# Anomalies in Commodity Futures Markets*

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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, and volatility-of-volatility. Other prominent variables, such as downside beta, idiosyncratic volatility, and MAX, are not priced in commodity futures markets. Commodity markets have a large fraction of institutional traders and low limits to arbitrage. Thus the former anomalies may be risk-based while the latter are likely due to behavioral biases.

**JEL classification:** G10, G11, G17

**Keywords:** Anomalies, commodity futures markets, behavioral finance, systematic risk

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# I Introduction

Several recent papers find evidence for a factor structure in commodity futures returns (Szymanowska et al., 2014; Boons & Prado, 2019; Bakshi et al., 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. If they are proxies for risk, anomalies and factors should be priced across markets because theoretically there should be one stochastic discount factor (SDF) that prices all assets.

This paper takes a large set of anomalies previously studied in equity markets and examines their abilities to price commodities. Our first 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, 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.

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, arguably more sophisticated, set of market participants. Furthermore, commodity futures markets are smaller and have historically been segmented from the stock market.[1] These differences, however, can help inform the debate about whether we should think of these factors are driven by rational or behavioral theories. Our second contribution is thus to help organize the anomaly zoo.

We use simple portfolio sorts with a holding period of one month to test for anomalies in commodity markets. Furthermore, 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

[1] 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 profitability of investment factors infeasible. Finally, investors in commodity markets may face margin constraints.

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, skewness, momentum, and volatility-of-volatility.

Based on the institutional differences between the two markets, we interpret it as more likely that behavioral theories can explain the anomalies present in equity but not in commodity futures markets. Thus, downside beta, idiosyncratic volatility, and the MAX measure my be priced in equity markets because of investors' behavioral biases. Those anomalies that are priced across markets likely reflect systematic risk. Thus, the pricing of jump risk, skewness, momentum, and volatility-of-volatility may have a risk-based explanation.

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.[2] Finally, we examine a longer holding period of 1 year, which also generates very similar results. One intriguing exception is momentum, which works far less well for an annual compared to a monthly holding period.

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), Lu et al. (2018), and Eisdorfer et al. (2018) 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. Drechsler & Drechsler (2014) and Engelberg et al. (2018) further show that investors require a compensation for shorting stocks and that equity anomalies are stronger the higher the lending fees are. Since it is much easier to hold short positions in commodity futures markets than in equity markets, we do not expect to see such a premium for short-selling risk. Thus, testing whether different

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

variables are present in commodity markets might give some indication whether these are related to behavioral distortions or not.

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).[3]

Some previous studies also examine the performance of strategies developed in equity markets on commodity markets (e.g., Gorton & Rouwenhorst, 2006; Erb & Harvey, 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 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 category portfolios performs far less well when confronted 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 discuss potential limitations of the commodity futures setup. In Section V, we present further analyses and test the robustness of our main results. Finally, we draw conclusions in Section VI.

[3]Part of these studies argue 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.

# 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 maturities, 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.[4] We also check for standard no-arbitrage conditions and discard observations not fulfilling these.[5] 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

[4]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.

[5]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.

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. Finally, we collect data on the holdings of investors classified into different categories from the website of Commodity Futures Trading Commission (CFTC). 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 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 on 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 3 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 The Rationality of Commodity Markets

In general, individual investors are considered to be more heavily affected by behavioral biases than institutional investors (e.g., Long et al., 1990; Lee et al., 1991; Yu & Yuan, 2011; Stambaugh et al., 2012). Thus, the larger the fraction of traders (and actual trades) of retail investors in the market, the higher the likelihood that market prices will be affected by these cognitive biases. Among many others, De Bondt & Thaler (1985), Long et al. (1991), Barberis et al. (1998), and Boyer et al. (2009) argue and demonstrate how investors' behavioral biases can impact equity prices. In order for those effects to persist in the market, behavioral finance typically has, beside cognitive biases, a second cornerstone: limits to arbitrage. In the real world, there are several reasons why making use of price deviations from fundamental values is not as easy as the finance theory suggests. First, there is fundamental risk, i.e., the risk that the fundamental value of an asset may change while the "arbitrage" position is still open. Second, due to noise trader risk (e.g., De Long et al., 1990; Shleifer & Summers, 1990) the price may deviate even further from the fundamental value in the short-term, and, third, there are costs of implementing an arbitrage trade. Short-selling constraints are an essential component of such implementation costs. As documented by D'Avolio (2002), there are direct costs of entering a short position. Furthermore, short positions can be recalled at any time, which might lead to forced liquidation. Such risk poses a severe challenge for arbitrageurs, especially in the interaction with noise trader risk (Shleifer & Vishny, 1997). Finally, many institutional investors in equity markets, such as pension funds, face charters that prohibit them from taking short positions, even when there are only small costs and risks associated with a trade.

While the characteristics of equity markets facilitate price impacts of behavioral biases, several factors make commodity futures markets far less prone to these. First, the traditional actors in commodity markets are commercial hedgers and non-commercial traders, such as hedge funds. There are only few individual investors trading in commodity markets.[6] Thus, it is less likely that commodity futures prices will incorporate price deviations caused by cognitive biases. Furthermore, actors in commodity markets face no institutional restrictions on taking short positions in commodity futures markets. Second, commodity futures markets are also likely to be much less populated with noise traders, who are typically assumed to consist of uninformed (or wrongly-informed) retail traders.[7] Finally, and most importantly, the limits to arbitrage are considerably less severe for commodity futures markets. Furthermore, as opposed to equities, commodities are very easy to short. Short-selling does not require the borrowing of a commodity from an institutional investor. Instead, one simply takes the short position in the futures contract. Thus, there are only small direct trading costs and essentially no (external) risk that one has to close the position in an adverse market situation. In total, we expect that behavioral anomalies are substantially weaker in commodity markets than in equity markets.

Commodity futures markets thus provide a suitable testing ground to examine whether return anomalies are caused by behavioral mechanisms or if it is more likely that rational risk-based explanations are the primary channel. If we find equity anomalies that do not prevail in commodity futures markets, this lends support to the notion that cognitive biases may be their main drivers. On the other hand, if we find these anomalies with a similar magnitude in commodity futures markets, it is more likely that the sorting characteristics

[6] The Commodity Futures Trading Commission (CFTC) reveals information about traders in commodity markets. Based on the size of their open interest, the CFTC classifies traders into reportable and non-reportable traders. The first category is further classified into commercial (hedgers) and non-commercial (speculators) traders, which account for 70–90 % of the total open interest across commodity markets. The CFTC has an institutionalized system for classifying the traders that imposes "strict requirements". Thus, individual investors, which constitute a part of the non-reportable traders, represent only a small fraction in commodity futures markets and should have a negligible effect on futures prices. On the other hand, for the equity market, Blume & Keim (2017) report that the ownership of institutional investors made up to 67 % at the end of 2010. Moreover, one has to bear in mind that institutional investors in equity markets consist of a large share of passive index investors who do not participate actively in the price building mechanism at all. In commodity markets, on the other hand, all institutional investors have to trade since the futures expire regularly.

[7] Additionally, Palomino (1996) shows that, especially in markets populated by only few investors, noise traders can have severe impacts on prices, making arbitrageurs unwilling to trade in these markets at all. For commodity futures markets, beside likely fewer noise traders, there are typically far more active traders than for most single stocks in equity markets.

employed represent exposure to underlying aggregate risk factors.[8]

To set the stage, we first examine whether the presence of non-institutional investors, among which we typically suspect noise traders, is essentially related to sentiment in commodity futures markets. Yu & Yuan (2011) and Stambaugh et al. (2012), among others, suggest that investor sentiment is directly related to the degree of market rationality. The authors argue that high-sentiment periods are associated with higher participation of noise traders in the market. Yu & Yuan (2011) assert that these noise traders contaminate the mean–variance trade-off, while Stambaugh et al. (2012) show that several market anomalies are stronger during high-sentiment periods.

To examine whether this channel also holds for commodity markets, we use the CFTC data on institutional investor holdings as well as the sentiment index of Baker & Wurgler (2006).[9] We regress the change in the percentage share of institutional investors in commodity markets (hedgers and speculators) on the change in sentiment.[10]

In Table 2, we present the regression results. First, using a panel regression which includes all individual commodities, we find that changes in the share of institutional investors are statistically completely unrelated to changes in sentiment.[11] Second, for 23 out of 26 individual commodities, we cannot reject the hypothesis that changes in the share of institutional investors in commodity markets are unrelated to changes in sentiment. Only for platinum do we find a significantly negative relation. For Brent oil and rough rice, we even detect a positive relation between sentiment and the share of institutional investors in the commodity market. Hence, there is no evidence to indicate that an increase in sentiment does induce noise traders to enter the market.

This simple analysis underlines the notion that the impact of noise traders is reduced

[8]One might argue that the different trading incentives for the hedgers and speculators on the commodity market may also lead to various behavioral distortions. However, these are likely different from those in equity markets. Thus, following this line of reasoning it is still unlikely that we observe the same behavioral distortions in commodity markets as we do in equity markets.

[9]We use the sentiment index orthogonalized to macroeconomic variables. The data are available on Jeffrey Wurgler's website.

[10]To account for high autocorrelation and potential non-stationarity in the variables, we use the changes instead of the levels of the variables. Using the levels, we obtain qualitatively similar results.

[11]We present the results using a common intercept for all commodities. Relaxing this by introducing commodity-fixed dummy variables does not alter our result. The point estimate of the regression slope is practically identical while the corresponding standard error is even higher.

substantially in commodity markets. Since noise traders are an important ingredient for creating and sustaining "irrational" prices, we are confident in our notion that commodity markets provide an excellent environment to study the economic sources of return anomalies.

## B 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 coffee (10.86 %), cotton (7.72 %), lean hogs (10.48 %), rough rice (10.94 %), and wheat (9.54 %). On the other hand, some commodities show a very poor performance, indicated by negative annualized mean returns. Examples are cocoa (–1.85 %), natural gas (–4.65 %), palladium (–8.24 %), platinum (–0.76 %), soybeans (–4.42 %), and WTI oil (–1.27 %).[12] Overall, the patterns of our summary statistics are similar to those of Gorton & Rouwenhorst (2006) and Bakshi et al. (2019).

Table 3 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 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.[13]

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

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

Table 4 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 $Mom^{char}$ 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.[14] Interestingly, even though $MAX$ is sometimes interpreted as a measure of skewness, its correlation to $HistSkew$ is only moderate, amounting to 0.37.

## C Portfolio Sorts

At the end of each month, we sort the commodities into 3 portfolios according to the specific variable under study.[15] Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitudes of the sorting variable.[16] 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 half of the return on portfolio 1. The remaining half of the investment serves as collateral and earns the risk-free interest rate.[17] We rebalance the portfolios every month.

[14]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.

[15]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 C. These are very similar to those for 3 portfolios reported in this section.

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

[17]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.

Table 5 presents the results.

### (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 5). 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 alphas relative to all factor models are statistically significant. Thus, it seems 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 5). We find significant alphas relative to all factor models. 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 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 5). 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.

Thus, our results are consistent with the main disappointment-aversion theory put forward for the variable. The view that price impacts of downside risk, if they occur at all, are arbitraged away in commodity markets is strengthened further when viewing the long- and short-side contributions to the hedge portfolio return. According to the disappointment aversion theory, low downside beta stocks are overpriced and yield low returns in the future. For commodities, we observe the exact opposite: low downside beta commodity futures exhibit higher average returns than high downside beta commodity futures.

**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 5. 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.[18]

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 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. Our findings are consistent with

[18]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.

this notion. In commodity markets, where we expect substantially attenuated effects of behavioral biases and have lower limits to arbitrage, we do not detect an idiosyncratic volatility puzzle.[19]

**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 5). We find that the alphas relative to all factor models are statistically significant.[20] 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 with delayed price reactions based on idiosyncratic firm information.

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

[19]Looking at the individual portfolio returns further supports this notion. Under the behavioral theories, and also observed, e.g., by Ang et al. (2006b), high idiosyncratic volatility stocks are overpriced and yield low returns. In commodity futures markets, we find that the portfolio of the commodities with the highest idiosyncratic volatilities yields the overall highest average return.

[20]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.

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).

Our result that the momentum effect is also present in commodity futures markets supports a rational explanation. This result is consistent, e.g., with evidence provided by Birru (2015), who shows that the disposition effect does not suffice to explain momentum for the equity market.

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 5. 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.

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.

Thus, consistent with behavioral theories, the reversal effect is present in equity markets, at least in returns. Since we do not observe the same pattern in commodity markets, our evidence supports the notion that overreaction indeed creates these returns. On the other hand, the fact that empirical factor models seem to be able to explain the effect in both equity and commodity markets calls this interpretation and the existence of a reversal effect somewhat into question.

**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 5). 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 with 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.

Our finding that MAX is not priced in the cross-section of commodity futures returns, as opposed to that of equity returns, indicates that a probability-weighting bias of investors indeed creates the MAX anomaly in the equity market. Looking at the individual portfolios, we find that high-MAX commodity futures have positive average excess return of 5.12 %. The theory and empirical evidence for the stock market in Bali et al. (2011) indicates that especially high-MAX stocks should be/are overpriced. The positive average return we observe for commodity futures markets is in contrast to this theory and also points towards a behavioral explanation for the MAX effect in the equity market.

**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 5). 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. Thus, the presence of a value effect in commodity markets seems to strongly depend on the time period and commodity return specification.[21] 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 5). The alphas relative to all factor models are larger in magnitude compared to the mean return and statistically significant. 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.

[21]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.

The fact that the volatility-of-volatility premium also exists in commodity markets points toward a risk-based rather than to a behavioral explanation for the effect.

### (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 5). 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.[22]

Our findings are also in contrast to those in Amihud (2002) for the equity market, who observes a significant positive slope coefficient with 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 relation 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 5). Generally, we find insignificant alphas relative to the factor models. Only for the BGR

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

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 5). 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., Bollerslev et al., 2016; Hollstein & Prokopczuk, 2018). 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 5). 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.

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.[23] For (idiosyncratic) skewness, Mitton & Vorkink (2007); 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.

At first glance, these results appear puzzling since the pricing of skewness is behaviorally-based in theory. Thus, according to the reasoning outlined above, we should not be able to find a skewness risk premium in commodity markets, which we do. Fernandez-Perez et al. (2018) deliver a possible solution. 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. 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 and kurtosis seems to be either a proxy for

[23]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.

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 5). 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 5). 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 5). 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. It is therefore likely that the pricing of risk-neutral kurtosis in equity markets is created by individual investors who dislike assets with higher risk-neutral kurtosis and demand a risk premium. We do not detect such a risk premium in commodity markets.

# IV Potential Limitations

There are various reasons why commodity futures markets may be more efficient than equity markets. However, analyzing commodity futures markets only gives us an indication whether return premia are due to behavioral distortions or risk and no formal proof. There are several possibly confounding effects, which we discuss in detail in this section.

First, while retail investors are likely more strongly affected by behavioral biases, institutions are not immune to such biases. Frazzini (2006), Akbas et al. (2015), and Edelen et al. (2016), for example, show that mutual funds often invest on the "wrong" side of stock return anomalies. However, Akbas et al. (2015) also show that "smart money" provided by hedge funds attenuates mispricing. This finding is relevant since hedge funds are the main non-commercial actors in commodity markets (Brunetti et al., 2016). The lack of short-selling constraints likely makes it easier for "smart money" investors to materially reduce or arbitrage away mispricing in commodity markets as compared to equity markets.

Second, it is also possible that the holding costs, as opposed to direct trading costs are a major concern impeding arbitrage. Holding costs consist of opportunity costs of capital and idiosyncratic risk (Pontiff, 2006). Since futures only require a limited amount of direct collateral (margins), the major source of holding costs in commodity futures markets is idiosyncratic volatility. However, our finding that idiosyncratic volatility does not carry a significant risk premium in commodity markets cast serious doubt on a related explanation of differences in the results for commodity futures and equity markets.[24]

A third possibly confounding effect is that equity and commodity markets could be

[24] In the stock market, idiosyncratic risk is priced negatively. Stocks with high idiosyncratic volatility appear to be overpriced. One potential explanation is that this overpricing is not arbitraged away due to high holding costs induced by idiosyncratic volatility. This logic does not apply to commodity markets, where we cannot detect any return premium for exposure to idiosyncratic volatility.

segmented and different risks may drive the returns in these markets. Some traders in commodity markets may trade because of background risk or based on hedging motives. These actors may treat it as segmented from equity markets and contribute little to the efficiency of the market. A large body of literature, though, documents a financialization of commodity markets at least in recent decades (e.g., Cheng & Xiong, 2014; Adams & Glück, 2015; Basak & Pavlova, 2016). Examining individual trader positions, Büyükşahin & Robe (2014) find that a substantial fraction of non-commercial traders (those, which we usually associate with making prices "efficient") in commodity markets also engages in equity markets. Thus, to account for the possibility that market segmentation drives our main results, we also study the post-financialization period only, where markets are arguably much more integrated. We present these results, which are generally very similar to those for the full sample period, in Section V.D.

Finally, the return premia documented for the U.S. equity market may be the result of data snooping. In this case, studying the underlying variables in commodity markets also provides an out-of-sample test. To separate these rivaling explanations as well as possible, we focus on prominent variables that are mostly theoretically motivated. As Harvey et al. (2016) note, data mining is less likely as an explanation for variables based on economic theory. Furthermore, a substantial part of the variables we examine has also been replicated using data on international equities (e.g., Ang et al., 2009; Asness et al., 2013; Walkshäusl, 2014; Tsai et al., 2014). It is unlikely that the premia detected for variables that have already undergone an out-of-sample test are the result of data snooping.

# V 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 (anomaly) variables, we obtain substantially different results. For numerous variables examined in Table 5, 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 $R^2$s 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.[25]

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.

[25]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.

## B 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.[26,27] 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 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 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.

[26] 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.

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

## C 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. 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 affect 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.

## D 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 with 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 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.

## E 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 report 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.

# VI 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.

Due to a high share of commercial and hedge fund investors and low limits to arbitrage, one might expect fewer behavioral distortions in commodity futures prices than in equity prices. Following this logic, our results indicate that behavioral explanations are likely for downside beta, idiosyncratic volatility, and MAX. On the other hand, it is likely that "rational" risk-based explanations prevail for jump risk, momentum, and volatility-of-volatility.

# 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, 1996, "$MRP$") is the excess return on the equity market, using value-weighted returns from all firms in CRSP.

**Equity Size Factor** (Fama & French, 1996, "$SMB$") is the return difference between a portfolio of small and large stocks ("Small minus Big").

**Equity Value Factor** (Fama & French, 1996, "$HML$") 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 $\Delta VIX$ 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 (1996), 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

$$RNVar_{i,t} = \frac{e^{r\tau}V - \mu^2}{\tau}, \tag{3}$$

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

$$RNExKurt_{i,t} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2 V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3, \tag{5}$$

where $V$, $W$, $X$, and $\mu$ are computed as

$$V = \int_{K=0}^{S} \frac{2(1+\log[\frac{S}{K}])}{K^2} P(K)dK + \int_{K=S}^{\infty} \frac{2(1-\log[\frac{K}{S}])}{K^2} C(K)dK, \tag{6}$$

$$W = \int_{K=S}^{\infty} \frac{6\log[\frac{K}{S}] - 3(\log[\frac{K}{S}])^2}{K^2} C(K)dK - \int_{K=0}^{S} \frac{6\log[\frac{S}{K}] + 3(\log[\frac{S}{K}])^2}{K^2} P(K)dK, \tag{7}$$

$$X = \int_{K=S}^{\infty} \frac{12(\log[\frac{K}{S}])^2 + 4(\log[\frac{K}{S}])^3}{K^2} C(K)dK + \int_{K=0}^{S} \frac{12(\log[\frac{S}{K}])^2 + 4(\log[\frac{S}{K}])^3}{K^2} P(K)dK, \tag{8}$$

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V - \frac{e^{r\tau}}{6}W - \frac{e^{r\tau}}{24}X. \tag{9}$$

$r$ is the continuously compounded (annualized) interest rate for the period from $t$ to $t+\tau$, where $\tau$ indicates the time to maturity of each option. We express $\tau$ as a fraction of a year.[28] 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.[29] In the next step, we compute the corresponding option prices, using the Black & Scholes (1973) option pricing

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

[29] 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.

model. Finally, 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).[30]

**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 $\sigma_{i,d}^{iv}$.

[30]A horizon of 12 months would be more desirable to exclude any seasonal patterns in commodity volatilities. However, there is only limited data available on commodity options above 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 Oil | 0.0585 | 0.2914 | 1.1902 | 8.7608 | −0.9654 | 1.1599 | 677 | 31.08.1959 |
| Cocoa | −0.0185 | 0.2411 | 1.1994 | 9.4976 | −0.9239 | 0.8814 | 677 | 31.08.1959 |
| Coffee | 0.1086 | 0.3275 | 0.4497 | 6.2880 | −1.2030 | 1.3326 | 317 | 31.08.1989 |
| Corn | 0.0350 | 0.3055 | 0.6782 | 4.3679 | −1.1818 | 1.4283 | 677 | 31.08.1959 |
| Cotton | 0.0772 | 0.3304 | 0.3714 | 5.5903 | −1.2602 | 1.3579 | 393 | 29.04.1983 |
| Feeder Cattle | 0.0208 | 0.2363 | 0.6376 | 6.2230 | −0.8689 | 0.8964 | 677 | 31.08.1959 |
| Gold | 0.0598 | 0.2646 | 0.4369 | 4.8893 | −0.9420 | 1.1731 | 236 | 29.02.1996 |
| Heating Oil | 0.0368 | 0.1648 | −0.4698 | 5.4982 | −0.6045 | 0.6743 | 528 | 31.01.1972 |
| High Grade Copper | 0.0108 | 0.1935 | 0.4844 | 6.2515 | −0.6962 | 0.7600 | 491 | 28.02.1975 |
| Lean Hogs | 0.1048 | 0.2650 | 0.1758 | 5.1679 | −0.8796 | 1.2052 | 677 | 31.08.1959 |
| Live Cattle | 0.0799 | 0.3193 | 0.8946 | 7.4362 | −1.2109 | 1.2593 | 445 | 29.12.1978 |
| Lumber | 0.0532 | 0.3263 | 1.6490 | 11.499 | −1.1737 | 1.3338 | 586 | 31.03.1967 |
| Milk | 0.0532 | 0.3723 | 1.1827 | 6.5348 | −1.3093 | 1.5145 | 520 | 29.09.1972 |
| Natural Gas | −0.0465 | 0.2713 | 0.0999 | 3.1760 | −1.2144 | 1.1786 | 554 | 28.11.1969 |
| Oats | 0.0493 | 0.1623 | −0.2492 | 5.4700 | −0.5706 | 0.7009 | 612 | 29.01.1965 |
| Oranges | 0.0350 | 0.2513 | 0.1326 | 3.9913 | −1.0414 | 1.0266 | 597 | 29.04.1966 |
| Palladium | −0.0824 | 0.4850 | 0.6014 | 4.3127 | −2.0478 | 1.8740 | 308 | 31.05.1990 |
| Platinum | −0.0076 | 0.2910 | 2.3066 | 23.965 | −1.0576 | 1.0048 | 677 | 31.08.1959 |
| Rough Rice | 0.1094 | 0.3475 | 0.3695 | 5.9824 | −1.2187 | 1.4380 | 467 | 28.02.1977 |
| Silver | 0.0459 | 0.2733 | 0.4572 | 7.3223 | −0.9768 | 1.0321 | 573 | 30.04.1968 |
| Soybeans | −0.0442 | 0.2682 | 1.0327 | 7.8229 | −1.1480 | 1.0291 | 352 | 30.09.1986 |
| Soybean Meal | 0.0545 | 0.2575 | 1.4853 | 13.217 | −0.7885 | 1.0095 | 677 | 31.08.1959 |
| Soybean Oil | 0.0561 | 0.4235 | 1.1669 | 6.5380 | −1.5383 | 1.6760 | 659 | 28.02.1961 |
| Sugar | 0.0333 | 0.3105 | 0.7161 | 8.9322 | −1.1201 | 1.2662 | 630 | 31.07.1963 |
| Wheat | 0.0954 | 0.2917 | 2.0091 | 18.720 | −0.9204 | 1.1888 | 677 | 31.08.1959 |
| WTI Oil | −0.0127 | 0.2532 | 0.7644 | 6.8882 | −0.9937 | 0.9848 | 677 | 31.08.1959 |

## Table 2: Institutional Investors and Sentiment

*This table reports the results of regressions of the change in the share of reportable institutional investors according to the definition of the CFTC in the individual commodity markets on the innovation in sentiment. "Panel" indicates the results of a joint panel regression using all commodities. For individual commodities, In parentheses we present the standard errors. For the panel regression, we use double-clustered (by month and commodity) standard-errors of Cameron et al. (2011) wile for individual commodities, we use robust Newey & West (1987) standard errors with 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. "Adj. $R^2$" denotes the adjusted $R^2$ of the regressions.*

| | Panel | Soybean Oil | Corn | Brent Oil | Cocoa | WTI Oil | Cotton | Milk | Feeder Cattle | Gold | High Grade Copper | Heating Oil | Oranges | Coffee |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Constant* | 0.0009** | 0.0011* | 0.0012** | 0.0025 | 0.0003 | 0.0005 | 0.0010 | 0.0012 | 0.0006 | 0.0005 | 0.0023** | 0.0006 | 0.0009 | 0.0007 |
| | (0.0003) | (0.0006) | (0.0006) | (0.0015) | (0.0005) | (0.0006) | (0.0007) | (0.0019) | (0.0012) | (0.0005) | (0.0010) | (0.0008) | (0.0011) | (0.0008) |
| *Slope* | 0.0022 | 0.0062 | 0.0044 | 0.0527** | 0.0039 | 0.0008 | 0.0058 | 0.0014 | −0.0029 | −0.0094 | 0.0053 | 0.0076 | 0.0045 | −0.0074 |
| | (0.0032) | (0.0059) | (0.0062) | (0.0236) | (0.0068) | (0.0051) | (0.0059) | (0.0127) | (0.0093) | (0.0058) | (0.0081) | (0.0083) | (0.0099) | (0.0075) |
| *Adj.* $R^2$ | 0.0000 | −0.0004 | −0.0001 | 0.0959 | −0.0017 | −0.0028 | −0.0003 | −0.0047 | −0.0026 | 0.0017 | −0.0021 | −0.0005 | −0.0022 | −0.0004 |

| | Lumber | Live Cattle | Lean Hog | Natural Gas | Oats | Palladium | Platinum | Rough Rice | Soybeans | Sugar | Silver | Soybean Meal | Wheat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Constant* | 0.0008 | 0.0013* | 0.0031** | 0.0014* | 0.0004 | 0.0008 | 0.0009 | 0.0005 | 0.0011* | 0.0004 | 0.0005 | 0.0009 | 0.0010* |
| | (0.0019) | (0.0007) | (0.0015) | (0.0008) | (0.0014) | (0.0009) | (0.0007) | (0.0020) | (0.0007) | (0.0009) | (0.0006) | (0.0006) | (0.0005) |
| *Slope* | 0.0011 | −0.0087 | 0.0130 | −0.0063 | 0.0051 | −0.0076 | −0.0173** | 0.0242* | 0.0061 | 0.0085 | −0.0063 | 0.0060 | 0.0066 |
| | (0.0184) | (0.0067) | (0.0094) | (0.0048) | (0.0124) | (0.0096) | (0.0087) | (0.0130) | (0.0062) | (0.0082) | (0.0074) | (0.0065) | (0.0068) |
| *Adj.* $R^2$ | −0.0042 | 0.0026 | 0.0041 | −0.0009 | −0.0040 | −0.0016 | 0.0060 | 0.0082 | 0.0002 | 0.0003 | −0.0005 | −0.0005 | 0.0018 |

## Table 3: 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 4: 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 5: 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) alph 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.*

*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*** |
| | (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*** |
| | (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** |
| | (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* | −0.0556*** | −0.0165 | −0.0902*** | −0.0316* | −0.0392* | 0.0255* | −0.0183 | −0.0525*** | −0.0926*** | −0.0371** |
| | (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** | −0.0557*** | −0.0177 | −0.0933*** | −0.0313** | −0.0361* | 0.0286* | −0.0130 | −0.0569*** | −0.0938*** | −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 5: **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** | −0.0152 | 0.0020 | −0.0354** | −0.0423** | −0.0222 | −0.0163 | −0.0349** | −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** | −0.0432** | −0.0038 | −0.0229 | −0.0377** | −0.0532*** | −0.0151 | −0.0252 | −0.0379** | −0.0495** | −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*** | 0.0744*** | 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*** | 0.0760*** | 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*** | 0.0748*** | −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*** | 0.0632*** | 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*** | 0.0751*** | 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*** | −0.0241 | 0.0209 | 0.0451*** | 0.0024 | −0.0156 | −0.0651*** | −0.0337*** | 0.0111 | −0.0388*** | −0.0509*** | −0.0310** |
| | (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*** | −0.0500*** | 0.0038 | 0.0340*** | −0.0172 | −0.0281 | −0.0720*** | −0.0274** | −0.0246 | −0.0342** | −0.0537*** | −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 5: **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** |
| | (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** |
| | (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*** | −0.0286* | −0.0134 | −0.0683*** | −0.0397*** | 0.0309** | 0.0496*** | −0.0328* | −0.0284 | −0.0956*** | −0.0314*** |
| | (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*** | −0.0383** | −0.0145 | −0.0715*** | −0.0279* | −0.0132 | 0.0292** | −0.0328* | −0.0293 | −0.0970*** | −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*** | −0.0364 | 0.0009 | −0.0477*** | −0.0256** | −0.0018 | 0.0229* | −0.0111 | −0.0208* | −0.0421** | −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** | −0.0363** | −0.0440** | −0.0004 | −0.0430** | −0.0375** | −0.0309 | 0.0061 | −0.0175 | −0.0467*** | −0.0460** | −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 5: **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*** | 0.0353 | 0.0127 | −0.0350*** | 0.0144 | 0.0496* | 0.0656*** | 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*** | 0.0245 | 0.0015 | −0.0384*** | 0.0017 | 0.0399 | 0.0616*** | 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*** | 0.0174 | −0.0045 | −0.0382*** | −0.0059 | 0.0318 | 0.0578*** | 0.0318** |
| | (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*** | 0.0104 | −0.0036 | −0.0397*** | −0.0168 | 0.0375 | 0.0627*** | 0.0398*** |
| | (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*** | 0.0285 | −0.0011 | −0.0430*** | 0.0066 | 0.0442 | 0.0611*** | 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** | −0.0415** | −0.0223 | −0.0053 | −0.0445** | −0.0254* | −0.0100 | −0.0709*** | −0.0240* | 0.0193 | 0.0451*** |
| | (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** | −0.0523** | −0.0147 | −0.0102 | −0.0510** | −0.0512*** | −0.0205* | −0.0653*** | −0.0390** | −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*** | −0.0885*** | −0.0362*** | −0.0542** | −0.0598*** | −0.0452** | 0.0045 | −0.0730*** | −0.0447*** | −0.0424** | 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*** | −0.0870*** | −0.0357*** | −0.0540** | −0.0594*** | −0.0471** | 0.0034 | −0.0705*** | −0.0458*** | −0.0448** | 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) |

# The Economic Sources of Return Anomalies: Evidence from Commodity Futures Markets

Online Appendix

**JEL classification:** G10, G11, G17

**Keywords:** Anomalies, commodity futures markets, behavioral finance, systematic risk

## 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]. 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. "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*** | −1.2615** | 0.0005 | 0.0268 | −0.0458 | 0.2439*** | 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*** | −0.0015 | −0.5399* | 0.0100 | 0.0010 |
| | (0.1965) | (26.0703) | (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], 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. "Adj. $R^2$" denotes the average adjusted $R^2$ of the regressions.*

| | $AggVol^{VIX}$ | $AggVol$ | $AggJump$ | $DownBeta$ | $IdioVol^{FF3}$ | $IdioVol^{BGR}$ | $Momentum$ | $3Y Reversal$ | $5Y Reversal$ | $MAX$ | $Value$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *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*** | −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) |
| *Past perf.* | 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 | 36.2426 | −0.0098 | 0.0000 | −0.3460 | −0.0374* | −0.0050 | −0.5585 | 0.0382 | 0.0095 |
| | (0.2890) | (29.2430) | (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) |
| *Past perf.* | 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) alph 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.*

*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** | 0.0651** | −0.0391*** | −0.0463*** | −0.0639*** | −0.0705*** |
| | (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** |
| | (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** | −0.0371** | −0.0558** | −0.0622** |
| | (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*** | 0.0744*** | 0.0848*** | 0.0982*** | 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*** | 0.0751*** | 0.0840*** | 0.0911*** | 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*** | 0.0451*** | 0.0499*** | 0.0646*** | −0.0272*** | −0.0337*** | −0.0479*** | −0.0744*** | −0.0243** | −0.0310** | −0.0487*** | −0.0445** |
| | (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** | −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*** | 0.0496*** | 0.0665*** | 0.0553*** | −0.0222** | −0.0314*** | −0.0313** | −0.0362** |
| | (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*** | −0.0350*** | −0.0513*** | −0.0524*** | 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*** | −0.0430*** | −0.0552*** | −0.0594*** | 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*** | 0.0451*** | 0.0346** | 0.0376*** |
| | (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** | −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** | −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*** | −0.0362*** | −0.0462*** | −0.0841*** | −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 2001, and from December 2001 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.*

*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*** | | | −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** | | | −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*

| | $Momentum$ | | | | $3Y\,Reversal$ | | | | $5Y\,Reversal$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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*** | 0.0843*** | 0.0912*** | 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*** | 0.0910*** | 0.0876*** | 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*** | 0.0509** | 0.0579*** | 0.0208 | −0.0337*** | −0.0362* | −0.0548*** | −0.0071 | −0.0310** | −0.0478** | −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*** | 0.0035 | 0.0055 | 0.0015 | 0.0077 | −0.0333** | | −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*** | 0.0756*** | 0.0220 | 0.0345** | −0.0314*** | | −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*** | −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** | 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*** | −0.0146 | −0.0579*** | −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*** | −0.0143 | −0.0495** | −0.0498*** | 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*** | 0.0636*** | 0.0564*** | 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*** | | −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.*

*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** |
| | (0.0274) | (0.0301) | (0.0342) | (0.0107) | (0.0521) | (0.0413) | (0.0529) | (0.0134) | (0.0527) | (0.0392) | (0.0531) | (0.0151) |
| 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* |
| | (0.0427) | (0.0569) | (0.0513) | (0.0187) | (0.0710) | (0.0555) | (0.0649) | (0.0166) | (0.0559) | (0.0653) | (0.0701) | (0.0150) |
| BGR alpha | −0.0232 | −0.0274** | −0.0487*** | −0.0127 | −0.0742*** | −0.0542*** | −0.0254 | 0.0244 | −0.0287 | −0.0459*** | −0.0781*** | −0.0247* |
| | (0.0198) | (0.0137) | (0.0170) | (0.0121) | (0.0269) | (0.0108) | (0.0248) | (0.0167) | (0.0242) | (0.0143) | (0.0179) | (0.0141) |

*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*** | 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* | −0.0586*** | −0.0176 | −0.0015 | −0.0510*** | −0.0523** | −0.0254 | −0.0063 | −0.0340** | −0.0644** | −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) |

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 |
| | (0.0293) | (0.0309) | (0.0405) | (0.0122) | (0.0377) | (0.0334) | (0.0584) | (0.0180) | (0.0640) | (0.0449) | (0.0624) | (0.0308) |
| 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 |
| | (0.0591) | (0.0509) | (0.0585) | (0.0164) | (0.0669) | (0.0593) | (0.0738) | (0.0198) | (0.0902) | (0.0768) | (0.0603) | (0.0340) |
| BGR alpha | −0.0083 | −0.0355** | −0.0388** | −0.0153 | 0.0047 | −0.0367** | −0.0852*** | −0.0450*** | −0.0030 | −0.0384** | −0.0924*** | −0.0447** |
| | (0.0152) | (0.0149) | (0.0183) | (0.0124) | (0.0164) | (0.0145) | (0.0214) | (0.0139) | (0.0210) | (0.0174) | (0.0265) | (0.0180) |

*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* |
| | (0.0469) | (0.0318) | (0.0573) | (0.0263) | (0.0615) | (0.0411) | (0.0403) | (0.0175) | (0.0421) | (0.0285) | (0.0319) | (0.0127) |
| 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 |
| | (0.0729) | (0.0518) | (0.0674) | (0.0280) | (0.0712) | (0.0663) | (0.0641) | (0.0186) | (0.0631) | (0.0440) | (0.0405) | (0.0162) |
| BGR alpha | −0.0073 | −0.0551*** | −0.0416 | −0.0172 | −0.1040*** | −0.0315* | 0.0013 | 0.0527*** | −0.0123 | −0.0360*** | −0.0532*** | −0.0204 |
| | (0.0197) | (0.0115) | (0.0258) | (0.0189) | (0.0244) | (0.0179) | (0.0159) | (0.0139) | (0.0298) | (0.0128) | (0.0133) | (0.0134) |

*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*** | 0.0677** | 0.0051 | 0.0718** | 0.0556*** | 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*** | −0.0184 | 0.0087 | −0.0504*** | −0.0377*** | −0.0178 | 0.0163 | −0.0377* | −0.0208** | −0.0467*** | −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) |

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*** | 0.0296*** |
| | (0.0521) | (0.0290) | (0.0494) | (0.0243) | (0.0292) | (0.0420) | (0.0384) | (0.0112) | (0.0425) | (0.0381) | (0.0271) | (0.0113) |
| 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) | (0.0503) | (0.0732) | (0.0271) | (0.0480) | (0.0748) | (0.0651) | (0.0137) | (0.0752) | (0.0517) | (0.0565) | (0.0184) |
| BGR alpha | −0.0005 | −0.0523*** | −0.0508** | −0.0251 | −0.0282** | −0.0580*** | −0.0179 | 0.0051 | −0.0824*** | −0.0491** | 0.0229 | 0.0527*** |
| | (0.0193) | (0.0192) | (0.0222) | (0.0192) | (0.0114) | (0.0167) | (0.0151) | (0.0098) | (0.0146) | (0.0204) | (0.0144) | (0.0092) |

*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 |
| | (0.0292) | (0.0329) | (0.0308) | (0.0104) | (0.0273) | (0.0281) | (0.0382) | (0.0131) | (0.0320) | (0.0251) | (0.0318) | (0.0143) |
| 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** |
| | (0.0457) | (0.0447) | (0.0507) | (0.0128) | (0.0551) | (0.0392) | (0.0621) | (0.0241) | (0.0572) | (0.0397) | (0.0397) | (0.0178) |
| BGR alpha | −0.0208 | −0.0254* | −0.0614*** | −0.0203** | −0.0332 | −0.0461** | −0.0271* | 0.0030 | −0.0499** | −0.0401*** | −0.0186 | 0.0157 |
| | (0.0172) | (0.0137) | (0.0168) | (0.0093) | (0.0227) | (0.0194) | (0.0155) | (0.0116) | (0.0224) | (0.0110) | (0.0206) | (0.0164) |