings by overreaction. Analyzing the cross-section of stocks, however, Fama & French (1996) and Carhart (1997) provide evidence that both the 3- and 4-factor model can explain both the 3- and 5-year reversal. Thus, these results suggest that both effects are eventually captured by systematic risk factors and therefore one could argue that they are not priced in the cross-section of stocks. We obtain broadly similar results for commodities.

Several behavioral models try to explain long-term reversals. The key behavioral biases are herding behavior (Bikhchandani et al., 1992), representativeness (Barberis et al., 1998), overconfidence (Daniel et al., 1998; Hong & Stein, 1999), and sentiment (Baker & Wurgler, 2006, 2007). On the other hand, Berk et al. (1999) also provide a rational explanation for the reversal effect based on firms' investment decisions.

Maximum Daily Returns Going short a portfolio of commodities with the lowest average across the 5 largest daily returns during the previous 12 months and going long a portfolio of commodities with the highest 5 maximum daily returns over the previous 12 months generates an insignificant mean return of the hedge portfolio of –0.13 % p.a. (Panel D of Table 4). We find insignificant alphas relative to all factor models.

Our findings are in contrast to those in Bali et al. (2011), who find a significant negative average monthly 10–1 return spread of –1.03 % and a significant monthly 4-factor alpha of –1.18 % for the equity market. Bali et al. (2017a) report results of a similar magnitude. The authors argue that the investor preference for positively skewed assets along with overweighting of the probability of occurrence of these events according to cumulative prospect theory (Barberis & Huang, 2008) leads to overpricing of stocks with high MAX measures.

Value Going long (short) a portfolio with the highest (lowest) magnitude in value generates an insignificant mean return of 0.44 % (Panel D of Table 4). All equity factor models are able to explain the value effect, expressed by insignificant alpha estimates. On the contrary, we find significant alphas relative to both commodity factor models. It seems that equity rather than commodity factor models are able to explain the value effect in the cross-section of commodity returns.

Our results are inconsistent with those in Asness et al. (2013). Analyzing the cross-section of U.S. stocks and commodities, they find a significant annualized (non-collateralized) mean return of 3.7 % and 6.3 % for a 3–1 portfolio, respectively. The presence of a value effect in commodity markets thus seems to strongly depend on the time period and commodity return specification.[18] Thus, it is not entirely clear whether value is priced in commodity futures markets or not. In addition, the connection to equity value appears rather loose.

Volatility-of-Volatility Forming a long–short portfolio according to the volatility of option-implied volatility generates a weakly statistically significant negative mean return of –2.72 % p.a. (Panel D of Table 4). The alphas relative to all factor models are larger in magnitude compared to the mean return and statistically significant. In 3 out of 7 cases, the alphas are also statistically significant with respect to the multiple-testing adjustment. It seems that investors demand a premium for bearing volatility-of-volatility risk.

Our results are consistent with those in Baltussen et al. (2018) for the equity market. Analyzing the cross-section of stock returns, they find a significant mean excess return of –0.85 % per month for a 5–1 portfolio. Even though the return premium has the "wrong" sign to be consistent with ambiguity aversion, the authors motivate their findings by the ambiguity preferences of investors.

(ii) Trading Frictions

Illiquidity Forming a long–short portfolio, sorting according to the Amihud (2002) illiquidity measure, generates an insignificant mean return of –0.74 % p.a. (Panel E of Table 4). None of the factor model alphas on the hedge portfolio is statistically significant. Thus, there seems to be no illiquidity premium in commodity futures markets.

Our results are in contrast to Szymanowska et al. (2014), who find a significant negative relationship between Amivest liquidity (Amihud et al., 1997) and commodity futures returns, indicated by a significant mean return of a 4–1 portfolio of –9.40 % p.a. for their sample period 1986–2010. Thus, the results for whether and how (il-)liquidity is priced in commodity futures markets seems to strongly depend on how liquidity is computed, the sample period, and the number of portfolios selected.[19]

[18] Instead of buying and holding one commodity future, Asness et al. (2013) cumulate daily returns obtained from the most liquid futures contract on every day.

[19] Marshall et al. (2012) conclude that the Amihud (2002) measure, which we employ, measures liquidity in commodity futures markets best.

Our findings are also in contrast to those in Amihud (2002) for the equity market, who observes a significant positive slope coefficient of 0.162 based on Fama & MacBeth (1973) regressions. The author builds on the theory of Amihud & Mendelson (1986), stating that investors likely demand compensation for holding illiquid assets. Our findings indicate that this illiquidity is not positively priced in commodity markets. A possible explanation for our findings is that the commodity futures markets we examine are all highly liquid, especially in comparison to the markets for most individual stocks. Thus, investors may not require illiquidity premia, or they are too small to be detected.

(iii) Moments

In a final subsection, we examine historical and option-implied moments of the return distributions of the commodities.

Co-Skewness Sorting the commodities according to their co-skewness, we obtain an insignificant mean return of the hedge portfolio of 1.70 % p.a. (Panel E of Table 4). Generally, we find insignificant alphas relative to the factor models. Only for the BGR model do we detect a weakly positively significant alpha. It seems that, overall, co-skewness is not priced in the cross-section of commodity returns.

Our findings are in contrast with those in Harvey & Siddique (2000), who provide evidence for a significant negative relationship between co-skewness and stock returns. The authors motivate their findings (rationally) by investors' preference for a positively skewed portfolio. The fact that our results for commodity markets do not match these predictions, along with a weak performance of co-skewness as a control variable in cross-sectional regression tests on stocks (e.g., Bollerslev et al., 2016; Hollstein & Prokopczuk, 2018), indicates that co-skewness is largely unpriced in asset markets.

Co-Kurtosis Next, we sort the commodities according to their co-kurtosis. The 3–1 long–short portfolio generates an insignificant average spread return of –1.50 % p.a. (Panel E of Table 4). The alphas relative to all factor models are not statistically significant. Thus, it seems investors do not demand a risk premium for co-kurtosis in commodity markets.

These findings are in contrast to Dittmar (2002), who provides evidence for a significant relationship between co-kurtosis and stock returns, indicated by a significant monthly alpha of 1.15 %, relative to the 3-factor model. However, similar to co-skewness, co-kurtosis is typically not priced in cross-sectional asset pricing tests when employed as a control variable (e.g., Hollstein et al., 2020a). Thus, it seems that co-kurtosis is also not priced in asset markets in general.

Historical Variance Next, we turn the focus on historical return moments (Panel F of Table 4). First, we sort the commodities according to their historical variances. We find that the hedge portfolio has an insignificant mean return of 0.50 % p.a. The alphas relative to all factor models are not statistically significant.

For the cross-section of stock returns, Amaya et al. (2015) obtain an insignificant (weekly) 10–1 hedge portfolio return of 0.11 %, sorting stocks according to realized volatility. The results thus indicate that historical variance is priced neither in stock nor in commodity futures markets.

Historical Skewness Second, we sort the commodities according to their historical skewness. We observe that low-skewness portfolios outperform high-skewness portfolios, resulting in a significant negative mean return of –3.50 % p.a. Only the BGR model is able to explain the skewness effect, however: none of the equity factor models is able to do so. The mean return and the alphas toward all equity models are also significant with respect to the multiple-testing adjustment.

Fernandez-Perez et al. (2018) also provide evidence for a significant negative relationship between commodity futures returns and historical skewness. They use a reduced sample period of 1987–2014 and detect a significant annualized alpha estimate of –6.58 % relative to the FFFM model. Although we find that the skewness risk premium can be explained by the BGR model, our results are overall quite similar.

Our findings are consistent with those in Amaya et al. (2015), who detect an average weekly return spread of –0.19 % for the equity market.[20] For (idiosyncratic) skewness, Mitton & Vorkink (2007) and Barberis & Huang (2008) argue that investors' probability weighting behavior leads to overpricing in positively skewed stocks, which does not disappear because of short-selling restrictions in equity markets. Fernandez-Perez et al. (2018) also provide a

[20]The authors show that historical skewness computed using intraday rather than daily data might contain different information. Although we use daily data, we obtain similar results.

potential rational channel for the pricing of skewness in commodity markets. They argue that selective hedging under "rational" skewness preferences might well explain the results for commodity markets (Stulz, 1996; Gilbert et al., 2006).

Historical Kurtosis Third, sorting the commodities according to their historical kurtosis, we observe a positive relationship with future returns, indicated by a significant mean return of the hedge portfolio of 2.56 % p.a. Neither equity models nor commodity models are able to explain this positive relationship, indicated by significant alphas relative to all factor models subject to our investigation. The BGR alpha even significantly exceeds the mean return of the hedge portfolio, amounting to 4.51 % p.a. In 3 out of 7 cases, the alphas are also statistically significant with respect to the multiple-testing threshold. Thus, historical kurtosis seems to be priced in the cross-section of commodity returns.

Examining the cross-section of stock returns, Amaya et al. (2015) find a significant average weekly return of 0.10 % for a long–short portfolio. The results for historical kurtosis on stock and commodity markets are consistent. Thus, kurtosis could be a proxy for a "rational" risk or part of the consideration for selective hedging strategies in commodity markets.

Risk-Neutral Variance Sorting the commodities according to their risk-neutral variance estimates, we obtain an insignificant mean return of –1.54 % p.a. for the hedge portfolio (Panel G of Table 4). The alphas are insignificant relative to all equity factor models. In contrast, both commodity models show highly significant alpha estimates. Thus, the two commodity factor models do an extremely poor job in explaining an anomaly that is not even present in average returns.

Our results are similar to those of Conrad et al. (2013), who also find a negative, but insignificant, average return for a 3–1 portfolio on stock returns. Risk-neutral total variance thus seems to be priced neither in the cross-section of equity nor in that of commodity returns.

Risk-Neutral Skewness Analogously to the previous paragraph, a portfolio going long the commodities with the highest and simultaneously going short the commodities with the lowest risk-neutral skewness generates an insignificant mean return of 0.03 % p.a. (Panel G of Table 4). We find insignificant alphas relative to all factor models.

Our results differ from those of Conrad et al. (2013), who detect a significant 3–1 portfolio return of –0.8 % per month for equities. However, the results in the literature are not completely clear-cut. For risk-neutral skewness, e.g., Xing et al. (2010), Bali et al. (2017b), and Stilger et al. (2017) document a positive relation. Thus, given the ambiguity in the equity literature about the pricing of risk-neutral skewness, our results are broadly in line with those from the equity literature.

Risk-Neutral Excess Kurtosis For risk-neutral excess kurtosis, we obtain an insignificant mean return for the 3–1 portfolio of 0.31 % p.a. (Panel G of Table 4). We find insignificant alphas relative to all factor models.

Conrad et al. (2013) find a significant 3–1 portfolio return of 0.7 % per month for the equity market. Bali et al. (2017b) also obtain similar results using price target-based expected returns. Using Fama & MacBeth (1973) cross-sectional regressions, the authors find a highly significant positive relationship between excess kurtosis and these returns. Thus, as opposed to equity markets, the level of risk-neutral kurtosis does not seem to be compensated for in commodity markets.

IV Further Analyses and Robustness

A Commodity Factor Models

While our primary focus is on studying market anomalies, our paper also provides implications for factor models in commodity markets. Bakshi et al. (2019) forcefully argue that the BGR model succeeds in pricing the cross-section of commodity returns. They test their model for sorts on term-structure slopes, momentum, as well as commodity sectors, and find that the model cannot be rejected.

Testing the model on a large set of anomaly variables, we obtain substantially different results. For numerous variables examined in Table 4, the model yields economically and statistically significant alphas. In numerous cases, the abnormal returns relative to the BGR model, which is designed in particular for commodity markets, are even larger in magnitude and more strongly significant than those for the equity models. This is the case, e.g., for co-skewness, historical kurtosis, 3-year and 5-year reversal, risk-neutral variance, and value. On the other hand, only in rare cases does the BGR model perform substantially better in explaining the variable premia than the equity factor models (e.g., for historical skewness). The FFFM model yields better results, e.g., for co-skewness and 5-year reversal. However, it also rather under- than outperforms the equity factor models in terms of explaining the average portfolio returns in general.

Studying the factor models at the individual commodity level, in untabulated results, we find that the BGR and FFFM models do better in explaining the time-variation in commodity futures returns, with average adjusted R^2s of 22 % and 23 %, respectively. The equity factor models explain on average only about 1–2 % of the return variation. However, the equity factor models do a substantially better job in explaining average returns. In our dataset, 4 commodities have a significant alpha (at 10 %) relative to the CAPM, and 3 commodities relative to the 3-factor, 4-factor, and 5-factor models. On the other hand, 6 and 8 commodities have significant alphas relative to the BGR and FFFM models, respectively. This pattern is induced by the alpha point estimates rather than by differences in the standard errors. While there is only little difference in the latter, the average alphas are highest in magnitude for the commodity pricing models.[21]

Thus, our findings point toward substantial integration of commodity and equity market *risk factors*. Previous findings reveal that the markets themselves are not fully integrated (Bessembinder, 1992; Daskalaki et al., 2014). Our findings indicate that differences across the markets may, to some extent, be driven by behavioral biases manifesting themselves particularly in equity prices.

B Augmenting Factor Models

Based on the insight that part of the anomalies cannot be explained by existing equity and commodity factor models, we next analyze whether models augmented by the anomalies perform better in pricing other anomalies. That is, we use the Fama & French (2015) 5-factor model and the Fernandez-Perez et al. (2018) FFFM model and add those anomalies that perform best (have significant alphas relative to several factor models) in the main analysis:

[21]For example, the average alpha for the 3-factor model amounts to 2.14 %, while that for the BGR model is –3.11 %. The average standard errors of the two models are 5.12 % and 4.31 %, respectively.

aggregate jump risk, momentum, volatility-of-volatility, and historical skewness.[22] It could be that all these anomalies are driven by a common factor. In that case, simply augmenting existing models may lead to a better model, which is able to capture all (or at least more) anomalies. On the other hand, if there is no improvement for the augmented factor models, then the anomalies likely proxy for distinct risk factors or unrelated behavioral anomalies.

We present the results in Table 5. We find that the augmented models generally do not perform substantially better than the initial models. Thus, the aggregate jump risk, momentum, volatility-of-volatility, and historical skewness anomalies appear to be truly distinct. None of them helps substantially in explaining the other anomalies.

C Cross-Sectional Regressions

In this section, we perform Fama & MacBeth (1973) cross-sectional regressions. Table A1 of the Online Appendix reports the average coefficient estimates. Each month, we regress the commodity futures excess returns on a constant and the lagged value of the variable.[23,24] We compute robust Newey & West (1987) standard errors using 6 lags. The findings are generally consistent with our previous results. The variables that yield a significant 3–1 portfolio return generally also produce an average regression slope coefficient of the same sign and similar statistical significance. There is only one substantial difference: for $HistKurt$, we detect an insignificant slope estimate as opposed to a significantly positive 3–1 portfolio return. Small differences are observable for 3-year reversal where, for cross-sectional regressions, we find a slope estimate insignificantly different from zero. Finally, as opposed to portfolio sorts, we detect a weakly significant regression slope for risk-neutral variance.

Table A2 of the Online Appendix reports the average coefficient estimates using monthly Fama & MacBeth (1973) cross-sectional regressions, controlling for the average 12-months' roll yield and the average 12-months' past performance: the variables which serve as main ingredients for the BGR model in addition to the average factor. The results are essentially

[22]Note that we augment the model of Fernandez-Perez et al. (2018) rather than that of Bakshi et al. (2019) because the former performs overall better in our analysis and the latter is just a subset of the former with one fewer factor.

[23]We use uni- rather than multivariate cross-sectional regressions because the commodity cross-section is rather small, leaving only few degrees of freedom for the estimation.

[24]We run the regression only in months where data on at least 10 commodities are available.

similar to those without control variables. We only detect two noteworthy differences. First, again consistent with the portfolio sorts, risk-neutral volatility does not carry a significant price of risk. Second, volatility-of-volatility does not generate a positive risk premium when controlling for the roll yield and momentum. Thus, in commodity markets, volatility-of-volatility appears to be associated to these variables in the cross-section. An alternative explanation could be that the relation of volatility-of-volatility and future returns is non-monotonic, i.e., the medium portfolio generates a higher return on average compared to P1. Although the 3–1 spread is strongly significant, this pattern may prevent us from finding a clear relation in cross-sectional regressions.

D Portfolio Splits

We test the robustness of our results in three dimensions. First, we form different numbers of portfolios. We additionally consider the case of 2, 4, and 5 portfolios instead of 3 portfolios, as used for the main analysis. We then examine the returns of the 2–1, 4–1, and 5–1 hedge portfolio, respectively.

Table A3 of the Online Appendix summarizes the results. We observe that the different portfolio splits do not affect our overall conclusions in general. Whether we sort into 2, 3, 4, or 5 portfolios usually affects the results only marginally, while there are no clear patterns caused by the more or less granular sorting. Some effects get marginally stronger when building fewer, others when forming more portfolios. An exception is $RNVar$, where we find a highly significant mean return of –5.65 % p.a. for the 5–1 hedge portfolio and significant alphas relative to the factor models. It seems that in this case a finer classification of the commodities is associated with a strengthening of the effect. Further, in the case of $3YReversal$, $5YReversal$, and $HistKurt$, splitting commodities into 4 or 5 portfolios typically leads to insignificant mean returns and alpha estimates relative to the factor models. Thus, overall our results are largely independent of how many portfolios we build.

E Subsample Periods

For a second robustness test, we analyze the variable return premia in commodity markets for different subperiods. We use two distinct breakpoints. First, we examine an early time range from the beginning of our sample period until February 1986. The second subsample period starts in March 1986, the time Szymanowska et al. (2014) start their sample period, and ends in November 2000. The final subsample period starts in December 2000 with the passing of the Commodity Futures Modernization Act (CFMA), which can be regarded as a post-financialization period. The CFMA substantially eases speculation in commodity markets (Boons et al., 2012), and after its introduction, Tang & Xiong (2012) and Cheng & Xiong (2014) document a substantial increase in commodity trading activity.

Table A4 of the Online Appendix presents the results for the different subperiods. These are in general very similar as for the full sample. For aggregate volatility and aggregate jump risk, we obtain similar but statistically weaker results, indicating that reduced power due to a smaller sample size might be an issue. For idiosyncratic volatility, the results are consistent across subsamples. For momentum, we find a strong return premium in the first two subperiods, but interestingly a clearly weaker premium during the post-financialization period. Reversal appears to be overall unpriced in the cross-section of commodity futures returns.

For MAX, we find a clear pattern. Before the financialization period, there is no or at most a weak positive return premium. However, post-financialization, there is a strong and significant negative effect across all specifications. We detect a mean return of –4.1 % p.a. for the 3–1 portfolio. For value, we find no return premium throughout. For volatility-of-volatility, we detect weak results for the second subperiod and also overall slightly weaker results in the post-financialization period compared to the entire period. This pattern might be created by lower power of the statistical tests due to a reduced sample size. For illiquidity, there seems to be overall no premium.

For co-skewness, we obtain significantly positive average mean returns for the first subsample period, but no significant premia for the more recent periods. For co-kurtosis, the results are essentially similar across subperiods. For historical variance, we detect a positive effect in returns in the second subsample period and a rather negative one in the most recent subsample. The return premium for historical skewness is stronger from the second subsample period on, while the premium on historical kurtosis seems to vanish in the post-financialization period. For risk-neutral variance, skewness, and excess kurtosis, we obtain overall similar results across the subperiods.

Overall, the results are consistent across different time periods of our sample. There are few interesting patterns, though, especially for the post-financialization period, where MAX seems to be negatively priced. On the other hand, the momentum effect seems to be much attenuated during the post-financialization period.

F Annual Holding Period

Last, we examine the robustness of our results to a longer holding period. We hold the portfolios for 12 months instead of 1 month. Table A5 of the Online Appendix reports the results. Overall, the results are consistent with our previous findings. However, typically these are somewhat weaker. Interestingly, for the 12-month holding period, we find that the return on the momentum strategy is clearly smaller and the factor alphas are typically not statistically significant. Thus, for all anomaly strategies in commodity markets (and in particular for momentum), one should frequently rebalance the portfolios.

V Conclusion

In this study, we comprehensively examine prominent equity return anomalies in commodity futures markets. We find that jump risk, momentum, skewness, and volatility-of-volatility yield significant and robust risk premia in the cross-section of commodity returns. On the other hand, downside beta, idiosyncratic volatility, and MAX mostly yield average returns close to zero that are insignificant.

Appendix

A Factors

Commodity Long-only Factor (Bakshi et al., 2019, "EW") is the excess return of an equally-weighted monthly rebalanced portfolio that goes long all available commodity futures.

Commodity Term Structure Factor (Bakshi et al., 2019, "TS") is the excess return of a long–short (3–1) monthly rebalanced fully-collateralized portfolio sorted by the average past 12-months' roll yield. The roll yield for each commodity is the daily difference in the log prices of the first-nearby (referred to as "spot" in Section A) and second-nearest futures contract.

Commodity Momentum Factor (Bakshi et al., 2019, "MOM") is the excess return of a long–short (3–1) monthly rebalanced fully-collateralized portfolio sorted by the average 12-months' past performance.

Commodity Hedging Pressure Factor (Basu & Miffre, 2013, "HP") is the excess return of a monthly rebalanced fully-collateralized portfolio that buys (sells) the commodities with the lowest (highest) hedgers' hedging pressure and highest (lowest) speculators' hedging pressure. In doing so, we first split the average hedging pressure of hedgers over the past 12 months into two equal parts. We then sort according to the average 12-months' past hedging pressure of speculators and buy (sell) the 30 % of the lowest (highest) hedging pressure of hedgers for which speculators have the highest (lowest) hedging pressure.

Equity Market Factor (Fama & French, 1993, 2015, "MRP") is the excess return on the equity market, using value-weighted returns from all firms in CRSP.

Equity Size Factor (Fama & French, 1993, 2015, "SMB") is the return difference between a portfolio of small and large stocks ("Small minus Big").

Equity Value Factor (Fama & French, 1993, 2015, "HML") is the return difference between a portfolio of high and low book-to-market stocks ("High minus Low").

Equity Momentum Factor (Carhart, 1997, "UMD") is the return difference between a portfolio of stocks sorted by the past performance from month $t = -12$ to $t = -2$ ("Up minus Down").

Equity Profitability Factor (Fama & French, 2015, "RMW") is the return difference between a portfolio of robust and weak profitability stocks ("Robust minus Weak").

Equity Investment Factor (Fama & French, 2015, "CMA") is the return difference between a portfolio of conservative and aggressive investment stocks ("Conservative minus Aggressive").

B Characteristics

Aggregate Volatility (VIX) (Ang et al., 2006b, "$AggVol^{VIX}$") is the coefficient $\beta_{i,t}^{\Delta VIX}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{M}(r_{M,d} - r_{f,d}) + \beta_{i,t}^{\Delta VIX}\Delta VIX_d + \epsilon_{i,d}$, where $r_{i,d}$ is the daily excess return on commodity i over the period $d = 1, ..., D$, where D is the number of daily return observations, using daily data during the previous 12 months, and t indicates rebalancing days (month-ends). $r_{M,d} - r_{f,d}$ is the stock market excess return, and ΔVIX is the daily innovation (simple first difference) in the Volatility Index (VIX), which is provided by the Chicago Board Options Exchange (CBOE).

Aggregate Volatility (Cremers et al., 2015, "$AggVol$") is the coefficient $\beta_{i,t}^{VOL}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{M}(r_{M,d} - r_{f,d}) + \beta_{i,t}^{VOL} VOL_d + \epsilon_{i,d}$, where VOL is the volatility factor of Cremers et al. (2015), using daily data during the previous 12 months. All other variables are as previously defined.

Aggregate Jump (Cremers et al., 2015, "$AggJump$") is the coefficient $\beta_{i,t}^{JUMP}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{M}(r_{M,d} - r_{f,d}) + \beta_{i,t}^{JUMP} JUMP_d + \epsilon_{i,d}$, where $JUMP$ is the jump factor of Cremers et al. (2015), using daily data during the previous 12 months. All other variables are as previously defined.

Co-Skewness (Harvey & Siddique, 2000, "$CoSkew$") and **Co-Kurtosis** (Dittmar, 2002, "$CoKurt$") are the coefficients $\beta_{i,t}^{CS}$ and $\beta_{i,t}^{CK}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{M}(r_{M,d} - r_{f,d}) + \beta_{i,t}^{CS}(r_{M,d} - r_{f,d})^2 + \beta_{i,t}^{CK}(r_{M,d} - r_{f,d})^3 + \epsilon_{i,d}$, including the stock market risk premium, the squared and the cubed stock market risk premia, using daily data during the previous 12 months. All variables are as previously defined.

Downside Beta (Ang et al., 2006a, "$DownBeta$") is the coefficient $\beta_{i,t}^{Down}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{Down}(r_{M,d} - r_{f,d}) + \epsilon_{i,d}$. All variables are as previously defined. The regression is estimated using daily commodity excess returns only when the market excess return is below the average daily market excess return during the previous 12 months.

Historical Variance (Amaya et al., 2015; Fernandez-Perez et al., 2018, "$HistVar$") is the monthly variance, defined as $Var_{i,t}^{hist} = \sigma_{i,t}^2 = \frac{1}{D-1}\sum_{d=1}^{D}(r_{i,d} - \mu_{i,t})^2$, with $\mu_{i,t} = \frac{1}{D}\sum_{d=1}^{D} r_{i,d}$, using daily data during the previous 12 months. All other variables are as previously defined.

Historical Skewness (Amaya et al., 2015; Fernandez-Perez et al., 2018, "$HistSkew$") is the monthly skewness, defined as $Skew_{i,t}^{hist} = [\frac{1}{D}\sum_{d=1}^{D}(r_{i,d} - \mu_{i,t})^3]/\sigma_{i,t}^3$, with $\sigma_{i,t} = \sqrt{\sigma_{i,t}^2}$, using daily data during the previous 12 months. All other variables are as previously defined.

Historical Kurtosis (Amaya et al., 2015; Fernandez-Perez et al., 2018, "$HistKurt$") is the monthly kurtosis, defined as $Kurt_{i,t}^{hist} = [\frac{1}{D}\sum_{d=1}^{D}(r_{i,d} - \mu_{i,t})^4]/\sigma_{i,t}^4$, using daily data during the previous 12 months. All other variables are as previously defined.

Idiosyncratic Volatility (FF3) (Ang et al., 2006b; Ang et al., 2009, "$IdioVol^{FF3}$") is the standard deviation of the residuals $\hat{\epsilon}_{i,d}$ using the Fama & French (1993) 3-factor model $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{M}(r_{M,d} - r_{f,d}) + \beta_{i,t}^{SMB} SMB_d + \beta_{i,t}^{HML} HML_d + \epsilon_{i,d}$, where SMB and HML are the size and value factors of Fama & French (1993), using daily data during the previous 12 months. All other variables are as previously defined.

Idiosyncratic Volatility (BGR) (Ang et al., 2006b; Ang et al., 2009, "$IdioVol^{BGR}$") is the standard deviation of the residuals $\hat{\epsilon}_{i,d}$ using the BGR model of Bakshi et al. (2019) $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{EW} EW_d + \beta_{i,t}^{TS} TS_d + \beta_{i,t}^{MOM} MOM_d + \epsilon_{i,d}$, where EW, TS, and MOM are the long-only, term structure, and momentum factors of Bakshi et al. (2019), using daily data during the previous 12 months. All other variables are as previously defined.

Illiquidity (Amihud, 2002; Fernandez-Perez et al., 2018, "$ILLIQ$") is the ratio of the daily absolute commodity futures excess return to the daily dollar trading volume, averaged over the recent 12 months.

Momentum (Jegadeesh & Titman, 1993; Fernandez-Perez et al., 2018) is the average commodity futures excess return over the past 12 months.

3-year Reversal (De Bondt & Thaler, 1985, "$3YReversal$") is the average commodity futures excess return over the past 36 months.

5-year Reversal (De Bondt & Thaler, 1985, "$5YReversal$") is the average commodity futures excess return over the past 60 months.

Risk-Neutral Variance (Bakshi et al., 2003, "$RNVar$"), **Risk-Neutral Skewness** (Bakshi et al., 2003, "$RNSkew$"), and **Risk-Neutral Excess Kurtosis** (Bakshi et al., 2003, "$RNExKurt$") are defined as

$$RNVar_{i,t} = \frac{e^{r\tau}V - \mu^2}{\tau}, \tag{A1}$$

$$RNSkew_{i,t} = \frac{e^{r\tau}W - 3\mu e^{r\tau}V + 2\mu^3}{[e^{r\tau}V - \mu^2]^{3/2}}, \tag{A2}$$

$$RNExKurt_{i,t} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2 V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3, \tag{A3}$$

where V, W, X, and μ are computed as

$$V = \int_{K=0}^{S} \frac{2(1+\log[\frac{S}{K}])}{K^2} P(K)dK + \int_{K=S}^{\infty} \frac{2(1-\log[\frac{K}{S}])}{K^2} C(K)dK, \tag{A4}$$

$$W = \int_{K=S}^{\infty} \frac{6\log[\frac{K}{S}] - 3(\log[\frac{K}{S}])^2}{K^2} C(K)dK - \int_{K=0}^{S} \frac{6\log[\frac{S}{K}] + 3(\log[\frac{S}{K}])^2}{K^2} P(K)dK, \tag{A5}$$

$$X = \int_{K=S}^{\infty} \frac{12(\log[\frac{K}{S}])^2 + 4(\log[\frac{K}{S}])^3}{K^2} C(K)dK + \int_{K=0}^{S} \frac{12(\log[\frac{S}{K}])^2 + 4(\log[\frac{S}{K}])^3}{K^2} P(K)dK, \tag{A6}$$

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V - \frac{e^{r\tau}}{6}W - \frac{e^{r\tau}}{24}X. \tag{A7}$$

r is the continuously compounded (annualized) interest rate for the period from t to $t+\tau$, where τ indicates the time to maturity of each option. We express τ as a fraction of a year.[25] Further, K and S denote the strike and spot prices, respectively, where $C(K)$ and $P(K)$ represent the call and put prices at strike price K, respectively.[26] In the next step, we follow Hollstein et al. (2020b) and compute the corresponding option prices, using the Black (1976)

[25] We follow the literature and use the Ivy curve from OptionMetrics to proxy for the interest rate.

[26] We focus on out-of-the-money (OTM) option prices. To obtain a wide range of option prices, we follow Chang et al. (2012) and compute a grid of 1,000 equidistant interpolated moneyness levels, i.e., K/S, ranging from 0.3 % to 300 %. Subsequently, for each available moneyness level, we interpolate the implied volatility using a spline interpolation method. For moneyness levels outside of the moneyness range observed in the market, we simply use a nearest neighborhood algorithm to extrapolate the implied volatilities (Jiang & Tian, 2005). In practice, this means that if a moneyness level is lower (higher) than the lowest (highest) moneyness level available in the market, we simply use the implied volatility corresponding to the lowest (highest) level of moneyness available in the market.

option pricing model. Finally, as in Hollstein & Prokopczuk (2016) and Hollstein et al. (2019), we use a trapezoidal rule to approximate the integrals V, W, and X and thus we obtain the (annualized) risk-neutral measures with corresponding maturity. For our analysis, we linearly interpolate the measures to obtain risk-neutral measures with maturity 91 days (3 months).[27]

MAX Measure (Bali et al., 2011, "MAX") is the average of the five largest daily commodity futures excess returns during the past 12 months.

Value (Asness et al., 2013, "$Value$") is the ratio of the log of the average daily futures prices from 4.5 to 5.5 years ago to the current log futures price, using the first-nearby commodity futures contract.

Volatility-of-Volatility (Baltussen et al., 2018, "VoV") is computed as $VoV_{i,t} = \frac{\sqrt{\frac{1}{252}\sum_{d=t-251}^{t}(\sigma_{i,d}^{iv}-\bar{\sigma}_{i,t}^{iv})^2}}{\bar{\sigma}_{i,t}^{iv}}$, where $\sigma_{i,d}^{iv}$ is the daily implied volatility of commodity i, and $\bar{\sigma}_{i,t}^{iv}$ denotes the average implied volatility over the past 12 months. We use $\sqrt{RNVar_{i,d}}$ as measure of $\sigma_{i,d}^{iv}$.

[27]A horizon of 12 months would be more desirable to rule out any seasonal patterns in commodity volatilities. However, there is only limited data available on commodity options with more than 6 months to maturity.

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Table 1: Summary Statistics – Monthly Commodity Excess Returns

This table presents summary statistics about monthly commodity excess returns. We sample all data at the monthly frequency. "Average", "Std Dev", "Skewness", and "Kurtosis" denote the (annualized) mean, (annualized) standard deviation, skewness, and kurtosis, respectively. The next two measures represent the 10 % and 90 % quantile, respectively. "Nobs", and "First Obs." are the number of observations and the first observation available, respectively.

Variable	Average	Std Dev	Skewness	Kurtosis	10% Quantile	90% Quantile	Nobs	First Obs.
Brent Crude Oil	0.1086	0.3275	0.4497	6.2880	−1.2030	1.3326	317	31.08.1989
Cocoa	0.0350	0.3055	0.6782	4.3679	−1.1818	1.4283	677	31.08.1959
Coffee	0.0532	0.3723	1.1827	6.5348	−1.3093	1.5145	520	29.09.1972
Copper	0.1048	0.2650	0.1758	5.1679	−0.8796	1.2052	677	31.08.1959
Corn	−0.0185	0.2411	1.1994	9.4976	−0.9239	0.8814	677	31.08.1959
Cotton	0.0208	0.2363	0.6376	6.2230	−0.8689	0.8964	677	31.08.1959
Feeder Cattle	0.0368	0.1648	−0.4698	5.4982	−0.6045	0.6743	528	31.01.1972
Gold	0.0108	0.1935	0.4844	6.2515	−0.6962	0.7600	491	28.02.1975
Heating Oil	0.0799	0.3193	0.8946	7.4362	−1.2109	1.2593	445	29.12.1978
Lean Hogs	0.0350	0.2513	0.1326	3.9913	−1.0414	1.0266	597	29.04.1966
Live Cattle	0.0493	0.1623	−0.2492	5.4700	−0.5706	0.7009	612	29.01.1965
Lumber	−0.0465	0.2713	0.0999	3.1760	−1.2144	1.1786	554	28.11.1969
Milk	0.0598	0.2646	0.4369	4.8893	−0.9420	1.1731	236	29.02.1996
Natural Gas	−0.0824	0.4850	0.6014	4.3127	−2.0478	1.8740	308	31.05.1990
Oats	−0.0076	0.2910	2.3066	23.9651	−1.0576	1.0048	677	31.08.1959
Orange Juice	0.0532	0.3263	1.6490	11.4989	−1.1737	1.3338	586	31.03.1967
Palladium	0.1094	0.3475	0.3695	5.9824	−1.2187	1.4380	467	28.02.1977
Platinum	0.0459	0.2733	0.4572	7.3223	−0.9768	1.0321	573	30.04.1968
Rough Rice	−0.0442	0.2682	1.0327	7.8229	−1.1480	1.0291	352	30.09.1986
Silver	0.0333	0.3105	0.7161	8.9322	−1.1201	1.2662	630	31.07.1963
Soybean Meal	0.0954	0.2917	2.0091	18.7198	−0.9204	1.1888	677	31.08.1959
Soybean Oil	0.0585	0.2914	1.1902	8.7608	−0.9654	1.1599	677	31.08.1959
Soybeans	0.0545	0.2575	1.4853	13.2171	−0.7885	1.0095	677	31.08.1959
Sugar	0.0561	0.4235	1.1669	6.5380	−1.5383	1.6760	659	28.02.1961
Wheat	−0.0127	0.2532	0.7644	6.8882	−0.9937	0.9848	677	31.08.1959
WTI Crude Oil	0.0772	0.3304	0.3714	5.5903	−1.2602	1.3579	393	29.04.1983

Table 2: Summary Statistics

This table summarizes summmary statistics about the factors and variables used in this paper. We sample all data at the monthly frequency. "Average", "Std Dev", "Skewness", and"Kurtosis" denote the (annualized) mean, (annualized) standard deviation, skewness, and kurtosis, respectively. The final two statistics represent the 10 % and 90 % quantiles, respectively.

Variable	Average	Std Dev	Skewness	Kurtosis	10% Quantile	90% Quantile
Factors						
EW	0.0442	0.4724	0.1652	6.4959	−0.4918	0.5501
TS	0.0491	0.2740	−0.2475	3.6795	−0.2822	0.3628
MOM	0.0744	0.3295	0.0636	4.4322	−0.3234	0.4777
HP	0.0523	0.3939	0.0400	4.8443	−0.4304	0.5112
MRP	0.0599	0.5333	−0.5227	4.9253	−0.5798	0.6526
SMB	0.0304	0.3653	0.3733	6.2292	−0.4048	0.4384
HML	0.0415	0.3371	0.0456	5.1604	−0.3396	0.4482
UMD	0.0849	0.5079	−1.3695	13.715	−0.4728	0.5954
RMW	0.0293	0.2680	−0.3037	15.645	−0.2316	0.2771
CMA	0.0360	0.2415	0.2907	4.6797	−0.2344	0.3352
Variables						
$AggVol^{VIX}$	0.0108	0.1449	0.1980	3.5456	−0.1513	0.1762
$AggVol$	0.0058	0.0781	−0.2629	3.9450	−0.0813	0.0919
$AggJump$	−0.0025	0.0335	0.2899	3.6987	−0.0391	0.0350
$DownBeta$	0.1087	0.3063	0.0020	3.4029	−0.2203	0.4577
$IdioVol^{FF3}$	0.2520	0.0918	0.8388	3.9534	0.1593	0.3529
$IdioVol^{BGR}$	0.2082	0.0698	0.8640	3.8496	0.1377	0.2887
$Momentum$	0.0445	0.2889	0.2770	3.4417	−0.2658	0.3667
$3YReversal$	0.0481	0.1660	0.1474	3.2254	−0.1269	0.2392
$5YReversal$	0.0502	0.1300	0.2007	3.4487	−0.0862	0.1957
MAX	0.0454	0.0192	1.1780	4.8505	0.0271	0.0657
$Value$	0.9526	0.3349	−0.2655	9.7875	0.8708	1.0604
VoV	0.1457	0.0577	0.6413	3.0613	0.0908	0.2093
$ILLIQ$	0.0003	0.0006	2.1051	6.8580	0.0000	0.0010
$CoSkew$	−1.0000	11.833	−0.0861	3.5506	−14.039	11.530
$CoKurt$	−34.290	935.10	−0.0346	3.7577	−1044.5	947.03
$HistVar$	0.0774	0.0586	1.6070	6.0708	0.0286	0.1351
$HistSkew$	−0.0703	1.0402	−0.2005	5.1713	−1.0628	0.8221
$HistKurt$	8.6770	8.5927	2.1915	7.8006	3.4744	15.639
$RNVar$	0.0768	0.0580	1.2762	4.9523	0.0295	0.1324
$RNSkew$	0.0360	0.5871	−0.2511	3.1161	−0.6023	0.6245
$RNExKurt$	2.4557	2.9468	1.5136	5.2971	0.4208	5.3778

Table 3: Correlations

This table reports cross-sectional averages of time-series correlations of the sorting variables. For each commodity we first compute the pairwise correlations between the variables. Afterwards, we obtain average across commodities.

	$AggVol^{VIX}$	$AggVol$	$AggJump$	$DownBeta$	$IdioVol^{FF3}$	$IdioVol^{BGR}$	$Momentum$	$3YReversal$	$5YReversal$	MAX	$Value$	VoV	$ILLIQ$	$CoSkew$	$CoKurt$	$HistVar$	$HistSkew$	$HistKurt$	$RNVar$	$RNSkew$
$AggVol$	-0.21																			
$AggJump$	0.45	-0.71																		
$DownBeta$	-0.05	0.24	-0.29																	
$IdioVol^{FF3}$	-0.13	0.17	-0.17	0.10																
$IdioVol^{BGR}$	-0.11	0.13	-0.15	0.02	0.85															
$Momentum$	0.08	0.01	0.03	0.01	0.00	0.03														
$3YReversal$	-0.05	0.03	-0.01	-0.02	0.14	0.15	0.47													
$5YReversal$	-0.06	0.03	-0.02	0.02	0.12	0.09	0.41	0.64												
MAX	-0.02	0.13	-0.11	0.08	0.76	0.67	-0.08	-0.08	-0.05											
$Value$	0.00	-0.06	-0.01	-0.14	-0.10	-0.03	-0.47	-0.54	-0.67	-0.01										
VoV	0.00	-0.04	-0.01	-0.04	0.17	0.14	-0.01	-0.01	-0.07	0.13	0.06									
$ILLIQ$	-0.03	0.02	-0.06	0.05	0.25	0.28	0.04	0.05	0.03	0.20	-0.02	0.05								
$CoSkew$	0.11	-0.36	0.45	-0.46	-0.04	-0.05	-0.04	-0.04	-0.02	0.01	0.03	-0.05	-0.02							
$CoKurt$	-0.02	-0.01	0.00	0.29	-0.04	-0.05	-0.06	-0.04	-0.01	-0.06	0.01	0.03	-0.02	-0.08						
$HistVar$	-0.14	0.18	-0.19	0.15	0.91	0.81	-0.03	0.10	0.08	0.75	-0.10	0.16	0.23	-0.04	-0.04					
$HistSkew$	0.13	-0.05	0.05	-0.05	-0.02	-0.01	-0.22	-0.35	-0.30	0.37	0.21	0.00	-0.01	0.08	-0.07	-0.01				
$HistKurt$	0.04	0.00	0.02	-0.10	0.08	0.09	-0.08	-0.07	-0.04	0.21	0.10	0.09	-0.08	0.00	0.04	0.05	0.07			
$RNVar$	-0.18	0.16	-0.19	0.14	0.57	0.48	0.08	0.14	0.13	0.45	-0.15	0.24	0.07	-0.07	-0.01	0.57	-0.02	-0.02		
$RNSkew$	0.15	-0.06	0.07	-0.09	-0.08	-0.06	-0.02	-0.10	-0.12	0.03	0.10	0.03	0.09	-0.04	-0.05	-0.09	0.18	0.09	-0.04	
$RNExKurt$	0.07	0.00	0.03	-0.02	-0.07	-0.04	-0.06	-0.16	-0.12	-0.04	0.14	0.00	-0.05	0.04	-0.01	-0.06	0.05	0.08	-0.11	-0.20

Table 4: Portfolio Sorts

*This table presents the results for portfolio sorts. At the end of each month, we sort the commodities into 3 portfolios according to the variable indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the respective variable. We rebalance the portfolios each month and obtain fully-collateralized returns. The hedge portfolio P3–P1 simultaneously goes long portfolio P3 and short portfolio P1. "Mean return" denotes the annualized average excess return on the respective portfolio. In addition, we report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2019), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses, we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%.*

Panel A. Aggregate Volatility and Jump

	$AggVol^{VIX}$				$AggVol$				$AggJump$			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0376	0.0266	0.0050	−0.0163	−0.0391	0.0336	0.0321	0.0356^{**}	0.0507	0.0158	−0.0420	$-0.0463^{***,m}$
	(0.0314)	(0.0325)	(0.0286)	(0.0140)	(0.0410)	(0.0410)	(0.0440)	(0.0154)	(0.0453)	(0.0440)	(0.0386)	(0.0161)
CAPM alpha	0.0222	0.0099	−0.0059	−0.0141	−0.0589	0.0147	0.0131	0.0360^{**}	0.0322	−0.0035	-0.0619^{*}	$-0.0471^{***,m}$
	(0.0343)	(0.0333)	(0.0295)	(0.0143)	(0.0397)	(0.0396)	(0.0433)	(0.0154)	(0.0454)	(0.0424)	(0.0367)	(0.0165)
3-factor alpha	0.0160	0.0066	−0.0081	−0.0121	−0.0587	0.0128	0.0089	0.0338^{**}	0.0265	−0.0057	−0.0601	$-0.0433^{**,m}$
	(0.0323)	(0.0330)	(0.0290)	(0.0136)	(0.0395)	(0.0394)	(0.0419)	(0.0157)	(0.0448)	(0.0414)	(0.0371)	(0.0174)
4-factor alpha	0.0212	0.0016	−0.0052	−0.0132	−0.0551	0.0078	0.0033	0.0292^{*}	0.0215	−0.0074	−0.0599	-0.0407^{**}
	(0.0328)	(0.0336)	(0.0295)	(0.0133)	(0.0404)	(0.0393)	(0.0416)	(0.0168)	(0.0448)	(0.0407)	(0.0380)	(0.0186)
5-factor alpha	0.0259	0.0113	0.0005	−0.0127	−0.0654	0.0114	0.0019	0.0336^{**}	0.0222	−0.0142	−0.0630	-0.0426^{**}
	(0.0348)	(0.0355)	(0.0302)	(0.0142)	(0.0436)	(0.0426)	(0.0460)	(0.0169)	(0.0493)	(0.0442)	(0.0421)	(0.0193)
BGR alpha	−0.0226	$-0.0327^{*,m}$	$-0.0556^{***,m}$	−0.0165	$-0.0902^{***,m}$	$-0.0316^{*,m}$	$-0.0392^{*,m}$	0.0255^{*}	−0.0183	$-0.0525^{***,m}$	$-0.0926^{***,m}$	$-0.0371^{**,m}$
	(0.0183)	(0.0176)	(0.0161)	(0.0138)	(0.0211)	(0.0162)	(0.0215)	(0.0154)	(0.0220)	(0.0180)	(0.0216)	(0.0159)
FFFM alpha	−0.0204	$-0.0354^{**,m}$	$-0.0557^{***,m}$	−0.0177	$-0.0933^{***,m}$	$-0.0313^{**,m}$	-0.0361^{*}	0.0286^{*}	−0.0130	$-0.0569^{***,m}$	$-0.0938^{***,m}$	-0.0404^{**}
	(0.0179)	(0.0174)	(0.0162)	(0.0137)	(0.0207)	(0.0158)	(0.0211)	(0.0150)	(0.0222)	(0.0186)	(0.0214)	(0.0158)

Table 4: **Portfolio Sorts (continued)**

Panel B. Downside Beta and Idiosyncratic Volatility

	DownBeta				$IdioVol^{FF3}$				$IdioVol^{BGR}$			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0559**	0.0468**	0.0285	−0.0137	0.0450**	0.0298	0.0496*	0.0023	0.0358	0.0386	0.0529*	0.0085
	(0.0232)	(0.0231)	(0.0280)	(0.0136)	(0.0215)	(0.0248)	(0.0293)	(0.0146)	(0.0234)	(0.0254)	(0.0275)	(0.0135)
CAPM alpha	0.0498**	0.0396*	0.0154	−0.0172	0.0383*	0.0189	0.0388	0.0003	0.0296	0.0270	0.0435	0.0069
	(0.0241)	(0.0240)	(0.0294)	(0.0138)	(0.0225)	(0.0263)	(0.0309)	(0.0154)	(0.0248)	(0.0263)	(0.0288)	(0.0140)
3-factor alpha	0.0390	0.0356	0.0111	−0.0139	0.0347	0.0130	0.0311	−0.0018	0.0235	0.0207	0.0394	0.0080
	(0.0241)	(0.0240)	(0.0288)	(0.0135)	(0.0226)	(0.0265)	(0.0293)	(0.0147)	(0.0250)	(0.0270)	(0.0274)	(0.0138)
4-factor alpha	0.0339	0.0389	0.0123	−0.0108	0.0344	0.0156	0.0294	−0.0025	0.0217	0.0183	0.0435	0.0109
	(0.0256)	(0.0257)	(0.0297)	(0.0142)	(0.0234)	(0.0274)	(0.0312)	(0.0153)	(0.0258)	(0.0280)	(0.0289)	(0.0139)
5-factor alpha	0.0499*	0.0403	0.0232	−0.0133	0.0388	0.0274	0.0398	0.0005	0.0317	0.0342	0.0415	0.0049
	(0.0271)	(0.0263)	(0.0319)	(0.0153)	(0.0254)	(0.0293)	(0.0316)	(0.0155)	(0.0269)	(0.0299)	(0.0289)	(0.0136)
BGR alpha	−0.0147	−0.0153	$-0.0450^{**,m}$	−0.0152	0.0020	$-0.0354^{**,m}$	$-0.0423^{**,m}$	−0.0222	−0.0163	$-0.0349^{**,m}$	−0.0236	−0.0036
	(0.0152)	(0.0129)	(0.0176)	(0.0138)	(0.0137)	(0.0144)	(0.0178)	(0.0138)	(0.0142)	(0.0141)	(0.0177)	(0.0135)
FFFM alpha	−0.0357*	$-0.0327^{**,m}$	$-0.0432^{**,m}$	−0.0038	−0.0229	$-0.0377^{**,m}$	$-0.0532^{***,m}$	−0.0151	−0.0252	$-0.0379^{**,m}$	$-0.0495^{**,m}$	−0.0121
	(0.0183)	(0.0165)	(0.0218)	(0.0160)	(0.0162)	(0.0189)	(0.0205)	(0.0156)	(0.0195)	(0.0164)	(0.0201)	(0.0166)

Panel C. Momentum and Reversal

	Momentum				*3Y Reversal*				*5Y Reversal*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	−0.0251	0.0333	$0.1237^{***,m}$	$0.0744^{***,m}$	0.0159	0.0509**	0.0631**	0.0236*	0.0299	0.0293	0.0751**	0.0226
	(0.0223)	(0.0241)	(0.0278)	(0.0129)	(0.0221)	(0.0246)	(0.0306)	(0.0139)	(0.0269)	(0.0230)	(0.0311)	(0.0150)
CAPM alpha	−0.0352	0.0236	$0.1169^{***,m}$	$0.0760^{***,m}$	0.0046	0.0410	0.0575*	0.0265*	0.0195	0.0222	0.0688**	0.0247*
	(0.0226)	(0.0251)	(0.0296)	(0.0129)	(0.0223)	(0.0257)	(0.0333)	(0.0142)	(0.0275)	(0.0238)	(0.0331)	(0.0150)
3-factor alpha	−0.0415*	0.0189	$0.1082^{***,m}$	$0.0748^{***,m}$	−0.0005	0.0350	0.0493	0.0249*	0.0155	0.0146	0.0588*	0.0216
	(0.0226)	(0.0251)	(0.0292)	(0.0131)	(0.0224)	(0.0263)	(0.0320)	(0.0144)	(0.0274)	(0.0235)	(0.0328)	(0.0154)
4-factor alpha	−0.0299	0.0182	$0.0964^{***,m}$	$0.0632^{***,m}$	0.0051	0.0364	0.0396	0.0173	0.0197	0.0175	0.0501	0.0152
	(0.0231)	(0.0276)	(0.0297)	(0.0132)	(0.0235)	(0.0277)	(0.0322)	(0.0148)	(0.0289)	(0.0247)	(0.0329)	(0.0157)
5-factor alpha	−0.0301	0.0230	$0.1202^{***,m}$	$0.0751^{***,m}$	0.0042	0.0438	0.0617*	0.0287*	0.0196	0.0203	0.0769**	0.0287*
	(0.0249)	(0.0272)	(0.0323)	(0.0140)	(0.0237)	(0.0281)	(0.0339)	(0.0147)	(0.0289)	(0.0254)	(0.0339)	(0.0153)
BGR alpha	$-0.0693^{***,m}$	−0.0241	0.0209	$0.0451^{***,m}$	0.0024	−0.0156	$-0.0651^{***,m}$	$-0.0337^{***,m}$	0.0111	$-0.0388^{***,m}$	$-0.0509^{***,m}$	$-0.0310^{**,m}$
	(0.0136)	(0.0153)	(0.0152)	(0.0121)	(0.0139)	(0.0140)	(0.0162)	(0.0113)	(0.0169)	(0.0136)	(0.0168)	(0.0134)
FFFM alpha	$-0.0642^{***,m}$	$-0.0500^{***,m}$	0.0038	0.0340***	−0.0172	−0.0281	$-0.0720^{***,m}$	−0.0274**	−0.0246	$-0.0342^{**,m}$	$-0.0537^{***,m}$	−0.0145
	(0.0163)	(0.0188)	(0.0167)	(0.0128)	(0.0167)	(0.0184)	(0.0185)	(0.0134)	(0.0189)	(0.0153)	(0.0191)	(0.0152)

Table 4: **Portfolio Sorts (continued 2)**

Panel D. MAX, Value, and VoV

	MAX				*Value*				*VoV*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0538^{**}	0.0264	0.0512^{*}	−0.0013	0.0520	0.0253	0.0608^{**}	0.0044	0.0096	0.0189	−0.0448	-0.0272^{**}
	(0.0216)	(0.0234)	(0.0282)	(0.0130)	(0.0338)	(0.0237)	(0.0250)	(0.0140)	(0.0307)	(0.0303)	(0.0299)	(0.0121)
CAPM alpha	0.0475^{**}	0.0188	0.0389	−0.0043	0.0456	0.0183	0.0517^{**}	0.0031	−0.0068	0.0013	-0.0637^{**}	-0.0285^{**}
	(0.0227)	(0.0252)	(0.0288)	(0.0132)	(0.0354)	(0.0244)	(0.0261)	(0.0139)	(0.0311)	(0.0301)	(0.0294)	(0.0122)
3-factor alpha	0.0435^{*}	0.0092	0.0335	−0.0050	0.0358	0.0123	0.0469^{*}	0.0055	−0.0091	−0.0051	-0.0651^{**}	$-0.0280^{**,m}$
	(0.0229)	(0.0255)	(0.0274)	(0.0126)	(0.0349)	(0.0246)	(0.0253)	(0.0141)	(0.0310)	(0.0293)	(0.0294)	(0.0123)
4-factor alpha	0.0451^{*}	0.0075	0.0323	−0.0064	0.0231	0.0152	0.0562^{**}	0.0165	−0.0093	−0.0056	-0.0628^{**}	-0.0268^{**}
	(0.0234)	(0.0251)	(0.0303)	(0.0130)	(0.0355)	(0.0258)	(0.0269)	(0.0149)	(0.0313)	(0.0297)	(0.0297)	(0.0127)
5-factor alpha	0.0507^{**}	0.0246	0.0390	−0.0058	0.0478	0.0216	0.0548^{**}	0.0035	−0.0085	0.0020	-0.0750^{**}	$-0.0333^{**,m}$
	(0.0258)	(0.0280)	(0.0302)	(0.0136)	(0.0365)	(0.0264)	(0.0267)	(0.0143)	(0.0326)	(0.0302)	(0.0334)	(0.0130)
BGR alpha	−0.0018	$-0.0453^{***,m}$	$-0.0286^{*,m}$	−0.0134	$-0.0683^{***,m}$	$-0.0397^{***,m}$	$0.0309^{**,m}$	$0.0496^{***,m}$	-0.0328^{*}	−0.0284	$-0.0956^{***,m}$	$-0.0314^{***,m}$
	(0.0123)	(0.0130)	(0.0159)	(0.0117)	(0.0174)	(0.0146)	(0.0156)	(0.0121)	(0.0192)	(0.0206)	(0.0172)	(0.0119)
FFFM alpha	−0.0092	$-0.0646^{***,m}$	$-0.0383^{**,m}$	−0.0145	$-0.0715^{***,m}$	-0.0279^{*}	−0.0132	0.0292^{**}	-0.0328^{*}	−0.0293	$-0.0970^{***,m}$	-0.0321^{***}
	(0.0155)	(0.0159)	(0.0184)	(0.0135)	(0.0201)	(0.0168)	(0.0148)	(0.0124)	(0.0190)	(0.0206)	(0.0172)	(0.0117)

Panel E. Trading Frictions and Co-Moments

	ILLIQ				*CoSkew*				*CoKurt*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0141	−0.0129	−0.0007	−0.0074	0.0307	0.0345	0.0647^{**}	0.0170	0.0592^{**}	0.0449^{*}	0.0292	−0.0150
	(0.0318)	(0.0227)	(0.0343)	(0.0169)	(0.0267)	(0.0220)	(0.0270)	(0.0138)	(0.0237)	(0.0248)	(0.0274)	(0.0137)
CAPM alpha	−0.0032	−0.0259	−0.0218	−0.0093	0.0229	0.0258	0.0551^{*}	0.0161	0.0493^{**}	0.0377	0.0198	−0.0148
	(0.0335)	(0.0239)	(0.0320)	(0.0169)	(0.0278)	(0.0225)	(0.0288)	(0.0142)	(0.0249)	(0.0262)	(0.0282)	(0.0137)
3-factor alpha	−0.0117	−0.0303	−0.0208	−0.0046	0.0185	0.0196	0.0459^{*}	0.0137	0.0436^{*}	0.0318	0.0122	−0.0157
	(0.0338)	(0.0244)	(0.0311)	(0.0173)	(0.0272)	(0.0225)	(0.0278)	(0.0136)	(0.0245)	(0.0262)	(0.0279)	(0.0134)
4-factor alpha	−0.0085	−0.0292	−0.0120	−0.0018	0.0220	0.0183	0.0424	0.0102	0.0397	0.0299	0.0166	−0.0116
	(0.0339)	(0.0251)	(0.0320)	(0.0178)	(0.0292)	(0.0240)	(0.0290)	(0.0144)	(0.0266)	(0.0262)	(0.0293)	(0.0143)
5-factor alpha	−0.0019	−0.0290	−0.0121	−0.0051	0.0287	0.0246	0.0590^{*}	0.0151	0.0575^{**}	0.0412	0.0166	−0.0204
	(0.0344)	(0.0256)	(0.0322)	(0.0174)	(0.0303)	(0.0249)	(0.0309)	(0.0150)	(0.0266)	(0.0309)	(0.0294)	(0.0137)
BGR alpha	-0.0381^{*}	$-0.0474^{***,m}$	−0.0364	0.0009	$-0.0477^{***,m}$	$-0.0256^{**,m}$	−0.0018	0.0229^{*}	−0.0111	-0.0208^{*}	$-0.0421^{**,m}$	−0.0155
	(0.0197)	(0.0155)	(0.0249)	(0.0179)	(0.0154)	(0.0129)	(0.0171)	(0.0133)	(0.0170)	(0.0126)	(0.0185)	(0.0152)
FFFM alpha	$-0.0432^{**,m}$	$-0.0363^{**,m}$	$-0.0440^{**,m}$	−0.0004	$-0.0430^{**,m}$	$-0.0375^{**,m}$	−0.0309	0.0061	−0.0175	$-0.0467^{***,m}$	$-0.0460^{**,m}$	−0.0142
	(0.0199)	(0.0170)	(0.0223)	(0.0162)	(0.0180)	(0.0174)	(0.0224)	(0.0163)	(0.0168)	(0.0162)	(0.0222)	(0.0155)

Table 4: **Portfolio Sorts (continued 3)**

Panel F. Historical Moments

	HistVar				*HistSkew*				*HistKurt*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0460**	0.0300	0.0560*	0.0050	0.0826***,m	0.0353	0.0127	−0.0350***,m	0.0144	0.0496*	0.0656***,m	0.0256**
	(0.0215)	(0.0246)	(0.0298)	(0.0147)	(0.0227)	(0.0310)	(0.0228)	(0.0124)	(0.0279)	(0.0257)	(0.0203)	(0.0129)
CAPM alpha	0.0412*	0.0189	0.0454	0.0021	0.0782***,m	0.0245	0.0015	−0.0384***,m	0.0017	0.0399	0.0616***,m	0.0300**
	(0.0225)	(0.0260)	(0.0312)	(0.0154)	(0.0243)	(0.0327)	(0.0224)	(0.0121)	(0.0295)	(0.0265)	(0.0213)	(0.0132)
3-factor alpha	0.0373*	0.0124	0.0361	−0.0006	0.0718***,m	0.0174	−0.0045	−0.0382***,m	−0.0059	0.0318	0.0578***,m	0.0318**,m
	(0.0226)	(0.0261)	(0.0296)	(0.0146)	(0.0237)	(0.0330)	(0.0223)	(0.0125)	(0.0297)	(0.0262)	(0.0204)	(0.0133)
4-factor alpha	0.0358	0.0171	0.0323	−0.0018	0.0759***,m	0.0104	−0.0036	−0.0397***,m	−0.0168	0.0375	0.0627***,m	0.0398***,m
	(0.0234)	(0.0270)	(0.0313)	(0.0151)	(0.0240)	(0.0340)	(0.0241)	(0.0125)	(0.0296)	(0.0290)	(0.0215)	(0.0131)
5-factor alpha	0.0417*	0.0272	0.0443	0.0013	0.0849***,m	0.0285	−0.0011	−0.0430***,m	0.0066	0.0442	0.0611***,m	0.0273*
	(0.0252)	(0.0294)	(0.0316)	(0.0154)	(0.0252)	(0.0377)	(0.0242)	(0.0131)	(0.0334)	(0.0286)	(0.0222)	(0.0147)
BGR alpha	0.0031	−0.0358**,m	−0.0415**,m	−0.0223	−0.0053	−0.0445**,m	−0.0254*,m	−0.0100	−0.0709***,m	−0.0240*	0.0193	0.0451***,m
	(0.0139)	(0.0141)	(0.0176)	(0.0136)	(0.0131)	(0.0174)	(0.0130)	(0.0100)	(0.0149)	(0.0143)	(0.0145)	(0.0122)
FFFM alpha	−0.0229	−0.0378**,m	−0.0523**,m	−0.0147	−0.0102	−0.0510**,m	−0.0512***,m	−0.0205*	−0.0653***,m	−0.0390**,m	−0.0103	0.0275**
	(0.0165)	(0.0174)	(0.0211)	(0.0155)	(0.0143)	(0.0211)	(0.0145)	(0.0107)	(0.0171)	(0.0185)	(0.0164)	(0.0131)

Panel G. Risk-Neutral Moments

	RNVar				*RNSkew*				*RNExKurt*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0087	−0.0069	−0.0222	−0.0154	−0.0083	−0.0070	−0.0076	0.0003	−0.0123	−0.0034	−0.0062	0.0031
	(0.0281)	(0.0284)	(0.0345)	(0.0136)	(0.0265)	(0.0347)	(0.0324)	(0.0154)	(0.0357)	(0.0276)	(0.0312)	(0.0171)
CAPM alpha	−0.0030	−0.0299	−0.0394	−0.0182	−0.0204	−0.0265	−0.0278	−0.0037	−0.0264	−0.0227	−0.0251	0.0007
	(0.0281)	(0.0281)	(0.0359)	(0.0139)	(0.0304)	(0.0352)	(0.0302)	(0.0158)	(0.0393)	(0.0265)	(0.0305)	(0.0182)
3-factor alpha	−0.0082	−0.0316	−0.0425	−0.0171	−0.0251	−0.0314	−0.0280	−0.0014	−0.0321	−0.0248	−0.0269	0.0026
	(0.0270)	(0.0284)	(0.0352)	(0.0137)	(0.0292)	(0.0342)	(0.0308)	(0.0159)	(0.0384)	(0.0263)	(0.0304)	(0.0178)
4-factor alpha	−0.0134	−0.0248	−0.0409	−0.0138	−0.0224	−0.0328	−0.0247	−0.0011	−0.0340	−0.0216	−0.0241	0.0049
	(0.0278)	(0.0299)	(0.0358)	(0.0139)	(0.0300)	(0.0343)	(0.0308)	(0.0162)	(0.0400)	(0.0266)	(0.0302)	(0.0183)
5-factor alpha	−0.0115	−0.0360	−0.0374	−0.0129	−0.0230	−0.0279	−0.0364	−0.0067	−0.0255	−0.0304	−0.0300	−0.0023
	(0.0275)	(0.0309)	(0.0371)	(0.0142)	(0.0299)	(0.0367)	(0.0333)	(0.0164)	(0.0394)	(0.0287)	(0.0326)	(0.0179)
BGR alpha	−0.0161	−0.0543***,m	−0.0885***,m	−0.0362***,m	−0.0542**,m	−0.0598***,m	−0.0452**,m	0.0045	−0.0730***,m	−0.0447***,m	−0.0424**,m	0.0153
	(0.0206)	(0.0181)	(0.0167)	(0.0131)	(0.0224)	(0.0203)	(0.0201)	(0.0159)	(0.0247)	(0.0171)	(0.0195)	(0.0160)
FFFM alpha	−0.0156	−0.0572***,m	−0.0870***,m	−0.0357***	−0.0540**,m	−0.0594***,m	−0.0471**,m	0.0034	−0.0705***,m	−0.0458***,m	−0.0448**,m	0.0129
	(0.0201)	(0.0179)	(0.0163)	(0.0129)	(0.0226)	(0.0198)	(0.0205)	(0.0163)	(0.0240)	(0.0168)	(0.0195)	(0.0157)

Table 5: Augmented Factor Models

*This table presents the results for portfolio sorts. At the end of each month, we sort the commodities into 3 portfolios according to the variable indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the respective variable. We rebalance the portfolios each month and obtain fully-collateralized returns. The hedge portfolio P3–P1 simultaneously goes long portfolio P3 and short portfolio P1. We report the (annualized) alpha estimates based on the Fama & French (2015) 5-factor model and the FFFM model suggested by Fernandez-Perez et al. (2018), augmented by the long–short anomaly factor denoted in the first column ("Raw" refers to the unaugmented factor model, which is presented for comparison). In parentheses, we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%.*

	$AggVol^{VIX}$	$AggVol$	$AggJump$	$DownBeta$	$IdioVol^{FF3}$	$IdioVol^{BGR}$	$Momentum$	$3YReversal$	$5YReversal$	MAX	$Value$
5-factor model augmented by...											
Raw	−0.0127	0.0336**	−0.0426**	−0.0133	0.0005	0.0049	0.0751***,m	0.0287*	0.0287*	−0.0058	0.0035
	(0.0142)	(0.0169)	(0.0193)	(0.0153)	(0.0155)	(0.0136)	(0.0140)	(0.0147)	(0.0153)	(0.0136)	(0.0143)
$AggJump$	0.0066	0.0061		−0.0081	−0.0104	−0.0165	0.0496**	0.0270	0.0285	−0.0254	−0.0017
	(0.0164)	(0.0110)		(0.0182)	(0.0211)	(0.0194)	(0.0224)	(0.0183)	(0.0200)	(0.0171)	(0.0201)
$Momentum$	−0.0155	0.0247	−0.0368*	−0.0133	−0.0108	−0.0011		−0.0093	−0.0008	−0.0136	0.0373***,m
	(0.0136)	(0.0171)	(0.0203)	(0.0159)	(0.0162)	(0.0133)		(0.0127)	(0.0140)	(0.0145)	(0.0124)
VoV	−0.0028	0.0313*	−0.0428**	−0.0030	0.0115	0.0005	0.0678***,m	0.0306*	0.0336*	−0.0024	−0.0068
	(0.0153)	(0.0168)	(0.0192)	(0.0178)	(0.0176)	(0.0162)	(0.0187)	(0.0175)	(0.0193)	(0.0159)	(0.0160)
$HistSkew$	−0.0122	0.0292	−0.0421**	−0.0164	0.0034	0.0031	0.0666***,m	0.0117	0.0134	0.0078	0.0121
	(0.0143)	(0.0177)	(0.0198)	(0.0158)	(0.0161)	(0.0140)	(0.0135)	(0.0138)	(0.0149)	(0.0140)	(0.0140)
FFFM model augmented by...											
Raw	−0.0177	0.0286*	−0.0404**	−0.0038	−0.0151	−0.0121		−0.0274**	−0.0145	−0.0145	0.0292**
	(0.0137)	(0.0150)	(0.0158)	(0.0160)	(0.0156)	(0.0166)		(0.0134)	(0.0152)	(0.0135)	(0.0124)
$AggJump$	−0.0058	0.0034		−0.0246	−0.0132	−0.0165		−0.0152	−0.0067	−0.0188	0.0279*
	(0.0163)	(0.0097)		(0.0176)	(0.0196)	(0.0210)		(0.0155)	(0.0163)	(0.0158)	(0.0168)
VoV	−0.0106	0.0266*	−0.0407**	−0.0066	−0.0072	−0.0120		−0.0219	−0.0109	−0.0061	0.0247*
	(0.0141)	(0.0152)	(0.0160)	(0.0163)	(0.0162)	(0.0176)		(0.0147)	(0.0163)	(0.0145)	(0.0134)
$HistSkew$	−0.0171	0.0282*	−0.0415***,m	−0.0030	−0.0135	−0.0126		−0.0305**	−0.0158	−0.0089	0.0283**
	(0.0140)	(0.0156)	(0.0156)	(0.0164)	(0.0159)	(0.0163)		(0.0134)	(0.0153)	(0.0139)	(0.0124)

Table 5: **Augmented Factor Models (continued)**

	VoV	$ILLIQ$	$CoSkew$	$CoKurt$	$HistVar$	$HistSkew$	$HistKurt$	$RNVar$	$RNSkew$	$RNExKurt$
5-factor model augmented by...										
Raw	$-0.0333^{**,m}$	-0.0051	0.0151	-0.0204	0.0013	$-0.0430^{***,m}$	0.0273^{*}	-0.0129	-0.0067	-0.0023
	(0.0130)	(0.0174)	(0.0150)	(0.0137)	(0.0154)	(0.0131)	(0.0147)	(0.0142)	(0.0164)	(0.0179)
$AggJump$	-0.0300^{**}	0.0319^{*}	-0.0099	-0.0238	-0.0107	$-0.0567^{***,m}$	-0.0022	-0.0188	0.0105	0.0204
	(0.0147)	(0.0192)	(0.0215)	(0.0154)	(0.0200)	(0.0177)	(0.0175)	(0.0161)	(0.0197)	(0.0201)
$Momentum$	$-0.0339^{**,m}$	-0.0039	0.0207	-0.0149	-0.0118	$-0.0322^{***,m}$	$0.0421^{***,m}$	-0.0197	-0.0013	0.0088
	(0.0134)	(0.0170)	(0.0148)	(0.0145)	(0.0160)	(0.0124)	(0.0134)	(0.0143)	(0.0165)	(0.0164)
VoV		0.0023	-0.0205	-0.0165	0.0129	$-0.0553^{***,m}$	0.0148	-0.0120	-0.0009	0.0028
		(0.0173)	(0.0196)	(0.0141)	(0.0173)	(0.0158)	(0.0147)	(0.0143)	(0.0159)	(0.0176)
$HistSkew$	-0.0323^{**}	-0.0079	0.0253	-0.0219	0.0042		0.0242	-0.0198	0.0092	0.0049
	(0.0134)	(0.0187)	(0.0156)	(0.0143)	(0.0162)		(0.0150)	(0.0154)	(0.0160)	(0.0168)
FFFM model augmented by...										
Raw	-0.0321^{***}	-0.0004	0.0061	-0.0142	-0.0147	-0.0205^{*}	0.0275^{**}	-0.0357^{***}	0.0034	0.0129
	(0.0117)	(0.0162)	(0.0163)	(0.0155)	(0.0155)	(0.0107)	(0.0131)	(0.0129)	(0.0163)	(0.0157)
$AggJump$	-0.0314^{**}	0.0222	0.0101	-0.0327^{**}	-0.0145	-0.0219^{*}	0.0090	-0.0353^{**}	0.0182	0.0273
	(0.0134)	(0.0201)	(0.0181)	(0.0165)	(0.0188)	(0.0131)	(0.0149)	(0.0146)	(0.0211)	(0.0180)
VoV		-0.0048	0.0061	-0.0171	-0.0064	-0.0160	0.0263^{**}	-0.0376^{***}	0.0077	0.0177
		(0.0168)	(0.0166)	(0.0156)	(0.0160)	(0.0108)	(0.0132)	(0.0135)	(0.0156)	(0.0153)
$HistSkew$	$-0.0307^{***,m}$	-0.0059	0.0086	-0.0149	-0.0128		0.0278^{**}	$-0.0378^{***,m}$	0.0082	0.0137
	(0.0117)	(0.0154)	(0.0164)	(0.0160)	(0.0160)		(0.0130)	(0.0132)	(0.0161)	(0.0153)

Anomalies in Commodity Futures Markets

Online Appendix

JEL classification: G10, G11, G17

Keywords: Anomalies, commodity futures markets

Table A1: Univariate Cross-Sectional Regressions

*This table reports the average coefficient estimates from monthly Fama & MacBeth (1973) cross-sectional regressions. Each month, we regress the commodity futures returns on a constant and the lagged value of the variable [name in column] (denoted by Char). We run the regression only in months when at least 10 commodities are available. In parentheses, we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%. "Adj. R^2" denotes the average adjusted R^2 of the regressions.*

	$AggVol^{VIX}$	$AggVol$	$AggJump$	$DownBeta$	$IdioVol^{FF3}$	$IdioVol^{BGR}$	$Momentum$	$3YReversal$	$5YReversal$	MAX	$Value$
Constant	0.0217	0.0122	0.0086	0.0480**	0.0345	0.0317	0.0303	0.0404*	0.0361	0.0558	−0.0675
	(0.0259)	(0.0388)	(0.0401)	(0.0215)	(0.0448)	(0.0509)	(0.0194)	(0.0230)	(0.0252)	(0.0415)	(0.1319)
Char	−0.1854	$0.7318^{***,m}$	−1.2615**	0.0005	0.0268	−0.0458	$0.2439^{***,m}$	0.0255	0.1314	−0.2089	0.1204
	(0.1769)	(0.2464)	(0.5710)	(0.0534)	(0.7154)	(0.9111)	(0.0446)	(0.0881)	(0.1092)	(0.8439)	(0.1334)
Adj. R^2	0.0285	0.0313	0.0284	0.0504	0.0585	0.0438	0.0648	0.0561	0.0456	0.0562	0.0421

	VoV	$ILLIQ$	$CoSkew$	$CoKurt$	$HistVar$	$HistSkew$	$HistKurt$	$RNVar$	$RNSkew$	$RNExKurt$
Constant	0.0464	0.0044	0.0498**	0.0495**	0.0384	0.0435*	0.0562*	0.0482	−0.0041	−0.0147
	(0.0403)	(0.0240)	(0.0227)	(0.0219)	(0.0276)	(0.0227)	(0.0306)	(0.0324)	(0.0271)	(0.0318)
Char	−0.3895**	8.7910	−0.0015	0.0001	0.0825	$-0.0559^{***,m}$	−0.0015	−0.5399*	0.0100	0.0010
	(0.1965)	(26.070)	(0.0034)	(0.0001)	(0.2724)	(0.0189)	(0.0030)	(0.3118)	(0.0229)	(0.0072)
Adj. R^2	0.0164	0.0321	0.0430	0.0512	0.0727	0.0150	0.0156	0.0753	0.0149	−0.0082

Table A2: Multivariate Cross-Sectional Regressions

This table reports the average coefficient estimates from monthly Fama & MacBeth (1973) cross-sectional regressions. Each month, we regress the commodity futures returns on a constant, the lagged value of the variable [name in column] (denoted by Char), the lagged average 12-month roll yield, and the lagged average 12-months' past performance. We run the regression only in months when at least 10 commodities are available. In parentheses, we present robust Newey & West (1987) standard errors using 6 lags. *, **, *and* *** *indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%. "Adj.* R^2*" denotes the average adjusted* R^2 *of the regressions.*

	$AggVol^{VIX}$	$AggVol$	$AggJump$	$DownBeta$	$IdioVol^{FF3}$	$IdioVol^{BGR}$	$Momentum$	$3YReversal$	$5YReversal$	MAX	$Value$
Constant	0.0253	0.0236	0.0170	0.0050	0.0407	0.0601	0.0175	0.0245	0.0118	0.0566	0.0198
	(0.0261)	(0.0391)	(0.0417)	(0.0349)	(0.0521)	(0.0581)	(0.0391)	(0.0402)	(0.0350)	(0.0453)	(0.1222)
Char	−0.1355	0.5537^{**}	-1.1126^{*}	0.0439	−0.7933	−1.0873	$0.2291^{***,m}$	−0.0490	0.1487	−1.2613	−0.0054
	(0.1386)	(0.2400)	(0.6455)	(0.0731)	(0.9928)	(1.1040)	(0.0741)	(0.1479)	(0.1562)	(0.9814)	(0.1115)
Roll yield	0.8515	0.7959	0.4282	0.2880	0.0957	0.3961	0.5960	0.7741	0.6665	−0.1214	0.6914
	(0.7862)	(0.8336)	(0.9136)	(0.9053)	(0.9683)	(0.9203)	(0.8687)	(1.0848)	(0.9235)	(1.0479)	(0.8449)
Momentum	0.2043^{***}	0.1874^{**}	0.2162^{***}	0.2226^{***}	0.2573^{***}	0.2295^{***}		0.2425^{***}	0.1810^{**}	0.2476^{***}	0.2176^{***}
	(0.0628)	(0.0774)	(0.0759)	(0.0793)	(0.0766)	(0.0758)		(0.0795)	(0.0821)	(0.0800)	(0.0817)
Adj. R^2	0.1104	0.1062	0.1062	0.1089	0.1173	0.1071	0.0786	0.1171	0.1152	0.1122	0.0928

	VoV	$ILLIQ$	$CoSkew$	$CoKurt$	$HistVar$	$HistSkew$	$HistKurt$	$RNVar$	$RNSkew$	$RNExKurt$
Constant	0.0375	0.0001	0.0016	0.0066	0.0239	0.0106	0.0438	0.0524	0.0227	−0.0079
	(0.0549)	(0.0382)	(0.0379)	(0.0363)	(0.0359)	(0.0392)	(0.0489)	(0.0391)	(0.0369)	(0.0420)
Char	−0.3301	36.243	−0.0098	0.0000	−0.3460	-0.0374^{*}	−0.0050	−0.5585	0.0382	0.0095
	(0.2890)	(29.243)	(0.0072)	(0.0002)	(0.3807)	(0.0209)	(0.0041)	(0.3582)	(0.0282)	(0.0084)
Roll yield	0.2362	0.4913	0.2422	0.3647	0.0582	−0.1914	0.2906	−0.1123	1.1865	0.8811
	(0.8632)	(0.8954)	(0.8240)	(0.9164)	(0.9586)	(0.9456)	(0.8773)	(0.9124)	(0.9119)	(0.9257)
Momentum	0.2034^{***}	0.1994^{**}	0.1808^{**}	0.2487^{***}	0.2598^{***}	0.2209^{***}	0.2450^{***}	0.2955^{***}	0.2224^{***}	0.2035^{**}
	(0.0774)	(0.0783)	(0.0779)	(0.0757)	(0.0804)	(0.0742)	(0.0733)	(0.0829)	(0.0756)	(0.0805)
Adj. R^2	0.0789	0.0858	0.1064	0.1115	0.1298	0.0867	0.0873	0.1310	0.0850	0.0652

Table A3: Portfolio Sorts – Different Numbers of Portfolios

*At the end of each month, we sort the commodities into 2, 3, 4, or 5 portfolios, respectively, according to the variable indicated in the first row. Portfolio P1 (P2, P3, P4, and P5, respectively) contains the commodities with the lowest (highest) magnitude of the respective variable. We rebalance the portfolios each month and obtain fully-collateralized returns. The hedge portfolios P2–P1, P3–P1, P4–P1, and P5–P1, respectively, simultaneously go long portfolio P2, P3, P4, and P5, respectively, and short portfolio P1. "Mean return" denotes the annualized average excess return on the respective portfolio. In addition, we report the (annualized) alpha estimates based on the Fama & French (2015) 5-factor model, and the BGR model suggested by Bakshi et al. (2019). In parentheses, we present robust Newey & West (1987) standard errors using 6 lags. *, **, *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%.*

Panel A. Aggregate Volatility and Jump

	$AggVol^{VIX}$				$AggVol$				$AggJump$			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	−0.0129	−0.0163	−0.0194	−0.0282	0.0253**	0.0356**	0.0554^{**,m}	0.0651^{**,m}	−0.0391^{***,m}	−0.0463^{***,m}	−0.0639^{***,m}	−0.0705^{***,m}
	(0.0110)	(0.0140)	(0.0158)	(0.0179)	(0.0125)	(0.0154)	(0.0216)	(0.0257)	(0.0132)	(0.0161)	(0.0215)	(0.0235)
5-factor alpha	−0.0119	−0.0127	−0.0218	−0.0295*	0.0241*	0.0336**	0.0512**	0.0599**	−0.0363**	−0.0426**	−0.0600**	−0.0680^{**,m}
	(0.0110)	(0.0142)	(0.0148)	(0.0169)	(0.0132)	(0.0169)	(0.0238)	(0.0271)	(0.0167)	(0.0193)	(0.0250)	(0.0276)
BGR alpha	−0.0140	−0.0165	−0.0229	−0.0336*	0.0163	0.0255*	0.0362*	0.0438*	−0.0344^{**,m}	−0.0371^{**,m}	−0.0558^{**,m}	−0.0622^{**,m}
	(0.0112)	(0.0138)	(0.0151)	(0.0176)	(0.0120)	(0.0154)	(0.0217)	(0.0246)	(0.0136)	(0.0159)	(0.0229)	(0.0256)

Panel B. Downside Beta and Idiosyncratic Volatility

	$DownBeta$				$IdioVol^{FF3}$				$IdioVol^{BGR}$			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	−0.0084	−0.0137	−0.0044	−0.0165	0.0034	0.0023	0.0013	0.0084	0.0075	0.0085	0.0047	0.0027
	(0.0104)	(0.0136)	(0.0179)	(0.0197)	(0.0114)	(0.0146)	(0.0173)	(0.0179)	(0.0094)	(0.0135)	(0.0168)	(0.0179)
5-factor alpha	−0.0124	−0.0133	−0.0036	−0.0205	0.0027	0.0005	−0.0007	−0.0005	0.0101	0.0049	0.0025	−0.0052
	(0.0119)	(0.0153)	(0.0193)	(0.0223)	(0.0116)	(0.0155)	(0.0182)	(0.0182)	(0.0099)	(0.0136)	(0.0169)	(0.0177)
BGR alpha	−0.0102	−0.0152	−0.0087	−0.0175	−0.0169	−0.0222	−0.0231	−0.0147	−0.0034	−0.0036	−0.0077	−0.0136
	(0.0103)	(0.0138)	(0.0176)	(0.0197)	(0.0104)	(0.0138)	(0.0171)	(0.0173)	(0.0098)	(0.0135)	(0.0163)	(0.0172)

Table A3: **Portfolio Sorts – Different Numbers of Portfolios (continued)**

Panel C. Momentum and Reversal

	Momentum				*3Y Reversal*				*5Y Reversal*			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	$0.0556^{***,m}$	$0.0744^{***,m}$	$0.0848^{***,m}$	$0.0982^{***,m}$	0.0123	0.0236^{*}	0.0222	−0.0086	0.0173	0.0226	0.0109	0.0242
	(0.0099)	(0.0129)	(0.0163)	(0.0179)	(0.0102)	(0.0139)	(0.0184)	(0.0204)	(0.0115)	(0.0150)	(0.0174)	(0.0218)
5-factor alpha	$0.0559^{***,m}$	$0.0751^{***,m}$	$0.0840^{***,m}$	$0.0911^{***,m}$	0.0148	0.0287^{*}	0.0222	−0.0135	0.0222^{*}	0.0287^{*}	0.0137	0.0267
	(0.0108)	(0.0140)	(0.0172)	(0.0205)	(0.0108)	(0.0147)	(0.0196)	(0.0232)	(0.0117)	(0.0153)	(0.0181)	(0.0220)
BGR alpha	$0.0341^{***,m}$	$0.0451^{***,m}$	$0.0499^{***,m}$	$0.0646^{***,m}$	$-0.0272^{***,m}$	$-0.0337^{***,m}$	$-0.0479^{***,m}$	$-0.0744^{***,m}$	$-0.0243^{**,m}$	$-0.0310^{**,m}$	$-0.0487^{***,m}$	$-0.0445^{**,m}$
	(0.0090)	(0.0121)	(0.0156)	(0.0168)	(0.0092)	(0.0113)	(0.0146)	(0.0178)	(0.0102)	(0.0134)	(0.0162)	(0.0195)

Panel D. MAX, Value, and VoV

	MAX				*Value*				*VoV*			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	−0.0034	−0.0013	0.0051	0.0005	0.0038	0.0044	0.0151	−0.0100	-0.0197^{*}	-0.0272^{**}	-0.0252^{*}	-0.0305^{*}
	(0.0101)	(0.0130)	(0.0157)	(0.0175)	(0.0107)	(0.0140)	(0.0167)	(0.0207)	(0.0109)	(0.0121)	(0.0137)	(0.0167)
5-factor alpha	−0.0091	−0.0058	0.0038	−0.0053	0.0040	0.0035	0.0173	−0.0085	-0.0285^{**}	$-0.0333^{**,m}$	-0.0273^{*}	-0.0389^{**}
	(0.0108)	(0.0136)	(0.0169)	(0.0185)	(0.0109)	(0.0143)	(0.0175)	(0.0219)	(0.0119)	(0.0130)	(0.0149)	(0.0181)
BGR alpha	−0.0138	−0.0134	−0.0053	−0.0118	$0.0348^{***,m}$	$0.0496^{***,m}$	$0.0665^{***,m}$	$0.0553^{***,m}$	$-0.0222^{**,m}$	$-0.0314^{***,m}$	$-0.0313^{**,m}$	$-0.0362^{**,m}$
	(0.0089)	(0.0117)	(0.0150)	(0.0158)	(0.0092)	(0.0121)	(0.0145)	(0.0167)	(0.0102)	(0.0119)	(0.0141)	(0.0168)

Panel E. Trading Frictions and Co-Moments

	ILLIQ				*CoSkew*				*CoKurt*			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	−0.0182	−0.0074	0.0039	0.0030	0.0039	0.0170	0.0170	0.0102	−0.0069	−0.0150	−0.0168	−0.0126
	(0.0129)	(0.0169)	(0.0184)	(0.0225)	(0.0104)	(0.0138)	(0.0165)	(0.0200)	(0.0107)	(0.0137)	(0.0155)	(0.0192)
5-factor alpha	−0.0144	−0.0051	0.0055	0.0128	0.0031	0.0151	0.0133	0.0102	−0.0095	−0.0204	−0.0130	−0.0225
	(0.0131)	(0.0174)	(0.0185)	(0.0226)	(0.0112)	(0.0150)	(0.0178)	(0.0230)	(0.0112)	(0.0137)	(0.0161)	(0.0198)
BGR alpha	−0.0114	0.0009	0.0090	0.0032	0.0096	0.0229^{*}	0.0262^{*}	0.0242	−0.0055	−0.0155	−0.0171	−0.0136
	(0.0129)	(0.0179)	(0.0193)	(0.0213)	(0.0105)	(0.0133)	(0.0155)	(0.0198)	(0.0115)	(0.0152)	(0.0168)	(0.0200)

Table A3: **Portfolio Sorts – Different Numbers of Portfolios (continued 2)**

Panel F. Historical Moments

	HistVar				*HistSkew*				*HistKurt*			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	0.0045	0.0050	−0.0013	0.0071	$-0.0288^{***,m}$	$-0.0350^{***,m}$	$-0.0513^{***,m}$	$-0.0524^{***,m}$	0.0174	0.0256^{**}	0.0099	0.0113
	(0.0114)	(0.0147)	(0.0175)	(0.0179)	(0.0088)	(0.0124)	(0.0156)	(0.0171)	(0.0107)	(0.0129)	(0.0153)	(0.0157)
5-factor alpha	0.0022	0.0013	−0.0046	−0.0021	$-0.0359^{***,m}$	$-0.0430^{***,m}$	$-0.0552^{***,m}$	$-0.0594^{***,m}$	0.0208^{*}	0.0273^{*}	0.0133	0.0157
	(0.0116)	(0.0154)	(0.0182)	(0.0183)	(0.0093)	(0.0131)	(0.0163)	(0.0177)	(0.0125)	(0.0147)	(0.0177)	(0.0182)
BGR alpha	−0.0158	−0.0223	-0.0296^{*}	−0.0193	−0.0107	−0.0100	−0.0137	−0.0193	$0.0330^{***,m}$	$0.0451^{***,m}$	$0.0346^{**,m}$	$0.0376^{***,m}$
	(0.0102)	(0.0136)	(0.0168)	(0.0172)	(0.0074)	(0.0100)	(0.0115)	(0.0128)	(0.0099)	(0.0122)	(0.0137)	(0.0144)

Panel G. Risk-Neutral Moments

	RNVar				*RNSkew*				*RNExKurt*			
Portfolio	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1	P2 – P1	P3 – P1	P4 – P1	P5 – P1
Mean return	−0.0163	−0.0154	−0.0201	$-0.0565^{**,m}$	−0.0064	0.0003	0.0067	−0.0193	−0.0004	0.0031	0.0122	0.0179
	(0.0113)	(0.0136)	(0.0187)	(0.0229)	(0.0143)	(0.0154)	(0.0167)	(0.0226)	(0.0142)	(0.0171)	(0.0185)	(0.0276)
5-factor alpha	−0.0145	−0.0129	−0.0213	$-0.0615^{**,m}$	−0.0164	−0.0067	−0.0017	−0.0180	−0.0052	−0.0023	0.0118	0.0188
	(0.0123)	(0.0142)	(0.0197)	(0.0247)	(0.0154)	(0.0164)	(0.0181)	(0.0252)	(0.0146)	(0.0179)	(0.0201)	(0.0294)
BGR alpha	$-0.0315^{***,m}$	$-0.0362^{***,m}$	$-0.0462^{***,m}$	$-0.0841^{***,m}$	−0.0054	0.0045	0.0096	−0.0141	0.0092	0.0153	0.0261	0.0296
	(0.0111)	(0.0131)	(0.0176)	(0.0208)	(0.0138)	(0.0159)	(0.0164)	(0.0220)	(0.0142)	(0.0160)	(0.0169)	(0.0255)

Table A4: Portfolio Sorts – Subperiods

This table presents the results for portfolio sorts for different subperiods. That is, we report the results for the full sample period as well as the subperiods from August 1959 until February 1986, from March 1986 until November 2000, and from December 2000 until December 2015. At the end of each month, we sort the commodities into 3 portfolios according to the variable indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the respective variable. We rebalance the portfolios each month and obtain fully-collateralized returns. The hedge portfolio P3–P1 simultaneously goes long portfolio P3 and short portfolio P1. For each subperiod, we require at least 5 years of available data in order to report the results. "Mean return" denotes the annualized average excess return on the respective portfolio. In addition, we report the (annualized) alpha estimates based on the Fama & French (2015) 5-factor model, and the BGR model suggested by Bakshi et al. (2019). In parentheses, we present robust Newey & West (1987) standard errors using 6 lags. *, **, *** *indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%.*

Panel A. Aggregate Volatility and Jump

	$AggVol^{VIX}$				$AggVol$				$AggJump$			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	−0.0163		−0.0068	−0.0249	0.0356**			0.0227	−0.0463***,m			−0.0326*
	(0.0140)		(0.0230)	(0.0162)	(0.0154)			(0.0172)	(0.0161)			(0.0179)
5-factor alpha	−0.0127		−0.0118	−0.0164	0.0336**			0.0135	−0.0426**			−0.0167
	(0.0142)		(0.0224)	(0.0159)	(0.0169)			(0.0176)	(0.0193)			(0.0184)
BGR alpha	−0.0165		−0.0164	−0.0209	0.0255*			0.0127	−0.0371**,m			−0.0175
	(0.0138)		(0.0205)	(0.0169)	(0.0154)			(0.0164)	(0.0159)			(0.0158)

Table A4: **Portfolio Sorts – Subperiods (continued)**

Panel B. Downside Beta and Idiosyncratic Volatility

	DownBeta				*IdioVol*^{FF3}				*IdioVol*^{BGR}			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	−0.0137	−0.0383*	0.0190	−0.0040	0.0023	0.0039	0.0368*	−0.0339	0.0085	0.0235	0.0274	−0.0339
	(0.0136)	(0.0228)	(0.0235)	(0.0200)	(0.0146)	(0.0260)	(0.0208)	(0.0207)	(0.0135)	(0.0234)	(0.0184)	(0.0217)
5-factor alpha	−0.0133	−0.0278	0.0244	−0.0096	0.0005	0.0063	0.0360	−0.0315	0.0049	0.0283	0.0237	−0.0299
	(0.0153)	(0.0270)	(0.0276)	(0.0207)	(0.0155)	(0.0272)	(0.0228)	(0.0223)	(0.0136)	(0.0238)	(0.0186)	(0.0217)
BGR alpha	−0.0152	−0.0304	0.0251	−0.0274	−0.0222	−0.0304	0.0040	−0.0417**	−0.0036	0.0054	0.0112	−0.0355
	(0.0138)	(0.0242)	(0.0242)	(0.0190)	(0.0138)	(0.0227)	(0.0196)	(0.0204)	(0.0135)	(0.0217)	(0.0179)	(0.0242)

Panel C. Momentum and Reversal

	Momentum				*3YReversal*				*5YReversal*			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	0.0744^{***,m}	0.0843^{***,m}	0.0912^{***,m}	0.0412**	0.0236*	0.0300	0.0043	0.0325*	0.0226	0.0205	0.0300	0.0182
	(0.0129)	(0.0214)	(0.0240)	(0.0192)	(0.0139)	(0.0252)	(0.0213)	(0.0195)	(0.0150)	(0.0275)	(0.0249)	(0.0209)
5-factor alpha	0.0751^{***,m}	0.0910^{***,m}	0.0876^{***,m}	0.0356*	0.0287*	0.0237	0.0079	0.0281	0.0287*	0.0236	0.0242	0.0104
	(0.0140)	(0.0232)	(0.0237)	(0.0214)	(0.0147)	(0.0262)	(0.0225)	(0.0204)	(0.0153)	(0.0284)	(0.0271)	(0.0220)
BGR alpha	0.0451^{***,m}	0.0509^{**,m}	0.0579^{***,m}	0.0208	−0.0337^{***,m}	−0.0362*	−0.0548^{***,m}	−0.0071	−0.0310^{**,m}	−0.0478^{**,m}	−0.0140	−0.0198
	(0.0121)	(0.0215)	(0.0181)	(0.0169)	(0.0113)	(0.0189)	(0.0192)	(0.0172)	(0.0134)	(0.0225)	(0.0243)	(0.0174)

Table A4: **Portfolio Sorts – Subperiods (continued 2)**

Panel D. MAX, Value, and VoV

	MAX				*Value*				*VoV*			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	−0.0013	0.0078	0.0236	−0.0411***	0.0044	0.0162	−0.0114	0.0034	−0.0272**		−0.0200	−0.0327*
	(0.0130)	(0.0232)	(0.0204)	(0.0157)	(0.0140)	(0.0271)	(0.0179)	(0.0219)	(0.0121)		(0.0177)	(0.0167)
5-factor alpha	−0.0058	0.0169	0.0267	−0.0438***,m	0.0035	0.0055	0.0015	0.0077	−0.0333**,m		−0.0178	−0.0383**
	(0.0136)	(0.0236)	(0.0228)	(0.0166)	(0.0143)	(0.0285)	(0.0170)	(0.0225)	(0.0130)		(0.0212)	(0.0169)
BGR alpha	−0.0134	−0.0131	0.0078	−0.0426***	0.0496***,m	0.0756***,m	0.0220	0.0345**	−0.0314***,m		−0.0282	−0.0377**
	(0.0117)	(0.0194)	(0.0195)	(0.0155)	(0.0121)	(0.0217)	(0.0172)	(0.0173)	(0.0119)		(0.0189)	(0.0149)

Panel E. Trading Frictions and Co-Moments

	ILLIQ				*CoSkew*				*CoKurt*			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	−0.0074	−0.0446	−0.0189	0.0164	0.0170	0.0555***,m	−0.0129	−0.0192	−0.0150	−0.0209	0.0008	−0.0203
	(0.0169)	(0.0697)	(0.0221)	(0.0220)	(0.0138)	(0.0209)	(0.0261)	(0.0234)	(0.0137)	(0.0246)	(0.0253)	(0.0137)
5-factor alpha	−0.0051	−0.0096	−0.0185	0.0223	0.0151	0.0438*	−0.0146	−0.0204	−0.0204	−0.0427	−0.0023	−0.0253*
	(0.0174)	(0.0793)	(0.0230)	(0.0221)	(0.0150)	(0.0247)	(0.0244)	(0.0260)	(0.0137)	(0.0275)	(0.0260)	(0.0141)
BGR alpha	0.0009	0.0204	−0.0154	0.0196	0.0229*	0.0480**,m	0.0154	−0.0042	−0.0155	−0.0189	0.0144	−0.0316**
	(0.0179)	(0.0472)	(0.0242)	(0.0219)	(0.0133)	(0.0217)	(0.0229)	(0.0207)	(0.0152)	(0.0275)	(0.0260)	(0.0149)

Table A4: **Portfolio Sorts – Subperiods (continued 3)**

Panel F. Historical Moments

	HistVar				*HistSkew*				*HistKurt*			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	0.0050	0.0063	0.0404*	−0.0318	−0.0350***,m	−0.0146	−0.0579***,m	−0.0472***	0.0256**	0.0400*	0.0404**	−0.0131
	(0.0147)	(0.0264)	(0.0206)	(0.0197)	(0.0124)	(0.0219)	(0.0202)	(0.0167)	(0.0129)	(0.0226)	(0.0188)	(0.0188)
5-factor alpha	0.0013	0.0104	0.0405*	−0.0346*	−0.0430***,m	−0.0143	−0.0495**	−0.0498***,m	0.0273*	0.0393	0.0449**	−0.0072
	(0.0154)	(0.0273)	(0.0231)	(0.0206)	(0.0131)	(0.0250)	(0.0219)	(0.0160)	(0.0147)	(0.0277)	(0.0192)	(0.0187)
BGR alpha	−0.0223	−0.0314	0.0078	−0.0440**	−0.0100	0.0018	−0.0184	−0.0223	0.0451***,m	0.0636***,m	0.0564***,m	0.0003
	(0.0136)	(0.0224)	(0.0205)	(0.0194)	(0.0100)	(0.0180)	(0.0163)	(0.0150)	(0.0122)	(0.0218)	(0.0177)	(0.0159)

Panel G. Risk-Neutral Moments

	RNVar				*RNSkew*				*RNExKurt*			
Portfolio	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015	Full Sample Period	08.1959 – 02.1986	03.1986 – 11.2000	12.2000 – 12.2015
Mean return	−0.0154		−0.0133	−0.0171	0.0003		−0.0239	0.0192	0.0031		−0.0366	0.0340
	(0.0136)		(0.0180)	(0.0198)	(0.0154)		(0.0224)	(0.0200)	(0.0171)		(0.0263)	(0.0210)
5-factor alpha	−0.0129		−0.0048	−0.0219	−0.0067		−0.0285	0.0165	−0.0023		−0.0407*	0.0270
	(0.0142)		(0.0196)	(0.0210)	(0.0164)		(0.0212)	(0.0220)	(0.0179)		(0.0242)	(0.0231)
BGR alpha	−0.0362***,m		−0.0209	−0.0438**	0.0045		−0.0142	0.0237	0.0153		−0.0090	0.0371*
	(0.0131)		(0.0166)	(0.0188)	(0.0159)		(0.0192)	(0.0208)	(0.0160)		(0.0231)	(0.0212)

Table A5: Portfolio Sorts – Annual Horizon

*At the end of each month, we sort the commodities into 3 portfolios according to the variable indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the respective variable. The hedge portfolio P3–P1 simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the average excess return on the respective portfolio. We report the alpha estimates based on the Fama & French (2015) 5-factor model and the BGR model suggested by Bakshi et al. (2019). In parentheses, we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. The superscript "m" indicates that the results are also statistically significant based on the multiple-testing adjustment of Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) with the false discovery rate set to 10%.*

Panel A. Aggregate Volatility and Jump

	$AggVol^{VIX}$				$AggVol$				$AggJump$			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0310	0.0463	0.0181	−0.0064	−0.0033	0.0153	0.0558	0.0295*	0.0592	0.0233	−0.0137	−0.0364**
	(0.0275)	(0.0301)	(0.0332)	(0.0104)	(0.0545)	(0.0426)	(0.0551)	(0.0156)	(0.0539)	(0.0379)	(0.0573)	(0.0150)
5-factor alpha	−0.0089	0.0242	0.0119	0.0104	−0.0392	−0.0313	0.0111	0.0252	0.0124	−0.0259	−0.0453	−0.0288*
	(0.0454)	(0.0608)	(0.0502)	(0.0191)	(0.0712)	(0.0563)	(0.0708)	(0.0193)	(0.0564)	(0.0669)	(0.0727)	(0.0157)
BGR alpha	−0.0232	−0.0274**,m	−0.0487***,m	−0.0127	−0.0742***,m	−0.0542***,m	−0.0254	0.0244	−0.0287	−0.0459***,m	−0.0781***,m	−0.0247*
	(0.0184)	(0.0127)	(0.0166)	(0.0121)	(0.0270)	(0.0100)	(0.0237)	(0.0166)	(0.0231)	(0.0133)	(0.0170)	(0.0144)
FFFM alpha	−0.0209	−0.0278**,m	−0.0483***,m	−0.0137	−0.0607***,m	−0.0535***,m	−0.0215	0.0196	−0.0218	−0.0507***,m	−0.0628***,m	−0.0205
	(0.0169)	(0.0118)	(0.0166)	(0.0117)	(0.0203)	(0.0113)	(0.0284)	(0.0170)	(0.0236)	(0.0142)	(0.0145)	(0.0138)

Panel B. Downside Beta and Idiosyncratic Volatility

	$DownBeta$				$IdioVol^{FF3}$				$IdioVol^{BGR}$			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0676**	0.0645***,m	0.0556*	−0.0060	0.0746	0.0393	0.0750	0.0002	0.0661	0.0552	0.0738	0.0039
	(0.0281)	(0.0220)	(0.0331)	(0.0115)	(0.0487)	(0.0286)	(0.0480)	(0.0235)	(0.0448)	(0.0359)	(0.0619)	(0.0276)
5-factor alpha	0.0819*	0.0869**	0.0628	−0.0096	0.0972	0.0619	0.0739	−0.0117	0.0879	0.0654	0.0802	−0.0038
	(0.0485)	(0.0414)	(0.0707)	(0.0167)	(0.0782)	(0.0508)	(0.0747)	(0.0281)	(0.0751)	(0.0569)	(0.0638)	(0.0231)
BGR alpha	−0.0234	−0.0232*,m	−0.0586***,m	−0.0176	−0.0015	−0.0510**,m	−0.0523**,m	−0.0254	−0.0063	−0.0340**,m	−0.0644**,m	−0.0291
	(0.0156)	(0.0123)	(0.0148)	(0.0127)	(0.0194)	(0.0197)	(0.0219)	(0.0193)	(0.0197)	(0.0151)	(0.0281)	(0.0215)
FFFM alpha	−0.0359*	−0.0116	−0.0477***,m	−0.0059	−0.0182	−0.0132	−0.0639**,m	−0.0228	−0.0068	−0.0147	−0.0734***,m	−0.0333**
	(0.0212)	(0.0126)	(0.0171)	(0.0117)	(0.0159)	(0.0175)	(0.0265)	(0.0170)	(0.0182)	(0.0151)	(0.0277)	(0.0164)

Table A5: **Portfolio Sorts – Annual Horizon (continued)**

Panel C. Momentum and Reversal

	Momentum				*3Y Reversal*				*5Y Reversal*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0523^{*}	0.0637^{**}	0.0726^{*}	0.0102	0.0526	0.0618^{*}	0.0724	0.0099	0.0569	0.0529	0.0862	0.0146
	(0.0281)	(0.0285)	(0.0398)	(0.0124)	(0.0365)	(0.0320)	(0.0596)	(0.0191)	(0.0618)	(0.0433)	(0.0646)	(0.0316)
5-factor alpha	0.0568	0.0866^{*}	0.0894	0.0163	0.0615	0.0658	0.1087	0.0236	0.0753	0.0673	0.1166^{*}	0.0206
	(0.0566)	(0.0483)	(0.0581)	(0.0170)	(0.0662)	(0.0578)	(0.0740)	(0.0209)	(0.0915)	(0.0786)	(0.0638)	(0.0353)
BGR alpha	−0.0083	$-0.0355^{**,m}$	$-0.0388^{**,m}$	−0.0153	0.0047	$-0.0367^{***,m}$	$-0.0852^{***,m}$	$-0.0450^{***,m}$	−0.0030	$-0.0384^{**,m}$	$-0.0924^{***,m}$	$-0.0447^{**,m}$
	(0.0151)	(0.0144)	(0.0189)	(0.0131)	(0.0157)	(0.0138)	(0.0227)	(0.0143)	(0.0210)	(0.0171)	(0.0282)	(0.0190)
FFFM alpha	−0.0050	$-0.0329^{**,m}$	$-0.0489^{***,m}$	-0.0219^{**}	0.0005	$-0.0380^{**,m}$	$-0.0656^{***,m}$	-0.0331^{**}	−0.0051	−0.0226	$-0.0787^{***,m}$	-0.0368^{**}
	(0.0185)	(0.0131)	(0.0128)	(0.0100)	(0.0249)	(0.0152)	(0.0180)	(0.0163)	(0.0231)	(0.0151)	(0.0251)	(0.0187)

Panel D. MAX, Value, and VoV

	MAX				*Value*				*VoV*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0666	0.0451	0.0773	0.0054	0.0654	0.0560	0.0777^{**}	0.0061	0.0247	0.0186	−0.0190	-0.0218^{*}
	(0.0468)	(0.0298)	(0.0560)	(0.0261)	(0.0651)	(0.0378)	(0.0385)	(0.0183)	(0.0428)	(0.0274)	(0.0324)	(0.0121)
5-factor alpha	0.0874	0.0644	0.0787	−0.0043	0.0932	0.0744	0.1003	0.0035	−0.0335	−0.0094	−0.0602	−0.0133
	(0.0746)	(0.0495)	(0.0653)	(0.0308)	(0.0750)	(0.0611)	(0.0645)	(0.0212)	(0.0669)	(0.0434)	(0.0400)	(0.0168)
BGR alpha	−0.0073	$-0.0551^{***,m}$	−0.0416	−0.0172	$-0.1040^{***,m}$	$-0.0315^{*,m}$	0.0013	$0.0527^{***,m}$	−0.0123	$-0.0360^{***,m}$	$-0.0532^{***,m}$	−0.0204
	(0.0210)	(0.0113)	(0.0257)	(0.0195)	(0.0268)	(0.0167)	(0.0155)	(0.0148)	(0.0293)	(0.0118)	(0.0125)	(0.0135)
FFFM alpha	−0.0100	$-0.0461^{***,m}$	−0.0428	−0.0164	$-0.0824^{***,m}$	−0.0095	−0.0161	0.0332^{***}	−0.0095	$-0.0332^{***,m}$	$-0.0524^{***,m}$	-0.0214^{*}
	(0.0192)	(0.0158)	(0.0284)	(0.0142)	(0.0227)	(0.0161)	(0.0191)	(0.0125)	(0.0248)	(0.0123)	(0.0129)	(0.0126)

Panel E. Trading Frictions and Co-Moments

	ILLIQ				*CoSkew*				*CoKurt*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0378	−0.0089	0.0219	−0.0080	0.0575	$0.0632^{***,m}$	0.0677^{**}	0.0051	0.0718^{**}	$0.0556^{***,m}$	0.0615^{*}	−0.0051
	(0.0489)	(0.0255)	(0.0486)	(0.0190)	(0.0365)	(0.0229)	(0.0288)	(0.0140)	(0.0335)	(0.0197)	(0.0325)	(0.0114)
5-factor alpha	0.0133	−0.0400	−0.0438	−0.0286	0.0752	0.0780^{*}	0.0809	0.0028	0.1001	0.0665	0.0660	−0.0170
	(0.0753)	(0.0532)	(0.0411)	(0.0216)	(0.0833)	(0.0416)	(0.0537)	(0.0192)	(0.0664)	(0.0410)	(0.0534)	(0.0129)
BGR alpha	−0.0358	$-0.0445^{***,m}$	−0.0184	0.0087	$-0.0504^{***,m}$	$-0.0377^{***,m}$	−0.0178	0.0163	-0.0377^{*}	$-0.0208^{**,m}$	$-0.0467^{***,m}$	−0.0045
	(0.0286)	(0.0153)	(0.0299)	(0.0195)	(0.0129)	(0.0120)	(0.0187)	(0.0132)	(0.0192)	(0.0086)	(0.0140)	(0.0129)
FFFM alpha	−0.0439	$-0.0436^{**,m}$	$-0.0532^{**,m}$	−0.0046	-0.0390^{**}	$-0.0300^{***,m}$	−0.0285	0.0052	$-0.0369^{**,m}$	$-0.0228^{*,m}$	-0.0361^{*}	0.0004
	(0.0318)	(0.0191)	(0.0262)	(0.0221)	(0.0189)	(0.0115)	(0.0217)	(0.0148)	(0.0146)	(0.0120)	(0.0200)	(0.0117)

Table A5: **Portfolio Sorts – Annual Horizon (continued 2)**

Panel F. Historical Moments

	HistVar				*HistSkew*				*HistKurt*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0761	0.0370	0.0774	0.0007	0.0821***	0.0578	0.0504	−0.0159	0.0236	0.0812**	0.0829***,m	0.0296***
	(0.0508)	(0.0274)	(0.0475)	(0.0238)	(0.0297)	(0.0409)	(0.0376)	(0.0119)	(0.0404)	(0.0370)	(0.0264)	(0.0109)
5-factor alpha	0.0972	0.0614	0.0749	−0.0111	0.0913*	0.0844	0.0573	−0.0170	0.0448	0.0868*	0.1014*	0.0283
	(0.0791)	(0.0484)	(0.0732)	(0.0280)	(0.0471)	(0.0774)	(0.0614)	(0.0151)	(0.0744)	(0.0482)	(0.0574)	(0.0180)
BGR alpha	−0.0005	−0.0523***,m	−0.0508**,m	−0.0251	−0.0282**,m	−0.0580***,m	−0.0179	0.0051	−0.0824***,m	−0.0491**,m	0.0229*	0.0527***,m
	(0.0200)	(0.0189)	(0.0219)	(0.0197)	(0.0112)	(0.0174)	(0.0144)	(0.0098)	(0.0144)	(0.0204)	(0.0138)	(0.0093)
FFFM alpha	−0.0167	−0.0162	−0.0638**,m	−0.0235	−0.0367***,m	−0.0289**,m	−0.0316	0.0026	−0.0649***,m	−0.0377**,m	0.0017	0.0333**
	(0.0161)	(0.0157)	(0.0267)	(0.0171)	(0.0131)	(0.0135)	(0.0232)	(0.0119)	(0.0199)	(0.0155)	(0.0243)	(0.0131)

Panel G. Risk-Neutral Moments

	RNVar				*RNSkew*				*RNExKurt*			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
Mean return	0.0098	0.0121	−0.0039	−0.0068	0.0142	0.0028	0.0018	−0.0062	0.0211	−0.0016	−0.0020	−0.0116
	(0.0278)	(0.0324)	(0.0312)	(0.0106)	(0.0258)	(0.0264)	(0.0387)	(0.0122)	(0.0303)	(0.0241)	(0.0308)	(0.0132)
5-factor alpha	−0.0207	−0.0513	−0.0319	−0.0056	−0.0197	−0.0300	−0.0524	−0.0164	0.0088	−0.0344	−0.0756*	−0.0422**
	(0.0461)	(0.0435)	(0.0538)	(0.0141)	(0.0570)	(0.0384)	(0.0639)	(0.0234)	(0.0580)	(0.0398)	(0.0397)	(0.0180)
BGR alpha	−0.0208	−0.0254**,m	−0.0614***,m	−0.0203**	−0.0332	−0.0461**,m	−0.0271*	0.0030	−0.0499**,m	−0.0401***,m	−0.0186	0.0157
	(0.0164)	(0.0119)	(0.0158)	(0.0093)	(0.0211)	(0.0181)	(0.0148)	(0.0108)	(0.0207)	(0.0104)	(0.0190)	(0.0155)
FFFM alpha	−0.0144	−0.0255**,m	−0.0607***,m	−0.0231**	−0.0253	−0.0468**,m	−0.0273*,m	−0.0010	−0.0409**,m	−0.0429***,m	−0.0177	0.0116
	(0.0142)	(0.0125)	(0.0145)	(0.0091)	(0.0186)	(0.0188)	(0.0141)	(0.0101)	(0.0178)	(0.0104)	(0.0179)	(0.0152)