Factor Momentum in Commodity Futures Markets

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Abstract

This paper examines the factor momentum in commodity futures markets. Using data from the developed markets from 1985 to 2022, we first show that a commodity factor's past returns positively predict its future returns. This predictability leads to sizable economic profits in a factor momentum strategy, is at its strongest over the one-month horizon, and could be explained by mispricing. Moreover, we show that the factor momentum indicates mean-variance inefficient common commodity factors, and negatively impacts the pricing efficiency of factor pricing models. We construct the time series of efficient factors, which exhibit higher Sharpe ratios and help improve the pricing performance of factor models. Our results point to the potential to time commodity factors, and highlight the importance of conditional asset pricing in commodity futures markets.

JEL classification: G11, G12.

Keywords: Return autocorrelation, Mispricing, Factor enhancement, Conditional asset pricing, Mean–variance optimization

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1 Introduction

The recent literature in equity markets documents the momentum in factor portfolios: the long-short characteristic portfolios that outperform in the past continue to generate higher returns in the future (Arnott et al., 2023; Ehsani and Linnainmaa, 2022a; Gupta and Kelly, 2019). Such phenomenon is referred to as factor momentum to differentiate it from the traditional momentum of Jegadeesh and Titman (1993) and Moskowitz et al. (2012). Ehsani and Linnainmaa (2022a) analyze the time-series factor momentum and show that factor returns are positively autocorrelated. The factor momentum is rationalized by mispricing as arbitrageurs shy away from trading against persistent sentiment (Arnott et al., 2023; Ehsani and Linnainmaa, 2022a; Kozak et al., 2018).

Our paper extends the idea of time-series factor momentum to commodity futures markets. First, we examine the existence of factor momentum in this market and explore possible economic explanations. Second, following Ehsani and Linnainmaa (2022b), we evaluate the efficiency of commodity asset pricing models based on factor momentum, and improve these models with enhanced factors. By exploring factor momentum, our paper aims to advance our understanding of asset pricing and risk premia in commodity futures markets, which are of vital interest to financial investors and firms with a commercial interest in these markets.

The commodity futures markets have become increasingly important over the past few decades, where the trading volume and investment in commodity futures have increased sharply (Basak and Pavlova, 2016; Cheng and Xiong, 2014; Tang and Xiong, 2012). According to the World Federation of Exchanges, more than 10 billion commodity futures contracts have been traded in 2021. A growing number of mimicking strategies based on cross-sectional characteristics are proven to generate sizable profits in commodity futures markets, such as those based on the basis (Gorton and Rouwenhorst, 2006; Koijen et al., 2018), basis-momentum (Boons and Prado, 2019), and hedging pressure (Kang et al., 2020; Szymanowska et al., 2014). In addition, commodity asset pricing models built upon these mimicking strategies are proposed with empirical success (Bakshi et al., 2019; Boons and Prado, 2019; Yang, 2013).

Why could factor momentum exist among commodity factors? Previous literature in equity markets rationalizes the factor momentum based on a mispricing channel (Ehsani and Linnainmaa, 2022a). Theoretical and empirical evidence suggests that the mispricing which matches factor risks cannot be traded away because arbitrageurs avoid taking factor risks, so that mispricing remains and leads to momentum in factor returns. This mechanism thus relates the factor momentum to the slow-moving mispricing correction from limits-to-arbitrage (Ma et al., 2023). In the literature on commodity futures markets, there also exists evidence of mispricing and limited arbitrage (Da et al., 2023; Fernandez-Perez et al., 2018; Girma and Paulson, 1999). Hence, factor momentum could exist in commodity futures markets due to mispricing.

We use a sample of 36 commodity futures contracts from developed markets, including those in the U.S. and U.K., from January 1985 to May 2022, to construct ten well-documented commodity factors. We find a significant factor momentum in these factors over the 1-month horizon, which leads to sizable economic gains. Specifically, the factor's returns in the prior month significantly predict its returns in the following month. The average factor earns a monthly return of 66 basis points (bps) (t-statistic = 3.57) following a month of positive returns, and an insignificant return of almost zero following a month of negative returns. Furthermore, a factor momentum strategy that buys (sells) the factors with positive (negative) returns in the previous month earns an annualized return of 4.37% (t-statistic = 2.80) and generates significant risk-adjusted returns under the two-factor models of Boons and Prado (2019).[1] We show that these risk-adjusted returns are indeed driven by the factor autocorrelation based on the return decomposition of Leippold and Yang (2021). Finally, we further explore the factor momentum in Chinese commodity futures markets as a robustness check and obtain consistent results.

We next examine whether the factor momentum stems from the mispricing. We follow Ehsani and Linnainmaa (2022a) and conduct the following test: if the mispricing channel is valid, the factor momentum should *concentrate* on systematic factors, i.e., mimicking portfolios that explains systematic variations in returns. Our results are consistent with this prediction. By extracting principal components (PCs) from factors in our sample, we observe that factor momentum predominantly concentrates on high-eigenvalue PCs, which serve as proxies for systematic factors. This concentration is pronounced in whole sample period and in the subsample after the financialization of commodities.

[1] Note that we always utilize models of Yang (2013) and Bakshi et al. (2019) whenever a pricing model for commodity futures contracts is needed throughout the study and obtain qualitatively the same results. Here, risk-adjust returns based on Yang (2013) and Bakshi et al. (2019) are also significant.

Furthermore, we explore the asset pricing implications of the factor momentum in commodity futures markets. Given autocorrelated factor returns, the factor momentum would lead to a *mismatch* between factor's returns and volatility if the factor volatility does not increase with past factor returns (Ehsani and Linnainmaa, 2022b). This mismatch gives rise to mean-variance inefficient factor portfolios and biased factors, sending distorted signals to traders (Grinblatt and Titman, 1987).

We empirically examine the efficiency of existing commodity asset pricing models. First, based on the model of Boons and Prado (2019), we find that the commodity market factor and basis-momentum are mean-variance inefficient: while the factor's returns increase with past returns, the factor's volatility remains largely unchanged. Second, we construct the time-series efficient factors following Ehsani and Linnainmaa (2022b). The efficient factors take dynamic positions in the original factor to minimize variance while maintaining the expected returns and exhibit higher Sharpe ratios. Specifically, the Sharpe ratio improvement in efficient market factor and efficient basis-momentum amounts to 0.24 (t-statistic = 2.71) and 0.13 (t-statistic = 2.76), respectively. Third, the model with enhanced factors is incrementally informative relative to its standard version at the 1% level (p-value = 0.00) in the spanning test. Particularly, the alphas of efficient market factor (t-statistic = 2.63) and efficient basis-momentum (t-statistic = 2.67) after controlling for standard model are both significant at the 1% level, indicating substantial improvement in the model's pricing ability. Meanwhile, the standard factors are fully spanned by the efficient model. Furthermore, our findings remain robust after the financialization of commodity futures. These results suggest that the time-series transformation significantly enhances the pricing power of commodity factor models, and provides economic gains for mean-variance utility investors.

Our study adds to the literature in two directions. First, we extend the literature on factor momentum by providing novel empirical evidence from commodity futures markets. The existing literature documents the factor momentum in equity (Ehsani and Linnainmaa, 2022a; Arnott et al., 2023; Gupta and Kelly, 2019; Ma et al., 2023; Yan and Yu, 2023) and foreign exchange markets (Zhang, 2022). Leippold and Yang (2021) question the existence of factor momentum and argue that the profitability of factor momentum strategy in equity markets is a manifestation of mean factor returns rather than factor return predictability. Our empirical analysis in commodity futures markets provides an out-of-sample investigation beyond the equity markets, contributing to the debate on the existence and rationale of the factor momentum.

This paper also contributes to the growing studies on conditional asset pricing. This strand of literature largely focuses on equity markets, which enhances the equity asset pricing models by utilizing various *conditioning* information, such as covariance structure (Daniel and Titman, 1997; Daniel et al., 2020), lagged factor volatility (Moreira and Muir, 2017; Zimmermann, 2022), lagged factor returns (Ehsani and Linnainmaa, 2022b), aggregated signals (Hollstein and Prokopczuk, 2023), and conditional risk (Gormsen and Jensen, 2022). Existing studies in commodity futures markets are limited to discussing the implication of the lagged factor volatility for commodity factor improvement (Sakkas and Tessaromatis, 2020; Kang and Kwon, 2021). We instead improve commodity asset pricing models based on lagged factor returns and our results shed light on the importance of conditional asset pricing in commodity futures markets.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and commodity factors returns. In Section 4, we examine the existence of factor momentum and explore its economic rationale. Section 5 conducts time-series transformation. Finally, Section 6 concludes.

2 Literature review

2.1 Factor momentum

A collection of research explores the factor momentum at the time-series level. Based on 22 equity factors, Ehsani and Linnainmaa (2022a) document the time-series factor momentum by showing that equity factor returns are positively autocorrelated. They rationalize this phenomenon by mispricing and analyze the relation between factor momentum and individual stock momentum (Jegadeesh and Titman, 1993). Gupta and Kelly (2019) extend Ehsani and Linnainmaa (2022a) and confirm the existence of factor momentum in Asia-Pacific and European equity markets. Zhang (2022) in turn documents significant factor momentum in currency markets, and finds that the factor momentum is concentrated on the systematic currency factors.

Meanwhile, Leippold and Yang (2021) question the existence of time-series factor momentum and argue that this phenomenon is merely a byproduct of factor returns. By decomposing the factor momentum into the buy-and-hold and pure factor timing portfolio components, they find that factor momentum returns based on 210 US equity factors are driven by the mechanical exposure to factor premiums, while the predictability of past performance is empirically weak. There are also studies investigating factor momentum at the cross-sectional level, which suggest that the factors outperforming others in the past continue to outperform in the future (Arnott et al., 2023; Avramov et al., 2017; Lewellen, 2002; McLean and Pontiff, 2016).

2.2 Conditional asset pricing and factor enhancement

Recent literature points out that the traditional asset pricing models tend to be inefficient because factor-mimicking portfolios are not mean-variance efficient (Daniel et al., 2020; Ehsani and Linnainmaa, 2022b; Gormsen and Jensen, 2022; Hollstein and Prokopczuk, 2023; Zimmermann, 2022). To mitigate this problem, these studies resort to conditional asset pricing, which utilizes conditioning information to improve the mean-variance efficiency of factor portfolios. Through factor enhancement, the factor portfolio's returns become a better representation of factor risk. Moreover, the factor models based on enhanced factor portfolios would move closer to the efficient frontier, and achieve improved asset pricing power (e.g., Daniel et al., 2020).

In particular, Daniel et al. (2020) focus on the mean-variance inefficiency within factors in the Fama-French five-factor model, and construct characteristic-efficient portfolios to improve individual factors and the factor model. Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Moreira and Muir (2017) improve the mean-variance inefficient equity factors by introducing volatility-managed portfolios. Zimmermann (2022) takes a step further by applying this volatility management to enhance the pricing power of equity factor models. Ehsani and Linnainmaa (2022a) utilize the conditioning information in factor momentum to construct time-series efficient factors. Hollstein and Prokopczuk (2023) and Gormsen and Jensen (2022) further enhance the equity market factor based on aggregated signals and conditional risk, respectively.

In the commodity futures markets, Sakkas and Tessaromatis (2020) construct volatility-managed factor portfolios and show that the managed momentum yields a significantly higher Sharpe ratio than the standard commodity momentum. Meanwhile, Kang and Kwon (2021) eliminate the impact of look-ahead bias by exploring the out-of-sample volatility management for real-time investors. They find no significant improvement in momentum, commodity market factor, basis-momentum, and two components of the basis-momentum.

Overall, our paper fills the gaps in the literature by extending the factor momentum and time-series factor enhancement to commodity futures markets.

3 Data and factor returns

We collect data on settlement prices, open interests, and volume of 36 actively traded commodity futures contracts in the developed markets, including 29 contracts traded in the U.S. and 7 in the U.K. The data spans from January 1985 to May 2022 and is sourced from the Bloomberg.[2] Our dataset covers commodities in four sectors: agriculture (16), energy (6), livestock (3), and metal (10). Table A.1 reports the detailed information for all commodity futures in our sample.

Following Gorton et al. (2013) and Han and Kong (2022), we utilize the first-nearby contracts to calculate the commodity futures excess returns on a fully collateralized futures position based on the roll-over strategy as follows:

$$Return_{i,d+1}^{(1)} = \begin{cases} \frac{F_{i,d+1}^{(1)}}{F_{i,d}^{(1)}} - 1, & \text{if no contract is rolled over at day } d, \\ \frac{F_{i,d+1}^{(1)}}{F_{i,d}^{(2)}} - 1, & \text{otherwise,} \end{cases} \tag{1}$$

where $F_{i,d}^{(1)}$ and $F_{i,d+1}^{(1)}$ denote the settlement price of the first nearby futures contract on day d and $d+1$, respectively, and $F_{i,d}^{(2)}$ is the settlement price of the second nearby futures contract on day d. We further compound the daily excess returns to obtain the monthly returns of each commodity.

Table 1 reports the summary statistics for the commodity futures excess returns. The mean returns vary across commodities. The highest annualized mean returns come from tin, gasoline blendstock, and soybean meal. Tin generates the highest annualized Sharpe ratio. There is a large variation in the volatility of commodity futures returns. The annualized standard deviation reaches the lowest in live cattle (14.29%) and the highest in natural gas (46.29%). More than half of the contracts are positively skewed and all

[2] Our sample starts from January 1985 with 7 factors. Due to the data availability of volume and open interest, the series of liquidity, hedging pressure, and open interest factors begin in September 1989, January 1994, and March 1995, respectively.

contracts show leptokurtic in returns.

Next, we construct ten commodity factors. Each factor is related to an existing trading strategy in the literature. In particular, the basis captures the information in the slope of futures term structure (Gorton and Rouwenhorst, 2006; Koijen et al., 2018); momentum exploits the cross-sectional predictability of past performance (Erb and Harvey, 2006; Miffre and Rallis, 2007; Shen et al., 2007); basis-momentum relates to the slope and curvature of the term structure of futures returns (Boons and Prado, 2019); hedging pressure reflects the mismatch in the amount of hedging and speculating activity (Kang et al., 2020; Szymanowska et al., 2014); skewness relates to the mispricing from investor with cumulative prospect theory preferences and selective hedging practices (Fernandez-Perez et al., 2018); open interest reflects future price initiation (Hong and Yogo, 2012; Szymanowska et al., 2014); currency β captures the changes in the U.S. dollar versus a basket of foreign currencies (Erb and Harvey, 2006; Szymanowska et al., 2014); inflation β reflects the impact from unexpected inflation (Szymanowska et al., 2014); and liquidity captures the liquidity risk of commodity futures trading (Szymanowska et al., 2014).

For each trading strategy, we construct the factor mimicking portfolios. We sort commodities into quintiles in month $t-1$ according to the predictive characteristic of a trading strategy. The long-short portfolio involves buying (selling) the quintile with the highest (lowest) predicted returns in month t. We compute the equally-weighted returns for each portfolio in month t. All portfolios are rebalanced at the monthly frequency. Finally, we use the S&P Goldman Sachs Commodity Index (GSCI) to represent the commodity market (MKT).[3] The detailed description of the commodity factors is summarized in the Appendix.

Table 2 reports the descriptive statistics for commodity factors. The skewness factor shows the strongest performance among all factors. It generates an annualized return of 10.33%, which is significant at the 1% level. Noticeably, the skewness factor is associated with exploiting mispricing in commodity futures markets (Fernandez-Perez et al., 2018). The substantial factor returns imply that the mispricing in commodity futures markets tends to be sizable, which aligns with the economic rationale behind factor momentum

[3] S&P GSCI is the industry-standard benchmark index for commodity investment in the developed markets. It is composed of commodity futures contracts traded in the U.S. and U.K. from the agricultural, energy, livestock, and metals sectors. We also consider an average commodity factor, which is the equally weighted portfolio of all sample commodity futures. The results from this alternative market factor are similar to those reported in our tables. These results are available from the authors upon request.

Ehsani and Linnainmaa (2022a). We formally test the mispricing channel in Section 4.4.

The basis, basis-momentum, and momentum factors generate sizable excess returns of 7.27%, 8.19%, and 8.21%, respectively, and are highly significant. The notable performance of these three factors is in line with their popularity, that is, all of them have been included in the existing commodity asset pricing models. The profitability of other strategies — currency β, inflation β, liquidity, hedging pressure, and open interest — is weaker in terms of mean returns and Sharpe ratios. Overall, our results for these commodity factors are largely consistent with the previous literature, such as Boons and Prado (2019), Daskalaki et al. (2014), and Fernandez-Perez et al. (2018).

4 Factor momentum

This section evaluates whether factor momentum exists in commodity futures markets. In particular, we conduct three related tests to evaluate the statistical and economic significance of factor momentum. First, we examine whether the factor's past returns predict its future returns. Second, if predictability exists, we investigate whether this predictability can be translated into a profitable investment strategy for commodity investors. Third, by decomposing the factor momentum strategy, we examine whether the profitability is driven by the return predictability or mean factor returns. Finally, we rationalize factor momentum based on mispricing.

4.1 Autocorrelated factors

We test the predictability of the factor's past returns for future returns over 5 different horizons: 1, 3, 6, 9, and 12 months. We estimate two predictive time-series regressions as follows:

$$Return_{f,t} = \alpha + \beta \times PastReturn_{f,t,h} + \epsilon_{f,t}, \tag{2}$$

$$Return_{f,t} = \alpha + \beta \times PastSign_{f,t,h} + \epsilon_{f,t}, \tag{3}$$

where $Return_{f,t}$ is factor f's returns in month t, and $PastReturn_{f,t,h}$ is factor f's past returns over the h-month horizon before month t. The $PastSign_{f,t,h}$ is a dummy variable that is equal to one if factor f's past returns over the h-month horizon before month t are positive, and zero otherwise. These regressions are estimated within each factor and pooled across all factors. Following Ehsani and Linnainmaa (2022a), the momentum factor is exclude from the pooled predictive analysis, and from the factor momentum construction over the following tests. This approach is designed to prevent the mechanical correlation between factor momentum and individual momentum.

Table 3 shows that factors' past returns significantly predict their future returns, and such predictability is strongest over the 1-month horizon. Panel A outlines the predictive results for the 1-month factor momentum. Our main interest lies in pooled tests, which evaluate the overall level of factor momentum in commodity futures markets. Results show that the pooled predictability of prior month factor returns for future returns is statistically significant across commodity factors. Based on nine non-momentum factors, an average factor's monthly returns significantly increase with its return in the previous month at the 1% level (t-statistic = 4.76). Following a month of positive returns, this average factor earns 66 bps (t-statistic = 3.57) per month. In contrast, when the factor's prior month return is negative, the monthly returns for the average factor is insignificant and almost zero. For individual factors, all of them exhibit positive slope coefficients under both regressions, suggesting positive factor autocorrelation. Additionally, although all commodity factors' unconditional returns are positive in Table 2 except for the liquidity factor, the intercepts of the second regressions show that six out of nine factors earn negative returns after a month of negative returns. Such pattern also suggests that factor returns are autocorrelated.

For longer horizons, the predictability of factor premiums becomes weaker. In Panel B, the pooled results from the first specification show that the monthly returns of an average factor positively relate to its return over the past three months at the 5% level (t-statistic = 2.19). Besides, under the second regression, the average factor earns 13 bps (t-statistic = 0.96) after a negative return over the past three months, and the returns increase to 45 bps (t-statistic = 2.43) after a positive return. For individual factors, several individual factors have negative slope coefficients. For the 6-, 9-, and 12-month horizons, the results are summarized in Table A.2. We find that the predictability for these horizons becomes more mixed.

In summary, the commodity futures factors are positively autocorrelated on average. The factor autocorrelation is most significant over the 1-month horizon. This factor autocorrelation should be appealing to commodity investors. Intuitively, for an investor who believes in factor momentum at the pooled level, she could observe the signs of factors' unconditional returns in the last month and make investment decisions.

4.2 Profitability of factor momentum strategy

Based on the substantial pooled factor autocorrelation, we buy (sell) factors with positive (negative) past returns to exploit this return predictability. Results in Table 4 show that the profitability of factor momentum strategy is most pronounced over the 1-month horizon. Panel A reports that the 1-month factor momentum strategy earns an annualized return of 4.37% (t-statistic = 2.80) and delivers significant risk-adjusted returns of 4.54% (t-statistic = 2.87) under the factor model of Boons and Prado (2019).

In Table 4, we also report the returns to the winner, loser and benchmark portfolios. The winner (loser) portfolios are the factors with positive (negative) past returns, and the benchmark portfolio takes equal weight across all factors in the sample. Examining returns to these three portfolios allow us to evaluate factor momentum, i.e., we expect the winner (lower) portfolio to outperform (underperform) the benchmark if factors' past performance predicts their future returns.

Panel A shows that, for the 1-month factor momentum, the winner portfolio generates a highly significant annualized return of 8.17% (t-statistic = 4.40) and outperforms the benchmark portfolio, which earns 4.43% (t-statistic = 3.52). Meanwhile, the loser portfolio underperforms the benchmark portfolio by earning an insignificant annualized return of -0.40% (t-statistic = -0.19). In Figure 1, we plot the cumulative returns of these three portfolios, which support the existence of factor momentum.

The profitability of the 3-month factor momentum strategy is weaker compared to that of the 1-month strategy. In Panel B, the 3-month factor momentum generates an annualized return of 3.11% (t-statistic = 2.20) with a risk-adjusted return of 2.58% (t-statistic = 1.82). Consistent with the weaker profitability of factor momentum strategy, the annualized returns of the winner portfolio decline to 6.85% (t-statistic = 3.58), while the returns of the loser portfolio increase to 1.52% (t-statistic = 0.76). For the comparison of two legs with the benchmark, the winners outperform the benchmark and the losers underperform the benchmark, suggesting that the factor returns over the past three months are still predictive of future factor returns. We provide results for the longer horizons over 6, 9, and 12 months in Table A.3, and find that the factor momentum strategies fail to generate significant profits.

To sum up, the factor momentum strategies based on the short-term information lead to significant profits, which are most sizable over the 1-month horizon. These findings are consistent with the results in Section 3.1 and confirm the significant predictive power of factor returns over the short term.

4.3 Factor momentum decomposition

The returns of factor momentum can stem from two sources: the mechanical exposure to factor risk premia in a static way, the predictable factor timing ability, or a combination of both (Leippold and Yang, 2021). We therefore decompose the factor momentum into two portfolios following Leippold and Yang (2021). The first portfolio is based on a buy-and-hold strategy (BH), which holds the factors without active timing and earns the factor premium. In particular, it longs (shorts) factors in month t with positive (negative) prevailing mean returns up to month $t-1$.

The second portfolio is based on a pure factor timing strategy (FT), which is designed to capture the economic benefits from factor return predictability. To rule out the profits from factor premiums, this strategy only works when the factor's past returns deviate from the prevailing mean returns. Specifically, it longs (shorts) factors in month t when their mean monthly returns over the past horizon are higher (lower) than their prevailing historical mean up to month $t-1$. Table 5 Panels A and B report the results for factor momentum decomposition over 1- and 3-month horizons, respectively.

Table 5 Panel A decomposes the 1-month factor momentum and shows that the factor timing strategy generates a highly significant return of 4.23% (t-statistic = 2.80) per year, while the buy-and-hold strategy earns an insignificant return of 1.41% (t-statistic = 0.96). These suggest that the timing ability of the 1-month factor autocorrelation is strong in commodity futures markets, whereas the commodity factor premiums are weak on average. Hence, the significant profitability of the 1-month factor momentum is not driven by the mean factor premiums.

We next use the spanning tests to examine the relation between factor momentum and two component portfolios. These spanning tests investigate whether these two components help to explain the return of the factor momentum strategy. We also revert the spanning tests to regress buy-and-hold and factor timing portfolios returns, respectively, on the factor momentum returns.

We obtain consistent spanning test results. First, while both components partially explain 1-month factor momentum returns, the explanatory power of the factor timing portfolio is much stronger than that of the buy-and-hold strategy. Specifically, in Columns (1) and (2) of Panel A, the slope coefficient of the factor timing portfolio is highly significant and sizable at 0.99% (t-statistic = 71.85) while that of the buy-and-hold portfolio is merely 0.11% (t-statistic = 2.22). Second, the factor timing portfolios can fully explain the factor momentum, but not for the buy-and-hold portfolio. This finding is evidenced by the results of intercepts. We find that the factor momentum generates a significant alpha of 0.35% (t-statistic = 2.70) after controlling for the buy-and-hold strategy, but produces an insignificant alpha of approximately zero after controlling for the factor timing strategy.

Third, we find that the 1-month factor momentum portfolio dominates both the factor timing and buy-and-hold components. The reverse spanning tests in Columns (3) and (4) of Panel A generate insignificant intercepts in both regressions, indicating that the factor momentum fully explains both strategies. Overall, we conclude that the outstanding profitability of the 1-month factor momentum strategy indeed stands for the economic significance of factor autocorrelation.

Results for the 3-month factor momentum are qualitatively the same. In Panel B, we find the factor timing strategy leads to significant returns of 2.50% (t-statistic = 1.74) per year while the buy-and-hold strategy generates an insignificant return of 1.37% (t-statistic = 0.94). Additionally, this factor timing portfolio shows superior explanatory power for the factor momentum, evidenced by a slope coefficient of 0.92% (t-statistic = 55.24). Table A.4 reports the decomposition results for factor momentum over the past 6, 9, and 12 months.

Overall, we find the profits of factor momentum strategies are indeed driven by the active timing ability, rather than being a simple byproduct of commodity factor premiums. Hence, the factor autocorrelation in commodity futures markets is *economically* significant, in contrast to the findings of Leippold and Yang (2021) in equity markets.

4.4 Factor momentum and mispricing

Following Ehsani and Linnainmaa (2022a), we test the mispricing explanation for the factor momentum by focusing on systematic factors. We extract the PCs from non-momentum factors and systematic factors are proxied by the high-eigenvalue PCs. We obtain two sets of PCs: the high set includes half of PC factors with higher eigenvalue, and the low set contains the other half of PC factors with lower eigenvalue. This procedure is a fully out-of-sample approach to avoid the look-ahead bias. In month t, we utilize the information up to month $t-1$ to calculate the returns of the PC factors, and construct the factor momentum portfolio returns. We use daily factor returns starting in January 1985 to compute the eigenvectors and require at least 5 years of data to extract the PCs. The returns on the factor momentum strategies therefore begin in February 1990.

Based on the prediction of the mispricing channel, the strongest momentum is expected to exist in high PC factors, which are the proxies for systematic factors. Table 6 shows consistent full sample results. We find that the strategy trading high PC factors generates monthly returns of 61 bps (t-statistic = 3.14), and offers significant risk-adjusted returns at the 1% level (t-statistic = 3.16). The factor momentum in the low PC factors are weaker, generating returns of 44 bps (t-statistic = 2.40).

We further use spanning tests to evaluate whether the high eigenvalue factors generate stronger momentum than the low eigenvalue factors. Specifically, Panel B spans the momentum in the high PC factors by the momentum in the low PC factors based on the following regression:

$$FMOM_t^{HighPC} = \alpha + \beta \times FMOM_t^{LowPC} + X' + \varepsilon_t, \tag{4}$$

where α represent the incremental returns of $\mathrm{FMOM}_t^{\mathrm{HighPC}}$ over $\mathrm{FMOM}_t^{\mathrm{LowPC}}$. The X' denotes a vector with MKT and basis-momentum. Panel C conducts the reverse spanning tests, which regress the factor momentum in low PC factors by momentum in high PC factors.

Our main focus is on the intercepts in Panel B and Panel C. Panel B shows that momentum in high PC factors generates significant abnormal returns over momentum in low PC factors. These results indicate that factor momentum in high eigenvalue factors significantly outperforms that in low eigenvalue factors. Moreover, Panel C finds such spanning results do not work both ways. The momentum in low PC factors is insignificant after controlling the momentum in high PC factors. Our findings confirm the concentration of factor momentum in the high PC set, i.e., systematic risks.

In addition, for the robustness check, we further consider a subsample after the financialization in commodity futures markets. Financialization, which begins in 2004, is associated with the rapid boom of commodity investment and an unprecedented entry of institutional investors into the markets (Cheng and Xiong, 2014; Singleton, 2014; Tang and Xiong, 2012). This transition is widely accepted as a structural break in commodity futures markets (Basak and Pavlova, 2016; Da et al., 2023; Goldstein and Yang, 2022).

We show that out results are qualitatively the same after the financialization. The right columns of Panel A report that, in the subsample, the high PC factors keep generating stronger factor momentum than the low PC set. Particularly, the factor momentum strategy based on high PC factors leads to a monthly return of 53 bps (t-statistic = 2.23) with significant risk-adjusted returns (t-statistic = 2.45), while the strategies based on low PC set show insignificant returns, equaling 24 bps (t-statistic = 1.15). Furthermore, the momentum in high PC factors earn significant abnormal returns (t-statistic = 2.14) in the spanning tests after controlling for the momentum in low PC set.

In summary, we find that the factor momentum concentrates on important systematic factors, consistent with the prediction of the mispricing channel. Our empirical evidence for mispricing channel is pronounced in the full sample and remains robust in the subsample after the financialization.

5 Time-series efficient asset pricing model

If the factor returns are positively autocorrelated while the factor's return variance does not increase with its past return, there exists a disconnection between factor premiums and factor risk. This disconnection indicates that the factor portfolios are not mean-variance efficient (MVE), which violates the fundamental assumption for asset pricing models and makes them inefficient (Grinblatt and Titman, 1987).

In this section, we focus on the commodity factor model of Boons and Prado (2019) and conduct analyses following three steps. First, we examine whether the commodity factors in Boons and Prado (2019) 's model are MVE. Second, we construct the corresponding time-series efficient factors by exploiting the factor momentum, and evaluate whether such time-series transformation improves the efficiency of these common factors. Third, we compare the asset pricing power of the efficient factor model and the original one.

5.1 Mean-variance inefficient factors

To examine the mean-variance efficiency of each factor, we regress the factor returns and factor returns volatility, respectively, on factor returns in the previous month. Table 7 Panel A examines the autocorrelation in factor returns and show that the returns of both factors are positively autocorrelated. For example, the prior month returns of MKT significantly predict its future returns by 16 bps (t-statistic = 3.43). Panel B examines the predictive power of prior month factor returns for future factor volatility. We find that the slope coefficients of lagged factor return on factor return volatility is -1 bps (t-statistic = -1.15) for MKT and -3 bps (t-statistic = -1.74) for Basis-momentum. These results indicate that the factor risk does not increase with lagged factor returns, in contrast to the positive time-series dependency between factor returns.

Furthermore, the pricing inefficiency remains pronounced after the financialization. Specifically, the factor returns are significantly autocorrelated for both MKT (t-statistic = 3.17) and Basis-momentum (t-statistic = 2.45) while the relation between lagged factor return and factor return volatility is insignificant for MKT (t-statistic = -1.23) and Basis-momentum (t-statistic = -1.46).

Our findings suggest that the factors in the pricing model of Boons and Prado (2019) are mean-variance inefficient: while their returns significantly increase with past returns, their volatilities are largely insensitive to the past returns. This mismatch suggests that the factor portfolio may load on *unpriced* sources of risk, thus the factor premiums are no longer the efficient representation of factor risk.

5.2 Time-series efficient factors

We follow Ehsani and Linnainmaa (2022b) and Ferson and Siegel (2001) to construct the time series of efficient factors. The intuition is that: once a mean-variance investor is aware of certain forecasting signals for future factor returns, she can utilize the information to dynamically change her position between this factor portfolio and risk-free assets, with the aim of minimizing variance for a given expected return. In other words, the investor can take a levered or conservative position in the factor, depending on the predictive information. Such a dynamic weighting program produces an MVE portfolio because no other portfolio has the same return at a lower variance (Ferson and Siegel, 2001).

The efficient factor, which invests x in the original factor portfolio and the remainder $1 - x$ in the risk-free asset, can be represented as follows:

$$r_{e,t} = x_t \times r_t, \tag{5}$$

where $r_{e,t}$ and r_t are the month t excess returns of the efficient factor and original factor, respectively. The x_t is the optimal weight on the original factor in month t.

Ehsani and Linnainmaa (2022b) narrow down the forecasting signal to be the prior month factor's returns, that is, the time series transformation. They suggest that, for each factor, the investor's optimal weight x_t on the factor in each month t is:

$$x_t = \mu \frac{SR^2 + 1}{SR^2 + \rho^2} \frac{\mu(1-\rho) + \rho r_{t-1}}{\left(\mu(1-\rho) + \rho r_{t-1}\right)^2 + \sigma_\epsilon^2}, \tag{6}$$

where μ, SR, and ρ denote the mean returns, Sharpe ratio, and autocorrelation coefficient of the original factor, respectively. The σ_ϵ^2 is the variance of the error term, which is calculated as $\sigma_\epsilon^2 = (1 - \rho^2)\,\sigma^2$.

To compute the returns of efficient factors in month t, we first estimate factors' means, volatility, and autocorrelations based on information up to month $t-1$, and construct the efficient factors using returns in month $t - 1$. Consistent with mean-variance efficiency tests in the last section, we separate the sample according to the financialization. We expect to observe larger efficiency gains from time-series transformation after 2004, when we observe a higher level of inefficiency.

We find a clear quantitative improvement in the Sharpe ratio for each factor in Boons and Prado (2019) 's model. Table 8 Panel A reports the annualized Sharpe ratios of the original factor and efficient factor, and their differences. Results show that the time-series transformation increases the Sharpe ratio of the MKT from 0.29 to 0.52 and basis-momentum from 0.43 to 0.56.

We next examine whether the increase in Sharpe ratios is statistically significant. We follow Daniel et al. (2020), Moreira and Muir (2017), and Zimmermann (2022) to use

Jensen's alpha to test whether the differences in Sharpe ratios are significant. A significant positive alpha implies that time-series transformation increases Sharpe ratios relative to the original factors, and improves the factor efficiency. The univariant regressions in Panel B suggest that the improvement is significant at the 1% level for both MKT and basis-momentum. Particularly, the efficient MKT generates a monthly alpha of 0.42 (t-statistic = 2.71) and efficient basis-momentum has an alpha of 25 bps (t-statistic = 2.76).

We also evaluate the performance of efficient factors after the financialization and find consistent results. The right columns of Table 8 show that the the efficient MKT and efficient basis-momentum create sizable Sharpe ratio improvement, equaling 0.40 and 0.38, respectively. Further, the improvement in both factors are highly significant, evidenced by the significant alphas in univariate regressions for MKT (t-statistic = 2.91) and basis-momentum (t-statistic = 2.83).

Overall, the time-series efficient factors for Boons and Prado (2019) 's model shows superior mean-variance efficiency than the original factors, evidenced by the increase in Sharpe ratios. The gains are economically and statistically significant for both MKT basis-momentum. Further, the improvements are robust to the financialization of commodity futures.

5.3 Improvement in asset pricing models

We compare the efficient asset pricing model as the model based on efficient MKT and efficient basis-momentum, to the standard asset pricing model as the one based on standard MKT and standard basis-momentum, by using spanning tests (Ehsani and Linnainmaa, 2022b; Zimmermann, 2022). In Table 9 Panel A, we regress the standard factor model on the efficient factor as follows:

$$Factor_t^e = \alpha + \beta_1 \times MKTt + \beta_2 \times Basismom_t + \epsilon_t, \tag{7}$$

where MKT_t and $Basismom_t$ are the returns of standard MKT and standard basis-momentum. $Factor_t^e$ represents the returns of the efficient factor in month t. We conduct this regression for efficient MKT and basis momentum factors. In Panel B, we conduct regressions of each standard factor against the efficient factor model as follows:

$$Factor_t = \alpha + \beta_1 \times MKT_t^e + \beta_2 \times Basismom_t^e + \epsilon_t, \tag{8}$$

where MKT_t^e and $Basismom_t^e$ are the returns in month t of efficient MKT and basis-momentum, respectively. The $Factor_t$ denotes the returns of standard factor.

Our main focus is on the intercept alpha, which measures the incremental information contents of each factor against the right-hand-side asset pricing model. In each panel of Table 9, we report the alphas and corresponding t-statistics for each regression. We also conduct the Gibbons et al. (1989) (GRS) tests to examine the joint significance for alphas of factors in the efficient or standard factor model. In our case, the p-value in the GRS test measures whether a factor model is incrementally informative against the other factor model jointly.

Results in Table 9 show that the efficient model generates higher asset pricing power than the standard model through the whole sample. From Panel A, we find that the efficient model is jointly more informative about future returns at the 1% level (p-value = 0.00) when controlling for the standard model. This model enhancement is driven by both efficient MKT and efficient basis-momentum. In particular, the efficient MKT shows a significant alpha against the standard factor model at 42 bps (t-statistics = 2.63) per month, and efficient basis-momentum at 24 bps (t-statistics = 2.67). Furthermore, in the reverse regressions in Panel B, we find both standard factors are uninformative after controlling for the efficient factor model.

Moreover, the enhancement of the factor model remains substantial after the financialization. Table 9 shows that the efficient model is informative than the standard version at the 1% level (p-value = 0.00), with efficient MKT and efficient basis-momentum generate significant alphas after controlling the standard model. Specifically, the alphas amount to 64 bps (t-statistics = 2.91) and 51 bps (t-statistics = 2.83) for efficient MKT and efficient basis-momentum, respectively.

The above results suggest that the time-series transformation significantly enhances the asset pricing power of the commodity factor model of Boons and Prado (2019). This approach enhances the asset pricing model by improving the mean-variance efficiency of common commodity factors. More specifically, it incorporates the conditional information from factor momentum to the individual common factor portfolios, and provides a better match between portfolio returns and volatility. We show that the enhancement of inefficient factors and factor models is pronounced in the full sample and remains sizable after the financialization of commodity futures. We find qualitatively the same improvement for asset pricing models of Yang (2013) and Bakshi et al. (2019) in Table A.5.

6 Robustness check: Evidence from China

In robustness check, we investigate the factor momentum in Chinese commodity futures markets, which are globally important for commodity futures trading. For example, according to the Futures Industry Association (FIA) report in 2022, among the globally most traded agricultural commodity futures, contracts traded in China dominated the top 10 and accounted for 16 of the top 20 contracts. Along with the active commodity trading, existing literature provides strong evidence of the factor structure in Chinese commodity markets. Those commodity factors documented in developed markets, such as basis, momentum, and basis-momentum, are also found to be profitable in China (Bianchi et al., 2021; Fan and Zhang, 2020; Kang and Kwon, 2017).

Noticeably, Chinese commodity futures markets differ from developed markets in various institutional features. For example, Chinese commodity futures markets are dominated by retail investors, in contrast to the developed markets where institutional investors dominate. While institutional investors explore mispricing and improve information efficiency, unsophisticated retail investors tend to be more irrational and create mispricing (Boehmer and Kelley, 2009; Campbell et al., 2009; Han and Kumar, 2013). Also, other institutional features in Chinese commodity markets, such as government-managed nature of exchanges, multilevel price limits, and limited access for foreign institutions, may impede the price discovery process and prevent rational arbitragers to correct for mispricing (Fan and Zhang, 2020).

Motivated by the unique features of commodity trading in China, we collect data of 65 actively traded commodity futures contracts in China from China Stock Market & Accounting Research (CSMAR) to construct commodity factors and re-conduct our main tests.[4] We follow Fan and Zhang (2020) to adopt 2004 as the start of sample and obtain

[4] Our sample includes contracts in four sectors. **Agriculture**: No.1 Soybean, Apple, No.2 Soybean, Corn, Cornstarch, Egg, Japonica Rice, Late Rice, Common Wheat, Early Rice, Sugar, Strong Wheat,

data from 2004 to 2022.

In Table 10, we observe significant predictability of a factor's prior month returns on its future returns. Specifically, the average factor earns a monthly return of 93 bps (t-statistic = 4.75) following a month of positive returns, and an insignificant return of almost zero following a month of negative returns. Furthermore, from Table 11, the strategy based on 1-month factor momentum generates significant raw and risk-adjusted returns, equaling 5.73% (t-statistic = 3.91) and 5.12% (t-statistic = 3.38), respectively. In addition, we show that the factor momentum in Chinese commodity futures markets is at its strongest over the 1-month horizon and becomes weaker over longer horizons. Finally, Table 12 show that commodity factor momentum concentrates more in high-eigenvalue factors, in line with the mispricing explanation. Hence, the results for factor momentum in China are highly consistent with findings in developed markets.

7 Conclusion

This paper explores the time-series factor momentum in commodity futures markets. Using data from developed markets, we find that the factor momentum in commodity futures markets is statistically significant and at its strongest over the 1-month horizon. It leads to sizable economic gains for investors in a factor momentum strategy. We explain this short-term phenomenon based on the mispricing and arbitrage activity: the mispricing aligning with factors premiums cannot be corrected because the arbitragers avoid taking factor risks. This explanation is confirmed empirically as we find that the factor momentum concentrates more on high-eigenvalue factors.

The existence of factor momentum poses a challenge to popular pricing models as autocorrelated factor returns suggest that pricing models based on them are mean-variance inefficient. To improve the efficiency of individual common factors, we construct the time-series efficient factors by exploiting the factor momentum. We show that the factor models based on efficient factors significantly outperform the original factor models.

Hard Wheat, Jujube, Peanut Kernel, Polished Rice, Live Hog, Soybean Meal, Rapeseed Oil, Palm Olein, Rapeseed Meal, Rapeseed, Soybean Oil; **Metal**: Silver, Aluminum, Gold, Copper, Iron Ore, Nickel, Lead, Steel, Rebar, Ferrosilicon, Silicon Manganese, Tin, Wire Rod, Zinc, Copper Cathode, Stainless Steel; **Energy**: Fuel Oil, Methanol, Crude Oil; **Industrial materials**: Plywood, Bitumen, Cotton, Cotton Yarn, Fiberboard, Flat Glass, Hot-Rolled Coil, Coke, Coking Coal, LLDPE, Polypropylene, Natural Rubber, PTA, PVC, Thermal Coal, Liquefied Petroleum Gas, Low Sulfur Fuel Oil, Polyester, Staple Fiber, Urea, TSR 20, Ethenylbenzene, Ethylene Glycol, Softwood Kraft Pulp, Soda Ash.

Our paper reveals the time-varying risk premiums of commodity factors, and shows that the asset pricing efficiency of existing benchmark models can be improved by timing factors' past returns. These findings help us gain a better understanding of the factor-based investment and provide important implications to practitioners and researchers.

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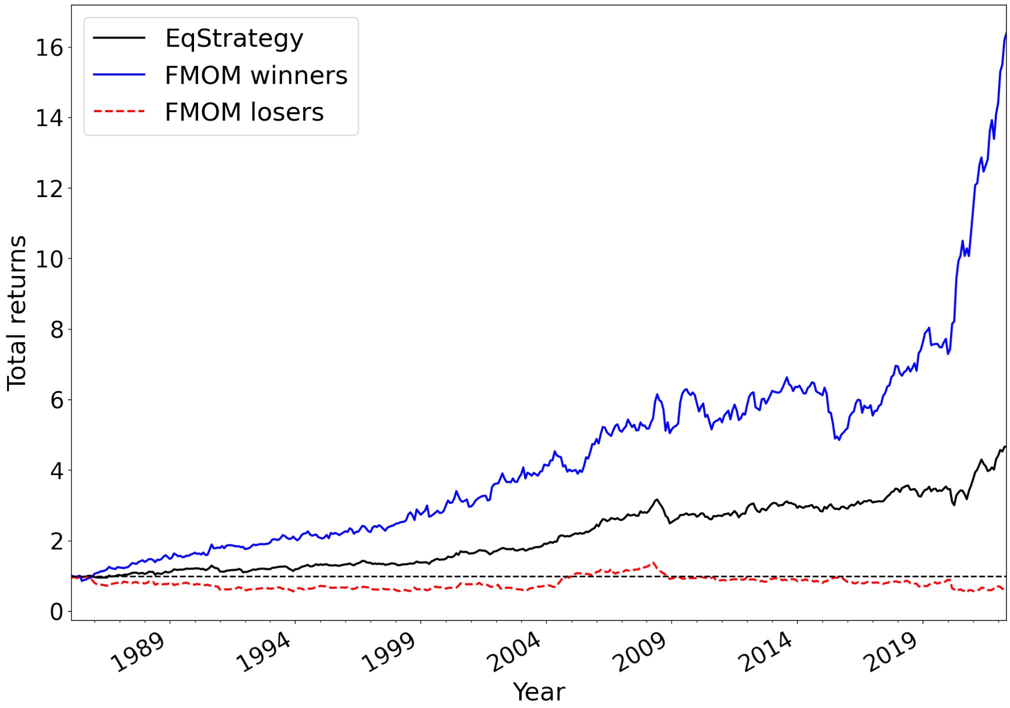
Figure 1: Profitability of factor momentum strategy

This figure plots the cumulative returns of the winner and loser portfolio for the factor momentum strategy. The winners and losers are factors with positive or negative returns over the previous month. We also include a benchmark as an equal-weighted portfolio of all factors. Panel A shows results for the factor momentum over the past one month, and Panel B shows results over the past three months. Each portfolio is rebalanced monthly.

(a) Past one month



(b) Past three months

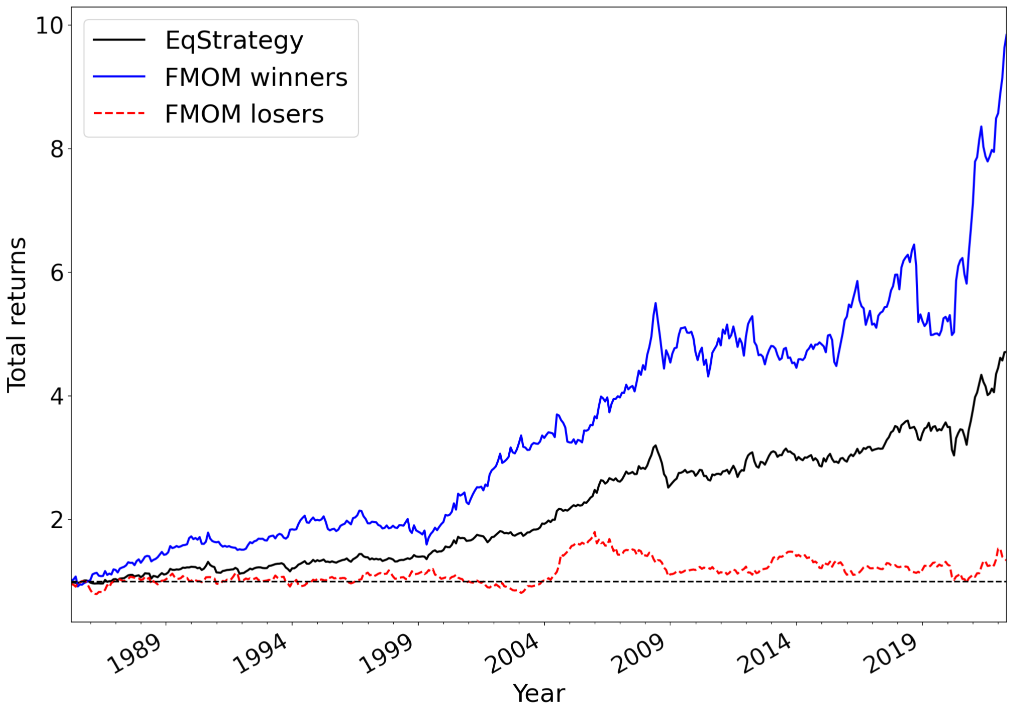


Table 1: Summary statistics for commodity futures

This table shows the descriptive statistic for the excess futures returns of 36 commodities from January 1985 to May 2022. Obs represents the observation number, Mean denotes mean returns, SD stands for standard deviation, SR denotes Sharpe Ratio, Kurt represents kurtosis, Skew is skewness, Min represents minimum returns, and Max represents maximum returns. Mean, SD, and SR are annualized.

Category	**Contract**	**Mean**	**SD**	**SR**	**Skew**	Kurt	**Max**	**Min**
Agriculture	Butter	-1.23	25.96	-0.05	0.18	3.30	32.81	-27.79
	Cocoa	-6.75	27.79	-0.24	0.12	5.60	29.69	-28.78
	Coffee	-8.52	35.36	-0.24	0.53	3.70	41.54	-36.92
	Corn	-5.62	25.68	-0.22	0.28	4.88	38.52	-25.88
	Kansas Wheat	-1.60	25.82	-0.06	0.13	7.46	30.74	-27.22
	Lumber	-0.59	35.36	-0.02	0.14	6.20	43.39	-46.68
	Milk	2.34	28.18	0.08	0.30	4.46	40.46	-32.58
	Oats	-1.81	31.63	-0.06	0.99	8.75	66.21	-31.12
	Orange Juice	-3.45	30.70	-0.11	0.31	8.95	44.93	-30.16
	Rough rice	-6.77	25.00	-0.27	0.24	5.12	38.52	-25.90
	Soybean Meal	7.50	24.90	0.30	0.11	4.79	26.35	-24.92
	Soybean oil	-1.95	24.48	-0.08	-0.13	4.86	23.57	-29.04
	Soybeans	3.16	22.42	0.14	-0.31	21.21	21.25	-24.95
	Sugar	0.89	32.14	0.03	0.21	6.19	42.31	-35.11
	Wheat	-5.36	26.32	-0.20	0.04	4.35	32.02	-28.30
	Cotton	-0.76	25.51	-0.03	-0.09	5.36	24.48	-25.67
Energy	Crude oil, Brent	6.60	33.76	0.20	-0.82	4.66	42.11	-63.38
	Crude oil, WTI	5.03	36.12	0.14	-0.61	4.12	48.31	-68.01
	Gasoil	6.09	32.71	0.19	-0.35	5.06	33.54	-40.49
	Gasoline, Unleaded	4.07	40.05	0.10	-2.78	5.67	28.89	-89.51
	Gasoline, blendstock	7.85	40.20	0.20	0.36	6.25	42.35	-38.83
	Heating Oil	6.25	31.74	0.20	-0.18	3.62	31.45	-38.37
	Natural Gas	-15.38	46.29	-0.33	0.06	3.27	42.07	-39.02
Livestock	Feeder Cattle	0.95	14.60	0.07	-0.31	8.54	12.90	-17.47
	Lean Hogs	-4.82	26.77	-0.18	-0.40	7.18	25.55	-30.06
	Live Cattle	1.84	14.29	0.13	-0.47	5.30	14.87	-23.69
Metals	Aluminum	-2.35	19.29	-0.12	0.01	6.91	14.84	-18.61
	Copper	3.79	25.08	0.15	-0.50	5.40	29.23	-45.37
	Gold	1.29	15.17	0.08	0.03	9.51	14.75	-20.41
	Lead	3.30	27.87	0.12	-0.33	9.01	23.58	-32.05
	Nickel	6.36	34.39	0.18	0.02	5.79	32.33	-27.76
	Palladium	7.49	31.60	0.24	-0.27	7.67	38.52	-41.45
	Platinum	1.65	22.02	0.08	-0.55	4.91	29.14	-37.93
	Silver	-0.82	27.54	-0.03	0.02	3.96	26.18	-32.82
	Tin	8.95	23.55	0.38	0.06	4.90	23.70	-24.10
	Zinc	0.43	26.00	0.02	-0.49	6.01	24.41	-42.37

Table 2: Commodity factor portfolios

This table shows the descriptive statistic for ten commodity factor portfolios. The sample spans from January 1985 to May 2022. Start represents the date of the first observation in our sample, mean denotes mean returns, SD stands for standard deviation, SR denotes Sharpe Ratio, and t-statistics is calculated for portfolio returns. Mean, SD, and SR are annualized.

Factor	**Start**	**Mean**	t**-statistics**	**SD**	**SR**
MKT	198501	5.90	1.74	20.67	0.29
Basis	198501	7.27	2.96	15.05	0.48
Momentum	198501	8.21	2.20	22.88	0.36
Basis-momentum	198501	8.19	2.63	19.04	0.43
Skewness	198501	10.33	3.28	19.24	0.54
Currency β	198501	4.03	1.04	23.69	0.17
Inflation β	198501	1.34	0.34	23.81	0.06
Liquidity	198909	-0.91	-0.30	17.43	-0.05
Hedging pressure	199401	1.30	0.41	17.10	0.08
Open interest	199503	0.83	0.27	16.30	0.05

Table 3: Factors returns conditional on their own past returns

This table reports estimation results from two time-series regressions. The first one, specified as the "return-to-return" regression, regress factor returns on the moving average of its past returns. The second one is the "return-to-sign" regression, where factor returns are regressed on a dummy variable indicating positive moving average in the past. These regressions are estimated for pooled tests across all factors and for each factor, over one month (Panel A) and three months (Panel B).

	Panel A. Past one month							
	Returns				Sign of the returns			
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.35***	3.78	**0.08*** **	**4.76**	0.02	0.16	**0.66*** **	**3.57**
MKT	0.42	1.49	0.16***	3.43	-0.04	-0.09	0.96*	1.69
Basis	0.55***	2.65	0.09**	1.98	0.09	0.30	0.93**	2.25
Momentum	0.66**	2.10	0.03	0.70	0.67	1.43	0.02	0.02
Basis-momentum	0.63**	2.41	0.08	1.62	0.49	1.25	0.33	0.63
Skewness	0.84***	3.15	0.03	0.64	0.55	1.35	0.53	0.99
Currency β	0.32	0.99	0.06	1.18	-0.11	-0.23	0.81	1.24
Inflation β	0.09	0.28	0.06	1.24	-0.26	-0.57	0.71	1.09
Liquidity	-0.07	-0.26	0.07	1.42	-0.23	-0.66	0.34	0.67
Hedging pressure	0.11	0.41	0.06	1.05	-0.04	-0.11	0.31	0.58
Open interest	0.07	0.26	0.08	1.36	-0.23	-0.63	0.59	1.14
	Panel B. Past three months							
	Returns				Sign of the returns			
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.36***	3.85	**0.06** **	**2.19**	0.13	0.96	**0.45** **	**2.43**
MKT	0.43	1.50	0.14*	1.81	-0.09	-0.20	0.99*	1.73
Basis	0.54**	2.57	0.14*	1.74	0.26	0.83	0.65	1.57
Momentum	0.67**	2.11	0.01	0.14	0.79*	1.65	-0.20	-0.32
Basis-momentum	0.59**	2.23	0.11	1.36	0.38	0.93	0.46	0.86
Skewness	0.78***	2.86	0.10	1.20	0.71*	1.66	0.23	0.42
Currency β	0.38	1.17	-0.07	-0.88	0.47	0.96	-0.20	-0.30
Inflation β	0.11	0.35	-0.01	-0.16	0.03	0.06	0.18	0.27
Liquidity	-0.06	-0.23	0.03	0.41	-0.12	-0.35	0.13	0.26
Hedging pressure	0.07	0.26	0.17**	1.92	-0.41	-1.04	0.95*	1.76
Open interest	0.08	0.32	-0.01	-0.15	-0.07	-0.19	0.30	0.57

Table 4: Profitability of factor momentum strategy

This table reports the returns for factor momentum portfolios (FMOM), which buy factors with positive past returns (Winners) and sell those with negative past returns (Losers). The benchmark portfolios take equal weight on all factors. The α and $t(\alpha)$ are reported for the risk-adjusted returns based on the model of Boons and Prado (2019). Panel A and Panel B focus on the past performance over one and three months, respectively. Mean denotes mean returns, t-statistics is calculated for portfolio returns, SD stands for standard deviation, and SR denotes Sharpe Ratio. Mean, SD, SR, and α are annualized.

Strategy	**Mean**	**t-statistics**	**SD**	**SR**	α_{BP2}	$t(\alpha_{BP2})$
			Panel A. Past one month			
FMOM	**4.37*** **	**2.80**	9.55	0.46	**4.54*** **	**2.87**
Winner	8.17***	4.40	11.35	0.72	6.31***	3.62
Loser	-0.40	-0.19	13.12	-0.03	-2.53	-1.24
EqStrategy	4.43***	3.52	7.68	0.58	2.10**	2.28
			Panel B. Past three months			
FMOM	**3.11** **	**2.20**	8.61	0.36	**2.58* **	**1.82**
Winner	6.85***	3.58	11.67	0.59	4.36***	2.61
Loser	1.52	0.76	12.09	0.13	-0.15	-0.08
EqStrategy	4.47***	3.55	7.68	0.58	2.17**	2.36

Table 5: Factor momentum decomposition

This table decomposes factor momentum portfolios into the buy-and-hold (BH) and factor timing (FT) components. Panel A and B reports the decomposition results for factor momentum over past one and three months, respectively. We report the returns of BH and FT in summary statistics, where Mean denotes mean returns, t-statistics is calculated for portfolio returns, SD stands for standard deviation, and SR denotes Sharpe Ratio. Mean, SD, and SR are annualized. Furthermore, we provide results for spanning tests. The t-statistics are in parentheses.

Panel A. Past one month				
	Summary statistics			
	Mean	t-statistics	SD	SR
BH	1.41	0.96	8.94	0.16
FT	**4.23*** **	**2.80**	9.23	0.46
	Spanning tests			
	(1)	(2)	(3)	(4)
	FMOM	FMOM	BH	FT
BH	0.11**			
	(2.22)			
FT		0.99***		
		(71.85)		
FMOM			0.10**	0.93***
			(2.22)	(71.85)
Constant	0.35***	0.01	0.08	0.01
	(2.70)	(0.39)	(0.67)	(0.41)
Obs.	448	448	448	448
Adj.#	1.1%	92.0%	1.1%	92.0%
Panel B. Past three months				
	Summary statistics			
	Mean	t-statistics	SD	SR
BH	1.37	0.94	8.94	0.15
FT	**2.50***	**1.74**	8.76	0.29
	Spanning tests			
	(1)	(2)	(3)	(4)
	FMOM	FMOM	BH	FT
BH	0.26***			
	(6.00)			
FT		0.92***		
		(55.24)		
FMOM			0.28***	0.95***
			(6.00)	(55.24)
Constant	0.23**	0.07	0.04	-0.04
	(2.02)	(1.61)	(0.35)	(-0.89)
Obs.	446	446	446	446
Adj.#	7.5%	87.3%	7.5%	87.3%

Table 6: Factor momentum in high- and low-eigenvalue factors

This table reports the performance of factor momentum in different sets of PC factors. We construct 1-month factor momentum strategies based on PCs extracted from commodity factors. The high set includes PC factors with higher eigenvalue. Panel A reports monthly descriptive statistics for momentum strategies, including the mean returns and $t-$statistics. Panels B and C report the results from spanning tests. We report results for the full sample and the subsample after the financialization.

Panel A. Factor momentum in subsets of PC factors ordered by eigenvalues

	Full sample			Subsample		
Sets of PCs	Mean	t-statistics	$t(\alpha_{BP2})$	Mean	t-statistics	$t(\alpha_{BP2})$
High	**0.61*****	**3.14**	**3.16**	**0.53****	**2.23**	**2.45**
Low	0.44**	2.40	2.34	0.24	1.15	1.22

Panel B. Explaining factor momentum in high-eigenvalue PC factors

	$\text{FMOM}^{\text{HighPC}}$	
	Full sample	Subsample
α	0.41**	0.48**
	(2.33)	**(2.14)**
$\text{FMOM}^{\text{LowPC}}$	0.49***	0.43***
	(10.08)	(6.04)
Controls	Y	Y
N	388	221
Adj.R^2	20.5%	13.8%

Panel C. Explaining factor momentum in low-eigenvalue PC factors

	$\text{FMOM}^{\text{LowPC}}$	
	Full sample	Subsample
α	0.16	0.06
	(1.00)	**(0.31)**
$\text{FMOM}^{\text{HighPC}}$	0.43***	0.33***
	(10.08)	6.04
Controls	Y	Y
N	388	221
Adj.R^2	20.5%	13.8%

Table 7: Predictability of MKT and basis-momentum

This table examines the mean-variance efficiency of two factors in Boons and Prado (2019)'s model: MKT and basis-momentum. We adopt two uni-variate regressions to examine the predictability of factor's returns for its future returns and volatility. We report the slope coefficients and corresponding t-statistics. The estimation is conducted within the full sample and the subsample after the financialization.

Panel A. Predicting returns

	Full sample		Subsample	
	β_{return}	$t(\beta_{return})$	β_{return}	$t(\beta_{return})$
MKT	0.16***	3.43	0.21***	3.17
Basis-momentum	0.08	1.62	0.16**	2.45

Panel B. Predicting volatility

	Full sample		Subsample	
	β_{return}	$t(\beta_{return})$	β_{return}	$t(\beta_{return})$
MKT	-0.01	-1.15	-0.02	-1.23
Basis-momentum	-0.03*	-1.74	-0.05	-1.46

Table 8: Time-series efficient factors

Panel A compares Sharpe ratios of standard factors (SR) to those of corresponding time-series efficient factors (SR*) for two commodity factors in Boons and Prado (2019)'s model. The time-series efficient transformation exploits the factor autocorrelation over the 1-month horizon. Panel B regresses each time-series efficient factor on the original version. The t-statistics are in parentheses. We provide results for the full sample and the subsample after the financialization.

Panel A. Improvement in Sharpe ratios				
	Full sample		Subsample	
	MKT	Basis-momentum	MKT	Basis-momentum
SR	0.29	0.43	0.38	0.31
SR*	0.52	0.56	0.78	0.70
$\triangle SR$	**0.24**	**0.13**	**0.40**	**0.38**

Panel B. Univariate regressions				
	Full sample		Subsample	
	MKT*	Basis-momentum*	MKT*	Basis-momentum*
α	0.42***	0.25***	0.64***	0.51***
	(2.71)	**(2.76)**	**(2.91)**	**(2.83)**
MKT	0.21***		0.22***	
	(8.03)		(6.90)	
Basis-momentum		0.85***		0.47***
		(51.96)		(13.80)
Adj.R^2	12%	85%	20%	47%

Table 9: Time-series efficient asset pricing models

This table compares the time-series efficient model of Boons and Prado (2019) with its original counterparties. Panel A spans factors from the efficient model by the standard model. Panel B reverts the tests to regress the factors in the standard model by the efficient model. We outline the alphas and report the$t$-statistics in parentheses. We further utilize the Gibbons et al. (1989) (GRS) test to examine the incremental informativeness of efficient models, and outline F-statistics and report p-values in square brackets. The asterisk (*) denotes the efficient versions. We conduct the estimation for the full sample and the subsample after the financialization.

Panel A. Efficient model regressed on standard model		
	Full sample	Subsample
	α_{BP2}	α_{BP2}
MKT*	0.41***	0.64***
	(2.63)	(2.91)
Basis-momentum*	0.24***	0.50***
	(2.67)	(2.72)
GRS F-statistic	**6.40**	**8.15**
	[0.00]	**[0.00]**
Panel B. Standard model regressed on efficient model		
	Full sample	Subsample
	α^*_{BP2}	α^*_{BP2}
MKT	0.17	-0.02
	(0.63)	(-0.05)
Basis-momentum	-0.13	-0.26
	(-1.34)	(-0.94)
GRS F-statistic	1.08	0.45
	[0.34]	[0.64]

Table 10: Factors returns conditional on their own past returns – China evidence

This table examines the factor momentum in China based on two time-series regressions. The first one, specified as the "return-to-return" regression, regress factor returns on the moving average of its past returns. The second one is the "return-to-sign" regression, where factor returns are regressed on a dummy variable indicating positive moving average in the past. These regressions are estimated for pooled tests across all factors and for each factor, over one month (Panel A) and three months (Panel B).

	Panel A. Past one month							
	Returns				Sign of the returns			
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.28***	2.87	**0.12*****	**5.17**	-0.19	-1.30	**0.93*****	**4.75**
Basis	1.25***	3.72	0.08	1.18	0.97*	1.75	0.59	0.87
Basis-momentum	1.06***	3.89	0.00	0.02	0.67	1.56	0.62	1.16
Momentum	1.46***	3.65	0.01	0.12	0.47	0.78	1.67**	2.14
Currency β	0.16	0.44	0.12*	1.76	-0.45	-0.87	1.22*	1.71
Hedging pressure	0.01	0.03	0.13*	1.94	-0.37	-0.99	0.76	1.45
Inflation β	0.19	0.52	0.15**	2.14	-0.30	-0.57	0.96	1.32
Liquidity	-0.11	-0.36	0.14**	2.06	-0.64	-1.43	0.99	1.59
MKT	0.00	0.00	0.22***	3.30	-0.86**	-2.41	1.62***	3.32
Open interest	0.05	0.20	-0.07	-1.12	0.09	0.29	-0.10	-0.22
Skewness	0.07	0.28	0.11*	1.66	-0.36	-0.93	0.83	1.58
	Panel B. Past three months							
	Returns				Sign of the returns			
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.31***	3.21	**0.06***	**1.69**	0.11	0.76	**0.40****	**2.07**
Basis	1.16***	3.35	0.07	0.66	1.11*	1.90	0.19	0.27
Basis-momentum	1.25***	4.55	-0.22*	-1.92	1.20***	2.71	-0.27	-0.50
Momentum	1.45***	3.40	-0.02	-0.16	0.88	1.28	0.80	0.96
Currency β	0.22	0.61	-0.11	-0.89	0.31	0.58	-0.21	-0.28
Hedging pressure	0.12	0.49	0.13	1.27	-0.29	-0.84	0.91*	1.79
Inflation β	0.34	0.96	-0.12	-1.07	0.56	1.09	-0.46	-0.64
Liquidity	-0.04	-0.13	0.22**	2.13	-0.45	-1.06	0.83	1.33
MKT	-0.04	-0.16	0.21**	2.06	-0.61	-1.67	1.05**	2.10
Open interest	0.06	0.26	-0.13	-1.06	0.52	1.64	-0.94**	-2.09
Skewness	0.08	0.31	0.10	0.95	-0.44	-1.16	1.03*	1.95

Table 11: Profitability of factor momentum strategy – China evidence

This table reports the returns for factor momentum portfolios (FMOM) in Chinese commodity futures markets, which buy factors with positive past returns (Winners) and sell those with negative past returns (Losers). The benchmark portfolios take equal weight on all factors. The α and $t(\alpha)$ are reported for the risk-adjusted returns based on the model of Boons and Prado (2019). Panel A and Panel B focus on the past performance over one and three months, respectively. Mean denotes mean returns, t-statistics is calculated for portfolio returns, SD stands for standard deviation, and SR denotes Sharpe Ratio. Mean, SD, SR, and α are annualized.

Strategy	**Mean**	***t*-statistics**	**SD**	**SR**	α_{BP2}	$t(\alpha_{BP2})$
			Panel A. Past one month			
FMOM	**5.73*** **	**3.91**	6.33	0.90	**5.12*** **	**3.38**
Winner	8.88***	4.18	9.19	0.97	7.24***	3.74
Loser	-2.27	-0.88	11.11	-0.20	-3.52	-1.41
EqStrategy	3.66***	2.58	6.16	0.59	2.20**	2.15
			Panel B. Past three months			
FMOM	**2.94** **	**2.17**	5.84	0.50	**2.42* **	**1.72**
Winner	6.93***	3.43	8.71	0.80	5.51***	3.11
Loser	1.20	0.56	9.12	0.13	-0.43	-0.22
EqStrategy	3.83***	2.68	6.18	0.62	2.33**	2.29

Table 12: Factor momentum in high- and low-eigenvalue factors – China evidence

This table utilize the Chinese data to examine the performance of factor momentum in different sets of PC factors. We construct 1-month factor momentum strategies based on PCs extracted from commodity factors. The high set includes PC factors with higher eigenvalue. Panel A reports monthly descriptive statistics for momentum strategies, including the mean returns and $t-$statistics. Panels B and C report the results from spanning tests.

Panel A. Factor momentum in subsets of PC factors ordered by eigenvalues			
	Mean	t-statistics	$t(\alpha_{BP2})$
High	**0.51*** **	**3.20**	**2.56**
Low	0.46**	2.37	2.18

Panel B. Explaining factor momentum in low-eigenvalue PC factors	
	Low
α	0.33
	(1.63)
$\text{FMOM}^{\text{HighPC}}$	0.26***
	(3.20)
Controls	Y
N	221
Adj.R^2	3.6%

Panel C. Explaining factor momentum in high-eigenvalue PC factors	
	High
α	0.35**
	(2.11)
$\text{FMOM}^{\text{LowPC}}$	0.18***
	(3.20)
Controls	Y
N	221
Adj.R^2	5.5%

Appendix: Description of Commodity Factors

Basis: The basis represents the price difference between futures and spot commodity contracts. For each commodity j, we follow Boons and Prado (2019) to use the following equation to calculate basis in month t:

$$\text{Basis}_t^j = \frac{F_{j,t}^{(2)}}{F_{j,t}^{(1)}} - 1, \tag{9}$$

where $F_{j,t}^{(2)}$ and $F_{j,t}^{(1)}$ are respectively the commodity j's futures prices for the second and first nearby contracts.

Momentum: For each commodity j, we follow Boons and Prado (2019) to calculate the characteristic for momentum in month t as the cumulative excess returns during past 12-month period:

$$\text{Momentum}_t^j = \prod_{s=t-11}^{t} \left(1 + R_{j,t,s}^{(1)}\right) - 1, \tag{10}$$

where $R_{j,t}^{(1)}$ represents the commodity j's returns in month t for the first nearby futures contracts.

Basis-momentum: For each commodity j, we follow Boons and Prado (2019) to quantify the characteristics for basis-momentum in month t based on the following equation:

$$\text{BasisMomentum}_t^j = \prod_{s=t-11}^{t} \left(1 + R_{j,t,s}^{(1)}\right) - \prod_{s=t-11}^{t} \left(1 + R_{j,t,s}^{(2)}\right), \tag{11}$$

where $R_{j,t,s}^{(2)}$ and $R_{j,t,s}^{(1)}$ represent commodity j's returns for the second and first nearby futures contract.

Liquidity: We follow Szymanowska et al. (2014) to calculate the liquidity as the averaged Amihud et al. (1997)'s measure, which divides the volume on a trading day by the absolute return on that trading day, over the two most recent months.

Skewness: We calculate the skewness following Fernandez-Perez et al. (2018). For each commodity j , the skewness in month t is defined as follows:

$$Sk_t^j = \frac{\frac{1}{d}\sum_{d=1}^{D}\left(R_{j,d}^{(1)} - \mu_{j,t}\right)^3}{\sigma_{j,t}^3}, \tag{12}$$

where $R_{j,d}^{(1)}$ denotes the commodity j's daily futures returns for the first-nearby contracts at day d during the past 12 months. D, μ, and σ respectively represent daily observation number, mean, and standard deviation estimates for daily returns over the past 12-month period.

Currency β: Following Szymanowska et al. (2014), the currency β $\left(\beta_{j,t}^{Currency}\right)$ for commodity j in month t is constructed from a 60-month rolling regression of monthly first-nearby commodity futures returns $\left(R_{j,t}^{(1)}\right)$ on changes in the U.S. dollar versus a basket of foreign currencies ($\Delta Currency$) as follows:

$$R_{j,t}^{(1)} = a_j + \beta_{j,t}^{Currency} \Delta Currency_s + e_{j,s}, s = t-59, \ldots, t. \tag{13}$$

Commodity market: We calculate the monthly returns of S&P GSCI to indicate the commodity futures markets.

Inflation β: Following Szymanowska et al. (2014), the inflation β factor is constructed according to the slope coefficient $\left(\beta_{j,t}^{CPI}\right)$ based on the prior 60-month regressions of monthly first-nearby commodity futures returns $\left(R_{j,t}^{(1)}\right)$ on unexpected inflation measured as the change in one-month U.S. CPI inflation rate (ΔCPI) as follows:

$$R_{j,t}^{(1)} = a_j + \beta_{j,t}^{CPI} \Delta CPI_s + e_{j,s}, s = t-59, \ldots, t. \tag{14}$$

Hedging pressure: We follow Bakshi et al. (2019) to calculate the hedging pressure for commodity j in month t as the net short open interest over the total open interest of commercial traders during the last 12 months of the commodity t:

$$HP_t^j = \sum_{i=0}^{12-1} \frac{Short_{j,t-i} - Long_{j,t-i}}{Long_{j,t-i} + Short_{j,t-i}} \tag{15}$$

where $Short_{j,t-i}$ and $Long_{j,t-i}$ respectively denote the short and long positions of commercial traders.

Open Interest: For each commodity j , we follow Sakkas and Tessaromatis (2020) to quantify the sorting variable in month t based on following equation:

$$\Delta OI_{j,t} = OI_{j,t} - OI_{j,t-1}, \tag{16}$$

where $OI_{j,t}$ and $OI_{j,t-1}$ stand for commodity j's aggregated open interest in month t and $t-1$, respectively.

Table A.1: Commodity futures data

This Table tabulates 36 commodities and lists the sector they belong to, the exchange and geographical market of trading, the Bloomberg ticker for data collection, and the date of the first observation in our sample. The commodity futures contracts are traded on the Chicago Mercantile Exchange (CME), the New York Mercantile Exchange (NYMEX), Chicago Board of Trade (CBOT), the Intercontinental Exchange (ICE), and the London Metal Exchange (LME).

Category	**Contract**	**Exchange**	**Market**	**Ticker**	**Start**
Agriculture	Butter	CME	U.S.	V6	200509
	Cocoa	ICE	U.S.	CC	198001
	Coffee	ICE	U.S.	KC	198001
	Corn	CBOT	U.S.	C	198001
	Cotton	ICE	U.S.	CT	198001
	Kansas Wheat	CBOT	U.S.	KW	198001
	Lumber	CME	U.S.	LB	198604
	Milk	CME	U.S.	DA	199601
	Oats	CBOT	U.S.	O	198001
	Orange Juice	ICE	U.S.	JO	198001
	Rough Rice	CBOT	U.S.	RR	198812
	Soybean	CBOT	U.S.	S	198001
	Soybean Meal	CBOT	U.S.	SM	198001
	Soybean Oil	CBOT	U.S.	BO	198001
	Sugar	ICE	U.S.	SB	198001
	Wheat	CBOT	U.S.	W	198001
Energy	Crude Oil Brent	ICE	U.K.	CO	198806
	Crude Oil WTI	NYMEX	U.S.	CL	198303
	Gasoil	ICE	U.K.	QS	198907
	Gasoline blendstock	NYMEX	U.S.	HU	200510
	Gasoline Unleaded	NYMEX	U.S.	XB	198604
	Heating Oil	NYMEX	U.S.	HO	198607
	Natural Gas	NYMEX	U.S.	NG	199004
Livestock	Feeder Cattle	CME	U.S.	FC	198001
	Lean Hogs	CME	U.S.	LH	198604
	Live Cattle	CME	U.S.	LC	198001
Metals	Aluminum	LME	U.K.	LA	199707
	Copper	NYMEX	U.S.	HG	198812
	Gold	NYMEX	U.S.	GC	198001
	Lead	LME	U.K.	LL	199707
	Nickel	LME	U.K.	LN	199707
	Palladium	NYMEX	U.S.	PA	198604
	Platinum	NYMEX	U.S.	PL	198604
	Silver	NYMEX	U.S.	SI	198001
	Tin	LME	U.K.	LT	199707
	Zinc	LME	U.K.	LX	199707

Table A.2: Factors returns conditional on their own past returns

This table reports estimation results from two time-series regressions. The first one is specified as the "return-to-return" regression, where we regress factor returns on the moving average of its past returns. The second one is the "return-to-sign" regression, where the factor returns are regressed on a dummy variable indicating positive moving average in the past. These regressions are estimated for pooled tests across all factors and for each factor over six, nine, and twelve months in Panel A to C.

Panel A. Past six months

	Returns				Sign of the returns			
	Intercept		Slope		Intercept		Slope	
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.38***	4.02	0.00	0.07	0.39***	2.76	-0.02	-0.11
Market	0.46	1.60	0.12	1.14	0.38	0.86	0.22	0.38
Basis	0.57***	2.63	0.12	1.10	0.34	0.97	0.48	1.11
Momentum	0.69**	2.13	-0.06	-0.48	0.75	1.55	-0.16	-0.26
Basis-momentum	0.65**	2.39	-0.03	-0.23	0.93**	2.08	-0.46	-0.83
Skewness	0.88***	3.13	-0.04	-0.36	0.86*	1.91	-0.03	-0.05
Currency β	0.42	1.26	-0.07	-0.57	0.66	1.35	-0.49	-0.74
Inflation β	0.13	0.41	-0.09	-0.71	0.22	0.48	-0.19	-0.29
Liquidity	-0.09	-0.34	-0.05	-0.41	-0.08	-0.22	-0.02	-0.03
Hedging pressure	0.07	0.27	0.04	0.30	0.02	0.05	0.11	0.21
Open interest	0.05	0.19	-0.13	-0.94	0.37	1.02	-0.69	-1.31

Panel B. Past nine months

	Returns				Sign of the returns			
	Intercept		Slope		Intercept		Slope	
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.39***	4.07	-0.03	-0.54	0.42***	2.91	-0.08	-0.41
Market	0.51*	1.73	0.00	0.03	0.34	0.74	0.26	0.45
Basis	0.53**	2.37	0.19	1.46	-0.01	-0.01	0.98**	2.24
Momentum	0.67**	2.06	0.03	0.22	0.58	1.22	0.21	0.33
Basis-momentum	0.70**	2.53	-0.07	-0.50	0.95**	1.97	-0.42	-0.73
Skewness	0.88***	3.06	0.03	0.24	0.86*	1.83	0.07	0.13
Currency β	0.44	1.32	-0.27*	-1.76	1.19**	2.41	-1.49**	-2.27
Inflation β	0.10	0.30	-0.11	-0.69	0.34	0.73	-0.50	-0.75
Liquidity	-0.12	-0.46	-0.04	-0.26	0.20	0.57	-0.69	-1.34
Hedging pressure	0.08	0.31	0.02	0.13	-0.07	-0.19	0.32	0.58
Open interest	0.05	0.20	-0.12	-0.69	0.09	0.23	-0.08	-0.15

Panel C. Past twelve months

	Returns				Sign of the returns			
	Intercept		Slope		Intercept		Slope	
	α	$t(\alpha)$	β	$t(\beta)$	α	$t(\alpha)$	β	$t(\beta)$
Pooled	0.39***	4.07	-0.03	-0.54	0.42***	2.91	-0.08	-0.41
Market	0.51*	1.73	0.00	0.03	0.34	0.74	0.26	0.45
Basis	0.56**	2.43	0.20	1.33	0.63*	1.69	0.07	0.15
Momentum	0.69**	2.06	0.00	-0.02	0.59	1.18	0.16	0.25
Basis-momentum	0.71**	2.54	-0.04	-0.22	1.24**	2.51	-0.76	-1.31
Skewness	0.92***	3.08	0.00	0.01	0.96**	1.99	-0.06	-0.11
Currency β	0.38	1.13	-0.16	-0.86	0.79	1.59	-0.82	-1.24
Inflation β	0.05	0.14	-0.03	-0.15	-0.03	-0.06	0.15	0.23
Liquidity	-0.06	-0.22	0.21	1.23	-0.41	-1.19	0.76	1.48
Hedging pressure	0.05	0.19	0.00	0.02	0.02	0.06	0.06	0.10
Open interest	0.04	0.14	-0.15	-0.73	-0.07	-0.18	0.19	0.35

Table A.3: Profitability of factor momentum strategy

This table reports the returns for factor momentum strategies over different horizons. The FMOM portfolios buy factors with positive past returns (Winners) and sell those with negative past returns (Losers). The benchmark portfolios take equal weight on all factors. The α and $t(\alpha)$ are reported for the risk-adjusted returns against the factor model of Boons and Prado (2019). Panel A to Panel C reports the results based on the past performance over six, nine, and twelve months. Mean denotes mean returns, t-statistics is calculated for portfolio returns, SD stands for standard deviation, and SR denotes Sharpe Ratio. Mean, SD, SR, and α are annualized.

Strategy	**Mean**	***t*-statistics**	**SD**	**SR**	α_{BP2}	$t(\alpha_{BP2})$
			Panel A. Past six months			
FMOM	0.16	0.11	9.02	0.02	-0.63	-0.429
Winner	4.47**	2.30	11.80	0.38	1.80	1.055
Loser	3.50*	1.76	12.04	0.29	2.04	1.059
EqStrategy	4.48***	3.53	7.70	0.58	2.14**	2.311
			Panel B. Past nine months			
FMOM	0.38	0.26	8.78	0.04	-0.89	-0.63
Winner	4.96***	2.60	11.58	0.43	2.03	1.238
Loser	3.57*	1.76	12.30	0.29	2.70	1.351
EqStrategy	4.41***	3.45	7.74	0.57	3.41*	1.835
			Panel C. Past twelve months			
FMOM	1.70	1.19	8.62	0.20	0.16	0.116
Winner	5.19***	2.76	11.34	0.46	2.05	1.32
Loser	1.86	0.90	12.51	0.15	0.90	0.441
EqStrategy	4.47***	3.47	7.78	0.57	3.86**	2.118

Table A.4: Factor momentum decomposition

This table decomposes factor momentum portfolios into the buy-and-hold (BH) and factor timing (FT) components. Panel A to C reports the decomposition results for factor momentum over past six, nine, and twelve months, respectively. We report the returns of BH and FT in summary statistics, where Mean denotes mean returns, t-statistics is calculated for portfolio returns, SD stands for standard deviation, and SR denotes Sharpe Ratio. Mean, SD, and SR are annualized. Furthermore, we provide results for spanning tests. The t-statistics are in parentheses.

Panel A. Past six months				
	Summary statistics			
	Mean	t-statistics	SD	SR
BH	1.18	0.80	8.96	0.13
FT	0.00	0.00	8.87	0.00
	Spanning tests			
	(1)	(2)	(3)	(4)
	FMOM	FMOM	BH	FT
BH	0.39***			
	(8.81)			
FT		0.92***		
		(45.51)		
FMOM			0.38***	0.89***
			(8.81)	(45.51)
Constant	-0.02	0.01	0.09	-0.01
	(-0.26)	(0.26)	(0.82)	(-0.24)
Obs.	443	443	443	443
Adj.R^2	1.5%	82.4%	1.5%	82.4%
Panel B. Past nine months				
	Summary statistics			
	Mean	t-statistics	SD	SR
BH	1.43	0.98	8.85	0.16
FT	-0.84	-0.61	8.40	-0.10
	Spanning tests			
	(1)	(2)	(3)	(4)
	FMOM	FMOM	BH	FT
BH	0.43***			
	(9.98)			
FT		0.92***		
		(38.67)		
FMOM			0.43***	0.84***
			(9.98)	(38.67)
Constant	-0.02	0.10*	0.11	-0.10*
	(-0.17)	(1.68)	(0.96)	(-1.77)
Obs.	440	440	440	440
Adj.R^2	18.5%	77.3%	18.5%	77.3%
Panel C. Past twelve months				
	Summary statistics			
	Mean	t-statistics	SD	SR
BH	1.39	0.94	8.96	0.16
FT	1.36	0.97	8.44	0.16
	Spanning tests			
	(1)	(2)	(3)	(4)
	FMOM	FMOM	BH	FT
BH	0.48***			
	(11.84)			
FT		0.84***		
		(30.68)		
FMOM			0.51***	0.81***
			(11.84)	(30.68)
Constant	0.09	0.05	0.04	0.00
	(0.84)	(0.69)	(0.40)	(-0.02)
Obs.	437	437	437	437
Adj.R^2	24.4%	68.4%	24.4%	68.4%

Table A.5: Time-series efficient models of Yang (2013) and Bakshi et al. (2019)

This table compares the time-series efficient model of Yang (2013) and Bakshi et al. (2019) with their original counterparties. We first span factors from the efficient model by the standard model, and then regress the factors in the standard model by the efficient model. We outline the alphas and report the$t$-statistics in parentheses. The Gibbons et al. (1989) (GRS) test examine the incremental informativeness of efficient models, and we outline the F-statistics and report p-values in square brackets. The asterisk (*) denotes the efficient versions. We estimate results for the full sample and the subsample after the financialization.

Panel A. Time-sereis efficient model of Yang (2013)		
	Full sample	**Subsample**
	α_{Yang2}	α_{Yang2}
MKT*	0.42***	0.64***
	(2.71)	(2.89)
Basis*	0.26**	0.38***
	(2.16)	(2.58)
GRS F-statistic	**5.72**	**6.88**
	[0.00]	**[0.00]**
	α^*_{Yang2}	α^*_{Yang2}
MKT	0.15	-0.13
	(0.55)	(-0.31)
Basis	0.09	-0.11
	(0.59)	(-0.56)
GRS F-statistic	0.32	0.19
	[0.73]	[0.83]
Panel B. Time-sereis efficient model of Bakshi et al. (2019)		
	Full sample	**Subsample**
	α_{BGR3}	α_{BGR3}
MKT*	0.36**	0.61***
	(2.32)	(2.85)
Basis*	0.24*	0.37**
	(1.99)	(2.54)
Momentum*	0.13	-0.05
	(1.12)	-0.26
GRS F-statistic	**3.19**	**4.47**
	[0.02]	**[0.00]**
	α^*_{BGR3}	α^*_{BGR3}
MKT	0.15	-0.14
	(0.56)	(-0.33)
Basis	0.12	-0.11
	(0.79)	(-0.55)
Momentum	-0.01	-0.07
	(-0.12)	(-0.22)
GRS F-statistic	0.31	0.17
	[0.82]	[0.92]