Commodity tail risk and equity risk premia

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Abstract

We explore the asset pricing implication of commodity tail risk in the cross section of Chinese stock returns. A commodity tail risk index is constructed by aggregating individual commodity's exposure to left-tail realizations of systematic risks. We obtain the commodity tail risk beta for each stock between 2005 to 2022 and find that the risk-adjusted return differential between stocks with extreme loadings of past commodity tail risk is 1.39% per month and significant at the 1% level, which cannot be explained by common risk factors or stock characteristics. We rationalize our findings by showing that a high level of commodity tail risk captures bad state of the world and signals adverse economic conditions, thus a low risk premium for stocks that hedge this tail risk. Our study highlights the informational role of commodity futures prices and sheds new light on the link between commodity and equity markets in China.

JEL classification: C58; G11; G12

Keywords: Commodity futures; Nonlinear tail dependence; Tail risk; Cross section of equity returns; Economic conditions.

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1 Introduction

In this study, we examine the impact of commodity tail risk on the pricing of cross-sectional stock returns. The evidence in the existing literature suggests two channels through which the commodity tail risk explains the cross section of stock returns. First, fluctuations in commodity futures prices serve as key indicators for the economic outlook (Driesprong et al., 2008; Fernandez-Perez et al., 2017; Jacobsen et al., 2019; Sockin & Xiong, 2015).[1] Nowadays, centralized trading of commodity futures aggregates useful information from market participants, including commercial hedgers and financial investors, to jointly form expectations on future economic outlook and facilitate price discovery (Garbade & Silber, 1983; Sockin & Xiong, 2015), which contain valuable information with pricing implication for the stock market.[2] In addition, commodities are important ingredients and outputs for both users and producers in the whole production chain. Equity and commodity returns are thus naturally and closely related as price changes in commodities ultimately affect the profitability and cash flows of individual firms (Brooks et al., 2016). Hence, there is ample evidence in the literature that variables in commodity futures markets are useful for predicting stock returns or the business cycle (Bakshi et al., 2012, 2019; Hong & Yogo, 2012; Jacobsen et al., 2019; Ready, 2018), and that commodity futures risk factors are priced in the cross section of equity returns (Boons et al., 2014; Brooks et al., 2016; Fernandez-Perez et al., 2017; Hou & Szymanowska, 2013).

The commodity futures tail risk, a measure of extreme left-tail realization, naturally reflects a pessimistic economic outlook and indicates rare but severe economy downturn with deteriorations in consumption and investment opportunities for investors (Ge & Tang, 2020; Hu & Xiong, 2013; Sockin & Xiong, 2015). Meanwhile, left-tail realizations of equity returns and dividend growth are also associated with negative extreme realizations of consumption in bad states of the economy (Schreindorfer, 2020). Hence, the commodity futures tail risk, through its informational role describing economic state, may be linked to

[1] These two markets are also linked through the spillover of returns, volatility, and higher-order moments (Ahmed & Huo, 2021; Zhang et al., 2023).

[2] The literature also highlights the information generation role of derivatives markets and their relation to the equity market (see Gu et al., 2022; Xing et al., 2010; Zhang et al., 2022, for instance). Saurav et al. (2023) and Wang & Yen (2018) focus on the left-tail risk.

the tail risk of equity markets. As risk averse investors demand additional compensation for holding assets with greater equity tail risk (Ang, Chen, & Xing, 2006; Bollerslev et al., 2022; Chabi-Yo et al., 2018, 2022; Kelly & Jiang, 2014), the commodity tail risk could exhibit a pricing impact by signaling overall bad state of the economy in the near future.

Motivated by the above strands of the literature, we focus on the commodity tail risk in this study and explore how extreme negative realizations of commodity prices impact stock returns. Such negative realizations may reflect adverse expectation for future commodity demand and supply, as well as the underlying economic fundamentals.[3]

Our empirical analyses are conducted based on the Chinese commodity futures and equity markets. Several characteristics stand out to make them interesting test markets for our research question. For the Chinese commodity futures market, despite a rapidly growing variety of products, increased trading volume, and enhanced market quality over the past few decades (Cai et al., 2020; Jiang et al., 2020; Tang & Zhu, 2016), the institutional environment means that the market is relatively poorly understood (Bianchi et al., 2021) with tight policy control and a significant barrier-to-entry for foreign institutional investors (Fan & Zhang, 2020). Thus it is not all that clear whether commodity futures prices in China are as informative as those in the developed futures markets. At the same time, the Chinese stock market, also on the receiving end of frequent policy changes, is known to be disconnected from the macroeconomy exhibiting historically low correlations between its returns and the GDP growth (Allen et al., 2023). Hence, it would be interesting to examine whether the consumption and price-related information contained in commodity futures prices (Erb & Harvey, 2006; Hou & Szymanowska, 2013) is able to impact equity prices.

Empirically, our measure of commodity tail risk follows Chabi-Yo et al. (2022), which argue that each stock's exposure to tail risk can be driven by systematic risk factors in addition to the market risk, thus a multivariate measure of risk better explains the cross section of stock returns. The multivariate setting in Chabi-Yo et al. (2022) lends itself naturally to our research question, as a single left-tail event for commodity futures con-

[3] We recognize that the upper-tail risk in commodity futures markets may also impact equity prices. However, our study aims at investigating the comovement between commodity and equity markets in bad market states and characterizing the crash aversion of investors. Hence our analysis focuses on the left-tail realizations in commodity futures market.

tracts cannot adequately describe the extreme adverse conditions in the market or reflect the widespread deterioration in the economy. Hence, we define a multivariate tail event in a commodity futures contract as the conditional probability of a contract's left-tail extreme realization given that at least one of the systematic factors simultaneously realizes a left-tail extreme event, and the multivariate tail index aggregates this information across all futures contracts.

This multivariate tail risk framework fits in well with the burgeoning literature that adopts linear factor models to price the cross section of commodity futures returns (see Bakshi et al., 2019; Szymanowska et al., 2014; Yang, 2013, for example). We measure the commodity tail risk with respect to factors in these pricing models, including the commodity market, basis, commodity momentum, and basis-momentum factors, all of which are theoretically motivated with empirical support. First, based on the theory of storage linking implicit benefits received by inventory holders to the slope of futures curve, the basis reveals an abundant or scarce state of physical inventory thus leading to a premium for the basis factor in commodity futures (Brennan, 1958; Erb & Harvey, 2006; Gorton et al., 2012; Working, 1949). Second, Miffre & Rallis (2007) motivate the commodity momentum factor through the theory of normal backwardation and Bakshi et al. (2019) rationalize the sizeable returns to the commodity momentum factor based on the trading behavior of speculators.[4] Finally, the basis-momentum factor is related to the imbalance between the supply and demand of futures contracts and the market-clearing ability of financial intermediaries and speculators, and shown to be a strong return predictor in the U.S. markets (Boons & Prado, 2019). Together with the commodity market factor, these systematic commodity risk factors capture distinct information of market conditions, are shown to generate significant returns in China empirically (Bianchi et al., 2021; Fan & Zhang, 2020), thus they are natural candidates from which we extract our multivariate tail risk measure. Interestingly, we find that these commodity risk factors are individually priced in the Chinese equity markets, consistent with evidence from the US markets (Brooks et al., 2016; Fernandez-Perez et al., 2017). This highlights the intricate

[4] Fernandez-Perez et al. (2017) show that backwardation and contango state variables constructed based on the basis and commodity momentum factor-mimicking portfolios are informative about future changes in investment opportunities and the business cycle.

link between commodity futures and equity markets and lends further motivation for our study.

We construct the commodity multivariate tail risk measure based on 65 commodity futures contracts traded in three Chinese futures exchanges from January 2003 to October 2022. Each month, we calculate each commodity's multivariate tail risk measure with respect to the four factors mentioned above at the 5% probability level on the left tail with a rolling window of 250 days. Since the input data are daily, it is necessary to consider the volatility clustering effect thus we combine the parametric GARCH(1,1) model with a non-parametric copula-based modelling approach. We then take the equally-weighted cross-sectional average tail risk of individual commodity futures to form the aggregated multivariate commodity tail risk measure on a monthly basis.

For each stock listed in the Shanghai and Shenzhen Stock Exchanges, we run monthly predictive regressions of excess stock returns on the aggregate multivariate commodity tail risk index to obtain the tail risk beta. In the univariate portfolio analysis, we find that the return difference between extreme portfolios with the highest and lowest commodity tail risk beta is economically large and statistically significant. In particular, the risk-adjusted return spread between extreme portfolios is 1.39% per month with a t-statistic of 3.27 based on the Fama-French 5-factor model. This translates to an annualized return of 16.7%. In the bivariate portfolio analysis, we control for a number of popular cross-sectional equity return predictors and show that the positive relation between commodity tail risk beta and one-month-ahead stock returns remains robust and statistically significant. We obtain consistent results in the Fama & MacBeth (1973) regressions when we simultaneously control popular predictive factors and firm characteristics. Additional robustness check corroborates the baseline findings.

To understand the economic mechanism behind the predictability of our multivariate commodity tail risk measure, we relate the commodity tail risk measure to the macroeconomy. Commodities naturally capture consumption and price-related information as they directly link to the aggregate consumption level and are able to hedge inflation risk (Boons et al., 2014; Erb & Harvey, 2006; Hou & Szymanowska, 2013). Commodity futures prices also reflect the market's consensus with regard to the outlook of the macroeconomy. Hence, the channel through which the commodity tail risk impacts cross-sectional stock returns could be via its relation with the macroeconomic conditions and economic outlook. We estimate an ARMA model to test this conjecture and find that a positive commodity tail risk shock is associated with a considerable decline in inflation, price levels, and industrial production. Such deterioration of economic condition is further verified by producer and consumer's worsening economic outlook. It indicates that an increase in commodity tail risk captures high marginal utility periods and reflects increasing concern by investors about the future economic outcomes in real terms, thus reducing their consumption demands.

In addition, we examine whether our commodity tail risk index is linked to the equity tail risk, as extreme negative realizations in commodity futures may indicate a severe situation in the state of economy potentially captured by the equity left-tail risk. We find that two stock market tail risk measures, proxied by the Value-at-Risk and expected shortfall, are positively associated with each other, and predated by the commodity tail risk. This result indicates that the commodity tail risk indeed signals the equity tail risk, which has been documented as a priced risk in cross-sectional equity returns.

These results collaborate our findings in the asset pricing tests, i.e., investors require additional compensation in the form of higher expected returns for holding stocks with greater predictive loading of the commodity tail risk. Meanwhile, stocks with lower predictive loading of the commodity tail risk are considered safer at times of high commodity tail risk and serve as effective hedges. Investors are willing to pay a premium for these stocks. The analysis of the economic mechanism underscores the role of commodity tail risk in signaling future economic activities and determining equilibrium asset prices.

By focusing on the extreme left-tail events in commodity futures markets, our paper contributes to the literature by uncovering another important link between commodity futures and equity markets. This also distinguishes our work from existing studies such as Fernandez-Perez et al. (2017) and Brooks et al. (2016) which focus on the entire distribution of commodity futures returns and the pricing of commodity risk factors in equity markets. More importantly, our study sheds light on the distinct information contained in the commodity tail risk, which captures the market's expectation of future macroeconomic prospect. The stock return predictability is a natural manifestation of this information.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and outlines the methodology. In Sections 4 and 5, we analyze empirical results and discuss the underlying economic mechanism, respectively. Section 6 provides robustness check. Finally, Section 7 concludes.

2 Related literature

Informational content of commodity futures markets – Variables in commodity markets serve as barometers of future economic conditions as they contain valuable information regarding the supply and demand of resources needed for the real economy. This information is shown to possess predictive ability for stock market returns (Bakshi et al., 2012, 2019; Hu & Xiong, 2013; Jacobsen et al., 2019; Ready, 2018; Sockin & Xiong, 2015). For instance, Hong & Yogo (2012) argue that movements in open interest are pro-cyclical and exhibit predictive power for economic activities and asset prices. More recently, Bakshi et al. (2019) regard the carry factor in commodity markets as an indicator for changes in the future investment opportunity set for investors with intertemporal hedging demand; and Jacobsen et al. (2019) show that price changes in industrial metal futures predict stock returns with rising futures prices indicating subsequent economic growth.

The predictive ability of commodity variables is also manifested in estimating the risk premia for the cross section of equities, highlighting a close interplay between the two markets and a directional information flow from the commodity to equity markets (Boons et al., 2014; Brooks et al., 2016; Fernandez-Perez et al., 2017). For example, Brooks et al. (2016) find that commodity risks are priced in the cross section of global equity returns. Under the framework of intertemporal capital asset pricing model, Fernandez-Perez et al. (2017) argue that commodity risk factors characterizing backwardation and contango phases are state variables in predicting return distributions and possessing long-term predictability for the aggregate stock market returns.

Given the strong theoretical and empirical evidence discussed in these studies, we are interested in exploring whether information contained in extreme negative realizations of commodity markets, which captures the likelihood of downside events, has implication for predicting equity returns as investors care about adverse economic outcomes. Our study extends this strand of the literature by focusing on the information content of extreme tail events in commodity futures markets.

Tail risk and its asset pricing role – Our study also speaks to the literature on tail events in rare disaster models and downside risk. The seminal paper of Roy (1952) introduces the concept of *safety first* and argues that risk-averse investors care asymmetrically about downside and upside events. In particular, agents place greater weight on adverse outcomes than gains in their utility function (Arzac & Bawa, 1977; Bawa & Lindenberg, 1977; Gul, 1991).[5] Hence, the occurrence of heavy left-tail events implies a risk premium. Based on heavy-tailed shocks to economic fundamentals, rare disaster risk models rationalize a number of asset pricing anomalies (Barro, 2006; Farhi & Gabaix, 2016; Gabaix, 2012; Rietz, 1988; Wachter, 2013). For instance, Barro (2006) develops a rare economic disaster risk model to reconcile the equity premium puzzle, which is extended to a dynamic setting in Gabaix (2012) and Wachter (2013). The rare disaster risk models also enjoy growing empirical support (Baron et al., 2023; Bollerslev & Todorov, 2011; Fan et al., 2022; Kelly & Jiang, 2014; Manela & Moreira, 2017). For example, Bollerslev & Todorov (2011) find that the time-varying compensation for rare disaster-type events explains a large fraction of equity and variance risk premia.

Closely related to these studies, the tail risk measurement and its asset pricing implication for stock returns are also an active research field. A large number of univariate tail risk measures (Atilgan et al., 2020; Chang et al., 2013; Chollete & Lu, 2011; Harvey & Siddique, 2000; Jang & Kang, 2019; Jondeau et al., 2019) and bivariate crash risk indicators (Ang, Chen, & Xing, 2006; Bollerslev et al., 2015; Chabi-Yo et al., 2018; Farago & Tédongap, 2018; Kelly & Jiang, 2014; Lu & Murray, 2019; Weller, 2019) have been developed in the literature. Fan et al. (2022) document substantial pricing implication of the equity tail risk in the foreign exchange markets. These studies highlight the role of systematic tail risk in explaining asset returns, equity risk premia, and market volatility.

[5] In behavioral finance, the prospect theory of Kahneman & Tversky (1979) also demonstrates that investors exhibit loss aversion preferences.

Compared with the tail risk inferred from equity markets, the tail risk obtained from derivatives markets has received less attention with the exception of Ammann et al. (2023). In our study, we measure the tail risk from commodity futures markets in a multivariate setting and exploit extreme downside realizations of a wide range of systematic commodity risk factors. Our measure follows Chabi-Yo et al. (2022), which defines the multivariate crash measure for an individual stock as the conditional probability of a stock's left-tail extreme realization given that at least one of multiple systematic factors simultaneously realizes a left-tail extreme event. This definition is built upon the intuition that investors are aware of disaster states driven by joint tail events of multiple risk factors. We implement this novel measure of tail risk in commodity futures markets and examine its impact on cross-sectional stock returns.

3 Data and variables

3.1 Data

For commodity futures contracts, we collect daily settlement prices (in RMB), open interest, and trading volume of 67 commodity futures with all available maturities traded in the Shanghai Futures Exchange (SHFE), Dalian Commodity Exchange (DCE), and Zhengzhou Commodity Exchange (ZCE) from the China Stock Market & Accounting Research (CSMAR) database. To ensure a sufficient number of commodities are available for constructing long-short portfolios, we require that the number of traded contracts in the cross section is larger than eight following Li et al. (2017). We retain delisted contracts such as Early rice and Hard wheat to avoid survivorship bias (Xu & Wang, 2021) but remove thinly traded contracts such as Green mung. The final unbalanced sample contains 65 commodities from January 2003 to October 2022.

We choose the third-nearest contracts to construct continuous time series as they are the most liquid (Fan & Zhang, 2020; Jiang et al., 2017). The contracts are rolled over on the last trading day before the front month and a price multiplier is applied in the rollover to avoid price jumps (Han & Kong, 2022; Li et al., 2017). Table A.1 summarizes descriptive statistics for the commodity futures contracts in our sample.

Our equity sample includes all A-listed stocks traded in the Shanghai and Shenzhen stock exchanges from January 2005 to October 2022. We collect firm-level daily and monthly data for returns, trading volume, shares outstanding, and accounting variables from the WIND database. To mitigate the impact of extreme price movement and illiquidity due to the IPO effect, we remove stock data within six months of the IPO. We require at least 72 available monthly observations for a stock to be included in the sample. In addition, we collect monthly excess returns on the market (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (UMD) factors. The aggregate stock market is represented by the Shanghai Stock Exchange Composite (SSEC) index. The risk-free rate used is the one-year deposit rate. These data are obtained from the CSMAR.

3.2 Multivariate tail risk

We follow Chabi-Yo et al. (2022) to construct the multivariate tail risk measure (MTail) as follows:

$$\mathrm{MTail}_i^{\boldsymbol{X}} := \mathbb{P}\left[T_p\left[R_i\right] \mid T_p[\boldsymbol{X}]\right] = \mathbb{P}\left[R_i \leq Q_p\left[R_i\right] \mid \bigcup_{j=1}^{N}\left\{X_j \leq Q_p\left[X_j\right]\right\}\right], \tag{1}$$

where R_i denotes returns of each asset i and $\boldsymbol{X} = (X_1, ..., X_N)'$ is a vector of returns of N priced risk factors. We define tail events as extreme realizations of R_i by $T_p[R_i] := \{Y \leq Q_p[R_i]\}$ with $Q_p[R_i] := \sup\{\mathbb{P}[R_i \leq r_i] \leq p\}$, indicating the upper p-quantile of R_i. Likewise, $T_p[\boldsymbol{X}] = \bigcup_{j=1}^{N}\left\{X_j \leq Q_p\left[X_j\right]\right\}$ stands for the multivariate tail events defined as the union of tail events realized by individual priced factors ($\boldsymbol{X}$). That is, at least one of these risk factors does not exceed its corresponding p-quantile.

In Equation (1), $\mathbb{P}\left[T_p\left[R_i\right] \mid T_p[\boldsymbol{X}]\right]$ implies the conditional probability that asset i realizes tail events given that at least one of these priced factors takes on an extreme realization at or below its p-quantile. Hence, MTail refers to the likelihood of left-tail extreme events realized by asset i conditional on a tail event induced by one or more systematic risk factors simultaneously. The value of MTail tends to be high (low) if asset i is more (less) likely to be adversely influenced by extreme realizations of systematic risk factors, indicating higher (lower) tail dependence of a given joint distribution.

To obtain the MTail for each asset (futures) i in month t, we specify a rolling window with the most recent 250 trading days to ensure sufficient observations and stable estimates (Ang & Chen, 2002). We further exclude missing values of each series and require each asset i to have at least 200 non-zero daily returns over the rolling window estimation period.[6] We apply the GARCH(1,1) model with skewed-t innovations to characterize marginal return distributions. We then conduct probability integral transforms of daily futures return series and factor return series to obtain marginal cumulative distribution functions. Finally, we implement a non-parametric copula approach and generate the conditional probability for the transformed returns as the multivariate tail risk measure given in Equation (1) for each commodity in each month.[7] Detailed estimation procedure is summarized in Appendix A.[8] We construct MTail with respect to four popular commodity risk factors, i.e., the commodity market factor (CMKT), basis factor (Basis), momentum factor (CMOM), and basis-momentum factor (Basis-Mom). Details of constructing these commodity risk factors are provided in Appendix B.

Figure 1 shows the aggregate multivariate commodity tail risk (MTail), constructed by averaging MTail estimates across individual futures contracts in month t with equal weights. We observe that the aggregate MTail is highly serially autocorrelated with a first-order autocorrelation of 0.95. It exhibits spikes and is more dispersed between 2008 to 2010 capturing the onset of the global financial crisis and recession. We also observe a striking increasing trend since 2020, which corresponds to the COVID-19 pandemic that substantially impacts the global economy and financial markets. The aggregate MTail is always higher than 5% as indicated by the red dotted line, below which the extreme realizations of commodity futures and factor returns are independent.

Figure 2 describes the contemporaneous relation between the commodity tail risk and

[6] This restriction alleviates the concern that commodity contracts with low liquidity may contaminate our MTail estimation. By doing this, a valid estimate of a commodity's tail risk is obtained only if there is a sufficient number of non-zero return observations over the estimation window.

[7] It is worth noting that the parameters in the GARCH(1,1) process and the cut-off point for left-tail events are determined within each rolling estimation window, without introducing the look-forward bias for the estimation of MTail.

[8] In terms of the estimation methodology for MTail, we also consider alternative rolling estimation horizons of the GARCH(1,1) model of 200, 300, 400, and 500 days. We also model the marginal distributions of commodity risk factors and futures return with the GJR-GARCH model of Glosten et al. (1993) and the AR(2)-GARCH(1,1) model to account for autocorrelation in returns. The results are qualitatively the same and available from the authors upon request.

stock market returns. Panel A plots the times series of commodity tail risk and stock market index. To facilitate comparison, we standardize both series to have zero mean and unit variance. The contemporaneous relation between the two time series is significantly negative with a correlation coefficient of -0.43 (p-value $= 0.00$). Furthermore, the commodity tail risk index appears counter-cyclical, especially during the earlier sample periods and the COVID-19 pandemic. In Panel B, we plot the monthly changes in the commodity tail risk index against the stock market index returns and add best-fitting lines based on simple linear regression (the blue line) and piecewise linear regression with a kink at zero (the red dashed line). We note that stock market returns negatively relate to changes in the commodity tail risk index with a slope coefficient of -0.029 (t-statistic $= -2.85$). When the stock market returns are smaller than zero, this contemporaneous relation becomes more negative with a slope coefficient of -0.053 (t-statistic $= -2.16$), indicating that the counter-cyclical pattern between commodity futures and equity markets is stronger in magnitude in market declines.

3.3 Commodity tail risk beta

To investigate whether the commodity tail risk predicts cross-sectional equity returns, we sort stocks into decile portfolios based on their commodity tail risk exposure in the previous month. If investors are concerned about the commodity tail risk, they would demand greater (less) compensation in the form of higher (lower) expected returns for an increase (decrease) in commodity tail risk. Following Kelly & Jiang (2014), we estimate the following predictive regression for stock i's one-period ahead expected returns $\mathbb{E}_t\left[R_{i,t+1}\right]$ on the commodity tail risk (MTail) over a 6-year fixed-length rolling window as follows:

$$\mathbb{E}_t\left[R_{i,t+1}\right] = \alpha_{i,t} + \beta_{i,t}^{MTail} \cdot MTail_t, \tag{2}$$

where $\beta_{i,t}^{MTail}$ is the loading of commodity tail risk for stock i in month t.

4 Empirical analyses and discussion

4.1 Summary statistics

Table 1 reports summary statistics and correlations for four commodity risk factors used to construct the multivariate commodity tail risk. Since no benchmark market index is available for commodity futures, we consider the equally-weighted cross-sectional average of all available contracts as the market portfolio. This simple commodity market factor (CMKT) performs poorly with an annualized average return of 2% and an annualized Sharpe ratio of 0.12. The other three factors all generate economically and statistically significant returns and Sharpe ratio. For example, the basis factor has an average annualized return of 14% and an annualized Sharpe ratio of 0.77. The average annualized return of the momentum factor is 18% with a significant t-statistic of 3.76. These results are in line with the evidence in Bakshi et al. (2019) for the US market, which include the CMKT factor, a term structure factor, and a momentum factor for pricing the cross section of commodity future returns. Consistent with Bianchi et al. (2021), we also find that the basis-momentum factor generates significant returns of 13% per year with a t-statistic of 4.65, making it another strong return predictor in the Chinese futures markets.

We need daily commodity risk factors to model the dependence between individual commodity futures and factor returns. The descriptive statistics for the daily factor return series are summarized in Table 1 Panel B. The patterns of daily returns series are largely consistent with those based on the monthly data. In Panel C, we tabulate the correlations between monthly factors and observe a modest positive correlation. For instance, the momentum and basis factors are positively correlated with a Pearson (Spearman) correlation coefficient of 0.42 (0.37), consistent with Bakshi et al. (2019). These varying degrees of correlation suggest that individual factors may contain distinct information. Finally, in Panel D we show the summary statistics of the MTail index, our key variable in this study.

Table 2 reports summary statistics and correlation for the commodity tail risk beta (β^{MTail}) estimated via Equation (2) along with several firm-level control variables to be used in asset pricing tests. Statistics reported here are obtained as the time-series averages of the cross-sectional means. In particular, the β^{MTail} has a mean of -0.27 and a standard deviation of 0.64. For the average cross section, the maximum and minimum values of β^{MTail} are 4.43 and -5.01, respectively.

We consider several popular firm characteristics, including the firm size (Fama & French, 1992), book-to-market ratio (Fama & French, 1992; Liu et al., 2019), momentum (Jegadeesh & Titman, 1993), market beta (Fama & French, 1992), short-term reversal (Jegadeesh, 1990), annual growth of total assets (Cooper et al., 2008), quarterly operating profitability (Liu et al., 2019), co-skewness (Harvey & Siddique, 2000), the Amihud's illiquidity measure (Amihud, 2002), turnover (Liu et al., 2019), lottery demand (Bali et al., 2017; Hou et al., 2023), idiosyncratic volatility (Ang, Hodrick, et al., 2006), and the equity left-tail risk (Atilgan et al., 2020). Details of these variables are summarized in Appendix C. Descriptive statistics for these firm-level control variables are reported in Panel A Table 2. In Panel B, we summarize the time-series average of the cross-sectional correlation between variables. It is worth noting that the correlations between β^{MTail} and firm-level variables are low, as the Pearson and Spearman correlation coefficients are all below 0.10. As β^{MTail} measures the sensitivity of each stock to the commodity tail risk, it is reasonable to expect that the β^{MTail} contains information not captured by traditional firm characteristics or financial variables.

4.2 Univariate portfolio sorts

At the end of month t, we sort all stocks into decile portfolios based on pre-ranking $\beta_{i,t}^{MTail}$ to obtain one-month-ahead excess returns for month $t+1$ with equal- and value-weighting schemes. We form zero-cost portfolios by taking long (short) positions in portfolios with the highest (lowest) $\beta_{i,t}^{MTail}$ to examine the return differential between them.

Table 3 reports the time-series means of predictive excess portfolio returns, annualized standard deviation and Sharpe ratio, skewness, and kurtosis for each β^{MTail}-sorted portfolios, and monthly risk-adjusted returns based on the CAPM, Fama-French 3-factor, Carhart 4-factor, and Fama-French 5-factor models. We also include the return spread and risk-adjusted return spread between long-short portfolios. Panels A and B summarize results for equal- and value-weighting schemes, respectively.

Results in Table 3 provide strong evidence in support of the predictive ability of the commodity tail risk beta. We find that stocks with greater β^{MTail} estimates have higher next-month returns than those with lower β^{MTail} estimates. In particular, stocks in the highest β^{MTail}-sorted decile generate monthly equal-weight (value-weighted) average excess returns of 0.58% (0.29%), whereas there is a clear and sharp decline in returns for the lowest β^{MTail}-sorted portfolio. The average returns of the equal-weighted (value-weighted) high-minus-low β^{MTail}-sorted spread are 0.81% (1.11%) per month with a t-statistic of 2.72 (2.73), translating to a sizeable annualized return differential of 9.7% (13.3%). The same pattern can be observed for risk-adjusted returns. For example, the Fama-French 5-factor model-adjusted return spread between extreme β^{MTail}-sorted portfolios are 0.97% (1.39%) per month with equal (value) weighting scheme. Hence, this significant and substantial return differential is not driven by exposure to standard risk factors. We also observe that risk-adjusted returns for portfolios with the lowest β^{MTail} tend to be negative and statistically significant, whereas all those for portfolios with the highest β^{MTail} are positive but insignificant. These imply that the significantly positive abnormal return spread is driven by the underperformance of low-β^{MTail} stocks. Intuitively, investors pay higher prices for stocks that effectively hedge the commodity tail risk and accept negative abnormal returns in the future.

In summary, the first set of empirical results based on univariate portfolio sorts is consistent with our prediction: risk-averse investors are willing to pay higher prices for stocks with negative or low β^{MTail} which hedge commodity tail risk, and they demand additional compensation for holding stocks with higher exposure to the commodity tail risk thus these stocks are discounted more heavily.

Next we examine how long the substantial return spreads last. Answer to this question may shed light on the nature of the information contained in commodity tail risk beta: if the information has little to do with the fundamental economic mechanism, the predictability tends to fade away rather quickly. In Table 4 Panel A, we summarize portfolio excess returns over longer horizons. From the second month after portfolio construction, extreme portfolios with the highest and lowest β^{MTail} generate value-weighted excess returns of 0.34% and −0.53% per month, respectively, with a return differential of 0.86% (t-statistic = 2.21) on a monthly basis. The substantial return differential between extreme portfolios remains significant all the way to the fifth month after portfolio formation. In particular, it is 0.99% with a t-statistic of 2.76 for month $t+5$. The predictive power of β^{MTail} continues to be positive with slightly reduced statistical significance until the twenty-fourth month when the return difference is 0.65% per month (t-statistic = 1.99). The predictability gradually disappears from the 24-month post-formation period onwards. In Panel B we find consistent results for risk-adjusted returns. Results in this table indicate that the predictive power of commodity tail risk beta is not a short-term affair and the information contained in the commodity tail risk beta is related to economic fundamentals.

To better understand the characteristics of commodity tail beta-sorted portfolios, we examine a set of firm-level attributes for each portfolio, including size, book-to-market ratio, momentum, market beta, short-term reversal, annual growth of total assets, quarterly operating profitability, co-skewness, the Amihud illiquidity measure, turnover, lottery demand, idiosyncratic volatility, and the equity left-tail risk in Table 5. We note that β^{MTail}-sorted portfolios exhibit little association with most of these stock characteristics except the size, market beta, and ROE. In particular, stocks with higher β^{MTail} tend to be larger, with greater market beta, and higher return-on-equity ratio.[9] Hence, consistent with low correlations reported in Table 2, the β^{MTail}-sorted portfolios are overall weakly correlated with the firm characteristics we examine here.

4.3 Transition matrix

A potential concern for the prior analysis is that the estimated commodity tail risk beta (β^{MTail}) is specific to the formation month but not the subsequent month over which we calculate portfolio excess returns. Hence, we examine the cross-sectional persistence of β^{MTail} by estimating the six- and twelve-month ahead portfolio transition matrix for

[9] In the following sections we will investigate whether the significant positive relation between β^{MTail} and expected equity returns is driven by some of these attributes based on the bivariate portfolio analysis and Fama & MacBeth (1973) cross-sectional regressions.

all stocks. In particular, after sorting stocks into decile portfolios in month t, we repeat the same procedure and compute the percentage of stocks that are classified into each decile portfolios in months $t + 6$ and $t + 12$.

In Table 6, we summarize the time series average of the transition probabilities that a stock in a decile portfolio (indicated by the row) in one month moves to another portfolio (indicated by the column) in the subsequent six and twelve months in Panels A and B, respectively. If the evolution for β^{MTail} of each stock is a random process and the lagged value of β^{MTail} is independent of the current value of β^{MTail}, all transition probabilities should be 10%. However, we observe that 52.9% of stocks sorted to the lowest β^{MTail} decile portfolio remain in the same portfolio six months later. Similarly, 52.4% of stocks sorted into the highest β^{MTail} portfolio stay in the same decile six months later. Turning to the twelve-month ahead horizon, 35.1% (34.9%) of stocks in the lowest (highest) decile remain in the same portfolio after twelve months. These findings suggest that a stock's sensitivity to commodity tail risk is persistent.

4.4 Bivariate portfolio analysis

We now perform the bivariate portfolio sorts to examine the relation between commodity tail risk beta and future equity returns by controlling for a set of return predictors and firm characteristics. Each month, we conduct sequential sorting exercises to assign stocks into decile portfolios based on one of 13 control variables collated in Appendix C and within each portfolio we further allocate stocks into deciles based on their β^{MTail}. All portfolios are re-balanced monthly. This bivariate portfolio analysis helps examine whether the return spreads between high and low commodity tail risk beta-sorted portfolios remain significant after controlling for existing firm-level characteristics.

Table 7 summarizes equal- (Panel A) and value-weighted (Panel B) portfolio returns. We note that the predictive power of β^{MTail} remains statistically significant and economically large after controlling for each variable. In Panel A, the return difference between the highest and lowest β^{MTail}-sorted portfolios ranges from 0.53% to 0.85% per month with t-statistics between 2.27 and 3.03. For value-weighted portfolios, we observe stronger results that the return differential ranges from 0.68% to 1.15% on a monthly basis with

t-statistics between 2.41 and 3.66. Furthermore, risk-adjusted return differentials based on the Fama-French 5-factor model are positively and highly significant across all control variables. The limited impact of control variables on the return spread is not surprising given the low correlation between β^{MTail} and firm characteristics shown in Table 2. Our bivariate portfolio analysis highlights the distinct information contained in the commodity tail risk beta.

4.5 Fama-MacBeth regressions

We perform the two-stage Fama & MacBeth (1973) regressions to test whether the commodity tail risk beta is able to explain cross-sectional future stock returns when simultaneously taking account of well-documented return predictors and firm characteristics. We consider the same set of variables as in the bivariate portfolio sorts and summarize the results in Table 8.

In Panel A, we report the coefficient estimates and their t-statistics based on the ordinary least squares regressions without controlling for the industry effects.[10] Next, in Panel B, we control for the industry effects by assigning each stock to one of the nine industries based on the China Securities Regulatory Commission (CSRC) industry classification code.[11] Our primary variable of interest is the β^{MTail} reported in the first row. We find that the slope coefficient for our commodity tail risk beta is consistently positive and remains significant as we add more return predictors and firm characteristics. In Model (14) when all variables are included, the coefficient for β^{MTail} is 0.29 with a t-statistic of 2.80. These indicate a strong positive relation between the commodity tail risk beta and the cross section of futures equity returns, which is not subsumed by existing risk factors or firm-level characteristics. We obtain qualitatively the same results after controlling for the industry effects in Panel B. The Fama & MacBeth (1973) regression results indicate that the information content of the commodity tail risk beta is distinct from that contained in popular return predictors and firm characteristics we consider.

[10] We also use the weighted least squares regressions in which the weights are defined as one plus observed stock returns in month $t-1$ (Asparouhova et al., 2013) to perform the Fama-MacBeth regressions. These results are qualitatively the same and available from the authors upon request.

[11] These industries include Mining, Manufacturing, Retail & Wholesale, Transportation, IT, Finance, Real estate, Utilities, and Other. We require each industry to have at least 50 stocks to avoid the potential small sample bias.

4.6 Spanning test

We construct a commodity tail risk beta factor and investigate whether it can be explained by well-documented common risk factors following Fama & French (1993). The spanning test helps us determine whether the commodity tail risk beta factor adds to the explanation of average stock returns on top of existing factors (Fama & French, 2018).

At the end of each month, we divide all stocks into two size groups based on market capitalization using the median value of the stock universe. Stocks are also sorted independently into three commodity tail risk beta groups using the 30th and 70th percentiles. We use the intersections of those groups to obtain six size-β^{MTail} combinations. The equal- (EW) and value-weighted (VW) returns of the β^{MTail} factor are calculated, respectively, as the equal- and value-weighted average returns of the two high-β^{MTail} minus the corresponding low-β^{MTail} portfolios.

Table 9 summarizes the commodity tail risk beta factor returns and risk-adjusted returns based on the same asset pricing models as those in previous sections. We find that the EW (VW) β^{MTail} factor generates average returns of 0.59% (0.61%) per month with a significant t-statistic of 2.87 (2.88). Furthermore, the risk-adjusted returns remain positive and highly significant with the t-statistics being 2.83, 3.19, 3.20, and 3.19, respectively, based on the CAPM, Fama-French 3-factor, Carhart 4-factor, and Fama-French 5-factor models for the equal-weighting scheme. Consistent results are obtained for the value-weighting scheme and, together, they indicate that existing common risk factors cannot explain the β^{MTail} factor.

4.7 Cross-sectional pricing of commodity tail risk beta factor

In this final baseline test, we analyze the pricing of commodity tail risk beta factor and traditional commodity risks in equity portfolios. We include commodity risk factors already shown to be priced in the US equity markets (see Brooks et al., 2016; Fernandez-Perez et al., 2017, for example) in addition to our commodity tail risk beta factor. Methodologically, we perform the Fama & MacBeth (1973) two-stage regressions to estimate portfolios' exposure to risk factors and prices of risks. In the first stage, we estimate the monthly time-series regressions to obtain equity portfolios' loading of risk factors as follows:

$$R_{p,t} = \beta_{0,t} + \boldsymbol{\beta}_{F,t}\boldsymbol{F}_t + \eta_{p,t}, \tag{3}$$

where $\boldsymbol{\beta}_{F,t}$ is a set of risk factors, including our commodity tail risk beta factor, the commodity market, basis, commodity momentum, and basis-momentum factors. In the second stage, we run the cross-sectional regression after obtaining the coefficients for risk factors as follows:

$$\bar{R}_p = \gamma_0 + \boldsymbol{\lambda}_F\hat{\boldsymbol{\beta}}_{F,p} + \epsilon_p, \tag{4}$$

where $\bar{R}_p$ is the sample average of excess returns of portfolio p, $\boldsymbol{\lambda}_F$ are prices of risk, $\hat{\boldsymbol{\beta}}_{F,p}$ are portfolio beta estimates from the first stage, γ_0 is the intercept, and ϵ_p is the pricing error of portfolio p.[12] To compare model efficiency, we compute the cross-sectional R^2 as follows:

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{p=1}^{N}\hat{\epsilon}_p^2}{\text{Var}\left(\bar{R}_p\right)}. \tag{5}$$

We also evaluate the root mean squared error (RMSE) for each model as follows:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\bar{R}_{p,t} - \hat{\bar{R}}_{p,t}\right)^2}, \tag{6}$$

where $\hat{\bar{R}}_p = \hat{\boldsymbol{\lambda}}_F\hat{\boldsymbol{\beta}}_{F,p}$ is the model implied average excess portfolio returns. We use 35 equity portfolios as test assets: the 25 size and book-to-market sorted and 10 β^{MTail}-sorted portfolios. Across all specifications, we control the market, size, value, and momentum factors of the equity market. We report t-statistics computed based on both the Newey & West (1986) approach and the Shanken (1992) correction.

In Table 10 we summarize the results for the second-stage Fama–MacBeth regressions. Across all specifications, we find that the commodity tail risk beta factor consistently carries significant positive risk premium ranging from 0.8% to 1.1% per month, which are close to the return spread between portfolios with the highest and lowest commodity tail risk beta β^{MTail} reported in Table 3 at 0.81%. Moreover, we observe declines in the RMSE and increases in the R^2 for models augmented with the commodity tail risk

[12] We also estimate Equation (4) without the intercept with qualitatively the same results. These are available from the authors upon request.

beta factor indicating improved model fit and incremental explanatory power of this factor to explain equity portfolio returns. These results underscore our commodity tail risk beta factor as a credible factor with incremental pricing information not contained in traditional commodity risk factors documented in the literature. In other words, the pricing ability of commodity tail risk is not subsumed by existing commodity risk factors. Finally, it is worth noting that the basis and commodity momentum factors command economically large and statistically significant risk premium in China. These findings are consistent with evidence in the US market that commodity risk factors are able to explain the cross section of stock returns (Brooks et al., 2016; Fernandez-Perez et al., 2017).

5 Economic mechanism

What is the economic channel through which commodity tail risk predicts stock returns? To answer this question, we propose a mechanism from a macroeconomic perspective that rationalizes the predictability of commodity tail risk. Commodities nicely capture consumption and price-related information as they directly link to the aggregate consumption level and are able to hedge inflation risk (Boons et al., 2014; Erb & Harvey, 2006; Hou & Szymanowska, 2013). Recognizing the poor quality of consumption expenditure data, Hou & Szymanowska (2013) argue that commodity futures contains more price-relevant consumption information than traditional assets such as stocks and bonds. Hence, we conjecture that the commodity tail risk index contains information useful for predicting future changes in macroeconomic variables such as inflation and industrial production, and the stock return predictability is a natural manifestation of the information.

To investigate this economic channel, we follow Bakshi et al. (2012) and Hou et al. (2023) and estimate an ARMA model as follows:

$$y_{t+1} = \alpha_y + \beta_y \Delta \text{MTail}_{t-3:t} + \theta_1 y_t + \theta_2 \epsilon_t + \epsilon_{t+1}, \tag{7}$$

where y_{t+1} is the growth rate of the dependent variable at time $t+1$, $\Delta\text{MTail}_{t-3:t}$ denotes shocks to the MTail series computed as the difference between MTail values at time t and $t-3$, and y_t and ϵ_t are first-order AR and MA terms, respectively. We first consider three macroeconomic variables: the consumer price inflation (CPI), producer price index (PPI), and industrial production (IP) as the dependent variable. Meanwhile, motivated by Gao & Süss (2015), we also examine whether the commodity tail risk is related to the consumer and producer's perception of future economic conditions, which are proxied by three economic outlook indices: the purchasing managers' index (PMI), consumer confidence index (CCI), and consumer expectation index (CEI). All variables are collected from the National Bureau of Statistics of China and the WIND database.

Table 11 summarizes estimation results for macroeconomic variables in Panel A and economic outlook indices in Panel B. In Panel A, for models with CPI, we observe that the coefficient for the commodity tail risk shocks is negative and statistically significant at the 5% level suggesting that an increase in commodity tail risk shocks is associated with a drop in CPI and price level in the future. Meanwhile, shocks to the MTail provide incremental predictive power for the inflation beyond its past data even when coefficients for both AR and MA terms are highly significant. We also find a negative and significant coefficient for models of the PPI. More importantly, in models with industrial production, negative and highly significant β_y indicates that higher commodity tail risk corresponds to lower subsequent industrial production growth. These results imply that heightened commodity tail risk is related to deteriorated prices and economic conditions in the future. Statistically, we observe that adding MTail shocks improves the goodness-of-fit of the models as both the log-likelihood function value (LLF) and Akaike information criterion (AIC) of augmented models are improved when MTail shocks are added. In Panel B, we observe that the coefficient for commodity tail risk shocks continues to be negative and significant for all indices of economic outlook, thus a positive shock to MTail predicts lower producer and consumer confidence and more pessimistic expectation for future economic conditions.

Next, we examine the relation between our commodity tail risk index and the equity tail risk as the low probability of negative realization of commodity futures may be reflected in the tail risk of equity market through the signal of bad state of economy. In particular, we estimate the following regression on a monthly basis to scrutinize the left-tail dynamics of the two markets:

$$\text{ETail}_{t+\xi} = b_0 + b_1 \text{MTail}_t + e_{t+\xi}, \tag{8}$$

where $\text{ETail}_{t+\xi}$ is the equity market tail risk and ξ ranges from -6 to $+6$ months.

To proxy the equity market tail risk, we follow Atilgan et al. (2020) and Bali et al. (2009) and use the VaR, which describes the level of losses over a given time horizon at a given probability, and ES, which measures the mean of losses over a given time horizon with a given probability. Each month, we compute the VaR as the $5th$ percentile of daily stock market returns over the past one year, i.e., 250 trading days, and evaluate ES as the conditional expectation of losses given that these losses are beyond the 5% threshold over the same time period.

Figure 3 shows the slope coefficient b_1 in bars for each time horizon ξ and the corresponding Newey & West (1986) t-statistics in red line. We observe a consistent pattern in both panels that the slope coefficient b_1 is positive over all ξ: high levels of commodity tail risk are more likely to coincide with and precede high equity tail risk. In particular, the slope coefficient b_1 is the largest and most significant when $\xi = 0$, suggesting a strong positive contemporaneous relation between tail risks emerged from both markets. Importantly, b_1 is also positive when ξ is greater than zero suggesting that heightened commodity tail risk predates more severe equity market conditions in the near future.

In summary, the commodity tail risk contains a significant predictive power for both macroeconomic variables and economic outlook measures. Our analysis shows that an increase in commodity tail risk indicates adverse conditions in the real economy and a deterioration of key economic indicators such as inflation and industrial production, exhibits strong association with, or predates, the equity tail risk. These findings point to the nature of information contained in commodity tail risk, as changes in commodity tail risk capture the states of the economy and this in turn helps determine equilibrium asset prices.

6 Robustness tests and further analysis

6.1 A volume-weighted commodity tail risk index

In our first robustness check, we construct a volume-weighted commodity tail risk index (VW-MTail) with weights corresponding to each commodity's trading volume in month t. Figure 4 shows the time series of the volume-weighted MTail. Although following a similar pattern, the volume-weighted index is more volatile compared to the equal-weighted one. To examine whether this alternative index has similar asset pricing implication for stock returns, we re-estimate the β_{VW}^{MTail} for each stock and perform the univariate portfolio analysis. In Table 12 Panel A for the equal-weighting scheme, the return spread between decile portfolios with the highest and lowest loadings of β_{VW}^{MTail} is 0.71% per month and highly significant at the 1% level (t-statistic = 2.73). Moreover, the risk-adjusted returns are all economically large and statistically significant at the 1% level regardless of the specific asset pricing model. We obtain consistent results for the value-weighted equity portfolios in Panel B. Overall, these findings reveal that our main results are robust with regard to the weighting scheme underlying the commodity tail risk index construction.

6.2 China-specific asset pricing model

As our focus is on the Chinese stock market, we investigate whether our main results are robust to a Chinese specific asset pricing model. Liu et al. (2019) propose a four-factor model (CH4) featuring the market, size, earnings-price ratio-based value, and turnover factors for the Chinese stock market. We follow Liu et al. (2019) and perform our baseline analysis again to obtain β^{MTail} after controlling for these four factors. We exclude the 30% smallest stocks to avoid potential contamination of corporate shell-value.[13] Specifically, we estimate β^{MTail} with respect to the following specification:

$$\mathbb{E}_t\left[R_{i,t+1}\right] = \alpha_{i,t} + \beta_{i,t}^{MTail} \cdot MTail_t + \boldsymbol{\beta}_{i,t}^{F} \cdot \mathbb{E}_t\left[\mathbf{F}_{t+1}\right], \tag{9}$$

[13] Under tight IPO rule, listed companies in China with the smallest size are more likely to be treated as potential shells in reverse mergers and their valuation is attributable to this shell value (Liu et al., 2019).

where $\mathbf{F}$ is a vector of four Chinese specific equity risk factors, including the market (MKT^{CH}), size (SMB^{CH}), EP-based value (VMG), and turnover (PMO) factors, which are obtained from Robert F Stambaugh's website. The sample period is from January 2005 to December 2021.

In Table 13 we summarize the univariate portfolio analysis results and observe that the predictive power of $\beta_{i,t}^{MTail}$ over future stock returns remains robust. The return difference between the high-$\beta_{i,t}^{MTail}$ and low-$\beta_{i,t}^{MTail}$ portfolios is 0.90% per month (t-statistic = 2.69) based on the equal-weighting scheme and 0.89% per month (t-statistic = 2.20) based on the value-weighting scheme. Furthermore, the monthly risk-adjusted returns relative to the Carhart 4-factor, CH4, and Fama-French 5-factor models are significant at 1.07% (t-statistic = 2.60), 1.18% (t-statistic = 2.24), and 1.12% (t-statistic = 2.54), respectively, for value-weighted portfolios. These findings corroborate our baseline results and show that the commodity tail risk beta based on the Chinese specific pricing model remains a strong and robust predictor of future equity returns.

6.3 The investor clientele effect

As our empirical findings suggest that the commodity tail risk matters for the marginal utility of investors, we further dissect the sources of the significant commodity tail risk premia through the investor clientele effect.

Financial intermediaries such as investment banks, insurance companies, and funds matter for asset prices (see Brunnermeier & Sannikov, 2014; He & Krishnamurthy, 2013; He et al., 2017; Hu et al., 2013, among others). Haddad & Muir (2021) argue that institutional investors demand a lower premium as they have lower risk aversion than retail investors. This motivates us to investigate whether the return premium measured by the return difference between stocks with the highest and lowest commodity tail risk beta varies with the investor clientele. Specifically, we form 25 portfolios by first sorting all stocks into quintile portfolios based on their institutional ownership. Within each ownership-sorted portfolio, stocks are further allocated into quintiles based on their β^{MTail}. We collect the quarterly institutional ownership data from the Wind database.

Table 14 reports the future excess returns for 25 bivariate portfolios and the return spreads between extreme β^{MTail}-sorted portfolios. In Panel A, for equal-weighted bivariate portfolios, we observe that taking long positions in the highest β^{MTail} stocks and short positions in the lowest β^{MTail} stocks generate statistically significant and economically large returns across all levels of institutional ownership. Interestingly, the magnitude of return spreads decreases with rising proportion of institutional ownership. For example, the return spreads between extreme β^{MTail}-sorted portfolios are 0.83% (t-statistic = 2.61) and 0.50% (t-statistic = 1.77) on a monthly basis for the lowest- and highest-institutional ownership portfolios, respectively, in Panel A. These results suggest that stocks with higher institutional ownership offer lower β^{MTail} premium, which are consistent with Haddad & Muir (2021) in that institutional investors have a higher risk appetite. We obtain qualitatively the same results for value-weighted portfolios in Panel B. Taken together, the evidence in Table 14 underscores a clear variation in commodity tail risk premium across stocks with different ownership, but institutional clientele effect cannot fully explain the risk premium.

6.4 Additional robustness tests

In this section, we use different model specifications of estimating β^{MTail} and additional data filters to check the robustness of our baseline results. First, we construct two additional measures of β^{MTail} as specified in Equation (9). In specification (1), we set $\mathbf{F} = [\mathrm{MKT}, \mathrm{SMB}, \mathrm{HML}, \mathrm{RMW}, \mathrm{CMA}]$, that is, the market, size, value, profitability, and investment factors. In specification (2), we set $\mathbf{F} = [\mathrm{MKT}, \mathrm{SMB}, \mathrm{HML}, \mathrm{UMD}, \mathrm{IML}]$, where UMD and IML are the momentum and liquidity factors, respectively. The liquidity factor is the illiquid-minus-liquid (IML) factor of Amihud et al. (2015). Second, we apply additional data filters to exclude stock in the ST/PT status and those in the finance industry.[14] Third, we follow Kelly & Jiang (2014) to apply a 10-year rolling window or an 8-year rolling window to estimate β^{MTail}. Finally, we examine whether our results are specific to the exact probability level p used as the cut-off point for left-tail events. Specifically, we set the threshold for left-tail events to $p = 2.5\%$ and $p = 10\%$ (instead of

[14] The special treatment (ST) or particular transition (PT) status are given to listed firms with financial losses or whose net asset is less than par value over at least two consecutive financial years. These stocks are more likely to experience potential financial distress.

$p = 5\%$).

Table 15 summarizes the results of these additional robustness tests. In Panel A, when $\beta_{i,t}^{MTail}$ is estimated after controlling for the Fama-French 5-factor model, the monthly risk-adjusted returns relative to the Carhart 4-factor and Fama-French 5-factor model are 0.878% (t-statistic = 2.96) and 0.884% (t-statistic = 2.70), respectively, for value-weighted portfolios. Panel C shows that after further excluding very small stocks, stocks in the ST/PT status or in the finance industry, the commodity tail risk premia remain highly significant and robust. Furthermore, in Panels D and E, we find that for value-weighted portfolios, excess returns and risk-adjusted returns are all positive and significant at the 5% level. For example, based on the 10-year rolling window in Panel E, the return difference between the extreme β^{MTail} decile portfolios is 0.80% per month with a t-statistic of 2.20. The Fama-French 5-factor model-adjusted return spread is 0.67% per month and highly significant at the 1% level. In Panels E and F, we obtain positive and significant results for the relation between β^{MTail} and future equity returns when we use alternative thresholds for left-tail events. These additional robustness test results corroborate our main finding that the commodity tail risk impacts the cross section of stock returns in China.

6.5 Industry-level evidence

In our final robustness check, we examine the significance of commodity tail risk premia for stocks in nine industries specified by the CSRC industry code, including Mining, Manufacturing, Retail & Wholesale, Transportation, IT, Finance, Real estate, Utilities, and Other. Each month, stocks in each sector are sorted into value-weighted quartile portfolios based on the monthly commodity tail risk beta (β^{MTail}).[15] From Table 16, we observe that the predictive relation between β^{MTail} and stock returns next month remains robust across different industries. For example, the return spread after controlling for the Fama-French 5-factor model are in the range of 0.710% and 1.095% per month and highly significant at the 5% level for stocks in Mining, Manufacturing, Retail & Wholesale, Transportation, IT, Finance, and Other industries. Overall, we find robust

[15] To guarantee a sufficient number of observations in each portfolio, we form quartile portfolios for this robustness test.

evidence for the significant commodity tail risk premia at the industry level.

7 Conclusion

In this study, we investigate the asset pricing implication of commodity tail risk in cross-sectional equity returns in the Chinese stock market. Given that commodity prices contain valuable information about the future economic conditions and capture the consumption level in the aggregate market, our paper focuses on the informational role of commodity prices' extreme negative realizations and their impact on the pricing of stocks. As a single left-tail event of one commodity may not fully describe adverse conditions in the market, we measure the commodity tail risk under a multivariate setting based on a set of well-documented systematic factors. Empirically, we provide comprehensive evidence that stocks vary in their exposure to the commodity tail risk and that their commodity tail risk betas exhibit significant predictive power for future equity returns in the cross section. Stocks that hedge commodity tail risk underperform their counterparts with high exposure to past commodity tail risk by 16.7% per year on the risk-adjusted basis. Such cross-sectional predictability is persistent for up to 24 months and is robust to controls of various common risk factors and firm characteristics.

We provide a potential economic channel to rationalize this return predictability from a macroeconomic perspective. We argue that the heightened commodity tail risk captures deteriorating economic conditions in the future and offer empirical evidence that an increase in commodity tail risk corresponds to a significant decline in macroeconomic variables in the subsequent period. These findings lend support to our conjecture that shocks to the commodity tail risk index reflect the states of the economy and describe changes in consumption and investment opportunities in the future. Our study sheds new light on the relation between commodity and equity markets, and dissects the role of commodity tail risk in explaining equity risk premia.

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Figure 1: **Commodity futures multivariate tail risk index**

This figure shows the time series of commodity multivariate tail risk index (MTail) estimated via a linear factor model with the market, basis, momentum, and basis-momentum factors. The MTail index, shown in blue solid line, is the equal-weighted cross-sectional average of multivariate tail risk estimated over all commodity futures contracts. The dark (shallow) area indicates the corresponding 25% and 75% quantiles (5% and 95% quantiles). The red dotted line is the benchmark probability under which asset i and one or more of risk factors do not realize a left-tail event simultaneously, i.e., they are independent. Gray shadow bars are National Bureau of Economic Research (NBER) recessions. The sample period is from January 2005 to October 2022.

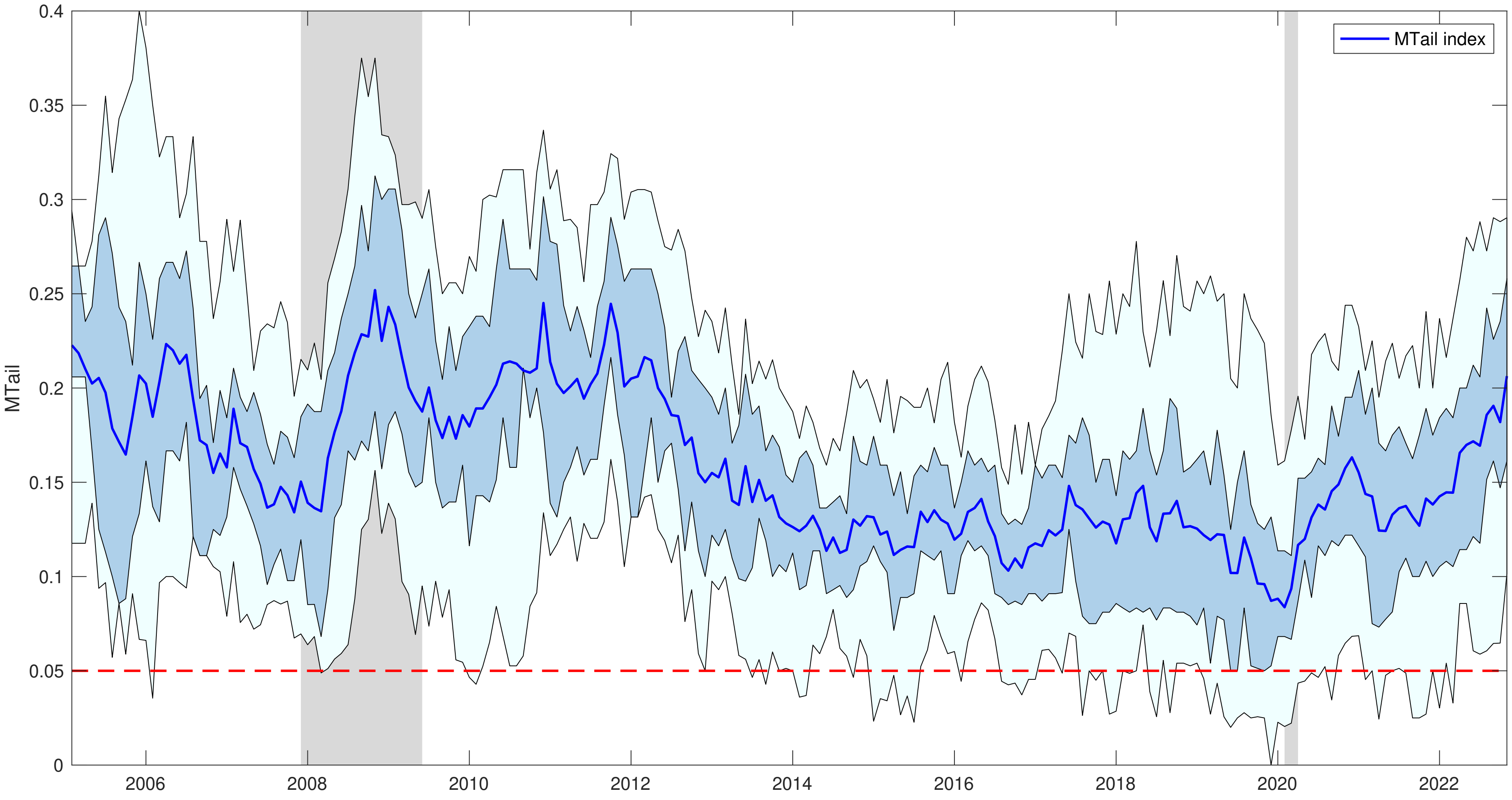

Figure 2: **Changes in commodity tail risk index versus stock market index returns**

This figure compares the commodity tail risk (MTail) index with the stock market index. Panel A plots the times series of monthly commodity tail risk (solid line) and stock market index (dashed line). Both time series are standardized to have zero mean and unit variance. Panel B shows the monthly changes in the commodity tail risk index against stock market index returns. The solid line is the best fitting line obtained from the linear regression, whereas the dashed line is the best fitting line from the piecewise linear regression with a kink at which the stock market index returns are zero. The sample period is from January 2005 to October 2022.

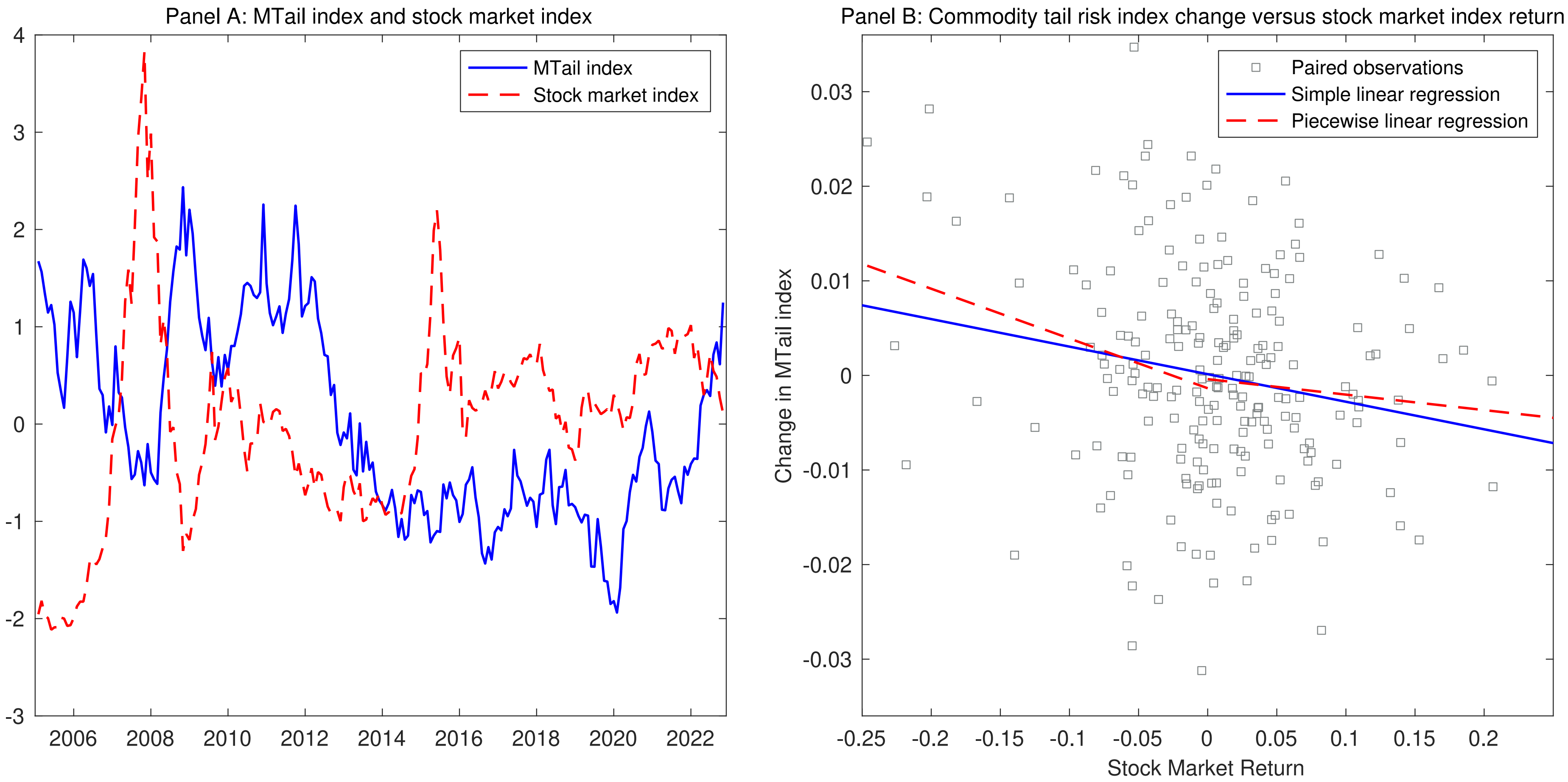

Figure 3: **Commodity tail index versus equity market tail risk**

In this figure, we estimate the following monthly regression: $\text{ETail}_{t+\xi} = b_0 + b_1 \text{MTail}_t + e_{t+\xi}$, where $\text{ETail}_{t+\xi}$ is the equity market tail risk and time horizon ξ ranges from -6 to $+6$ months. Following Atilgan et al. (2020) and Bali et al. (2009), we use the Value-at-Risk (VaR) (Panel A) which describes the level of losses over a given time horizon at a given probability, and expected shortfall (ES) (Panel B) which measures the mean of losses over a given time horizon with a given probability, to proxy equity market tail risk. Each month we compute the VaR as the $5th$ percentile of daily equity market returns over the past one year, i.e., 250 trading days, and obtain ES as the conditional expectation of losses given that these losses are beyond the 5% threshold over the same time period. We multiply these measures by -1 to facilitate comparison. The slope coefficients b_1 (left y-axis) and their corresponding Newey & West (1986) t-statistics (right y-axis) are in shaded bars and red lines, respectively. The sample period is from January 2005 to October 2022.

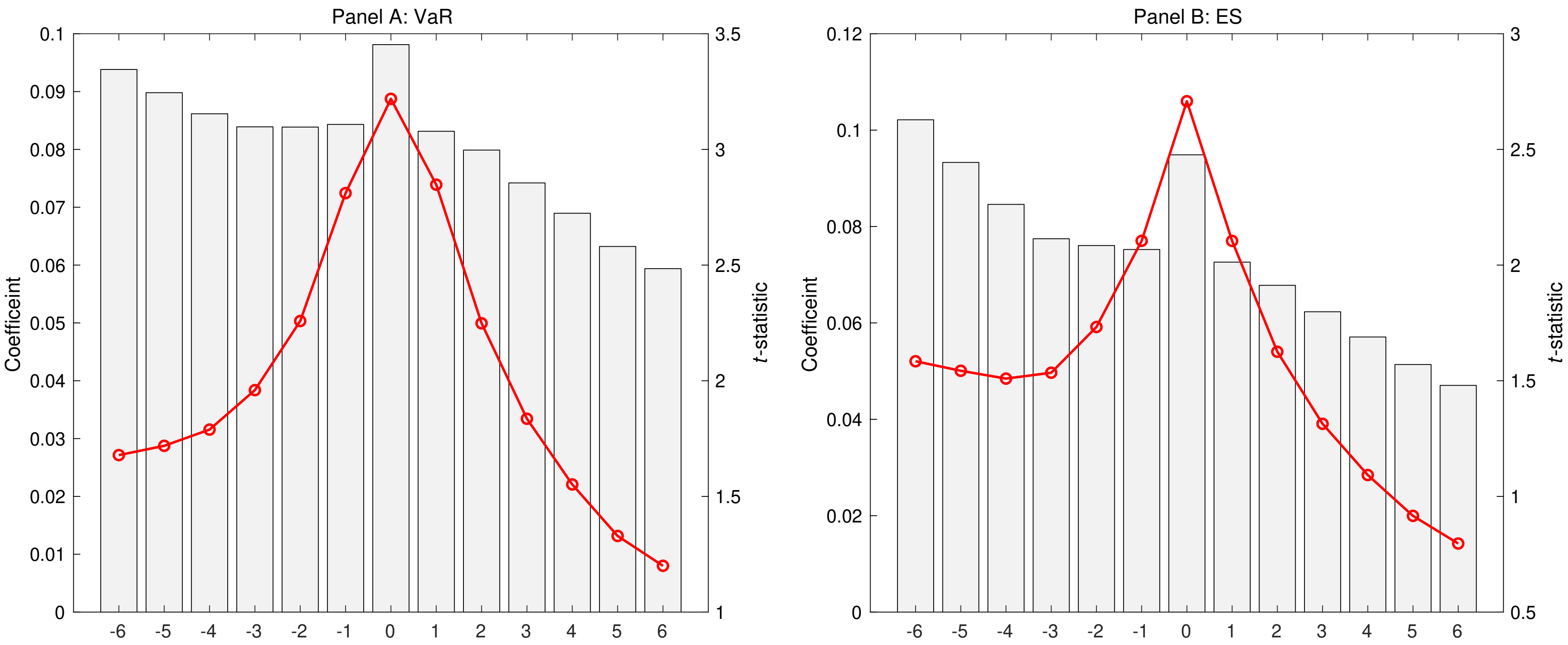

Figure 4: **Robustness: Volume-weighted commodity multivariate tail risk index**

This figure shows the time series of volume-weighted commodity multivariate tail risk index (MTail) estimated via a linear factor model with the market, basis, momentum, and basis-momentum factors. The MTail index, shown in blue solid line, is the volume-weighted cross-sectional average of multivariate tail risk estimated over all commodity futures contracts. The red dotted line is the benchmark probability under which the asset i and one or more of risk factors do not realize a left-tail event simultaneously, i.e., they are independent. Gray shadow bars are National Bureau of Economic Research (NBER) recessions. The sample period is from January 2005 to October 2022.

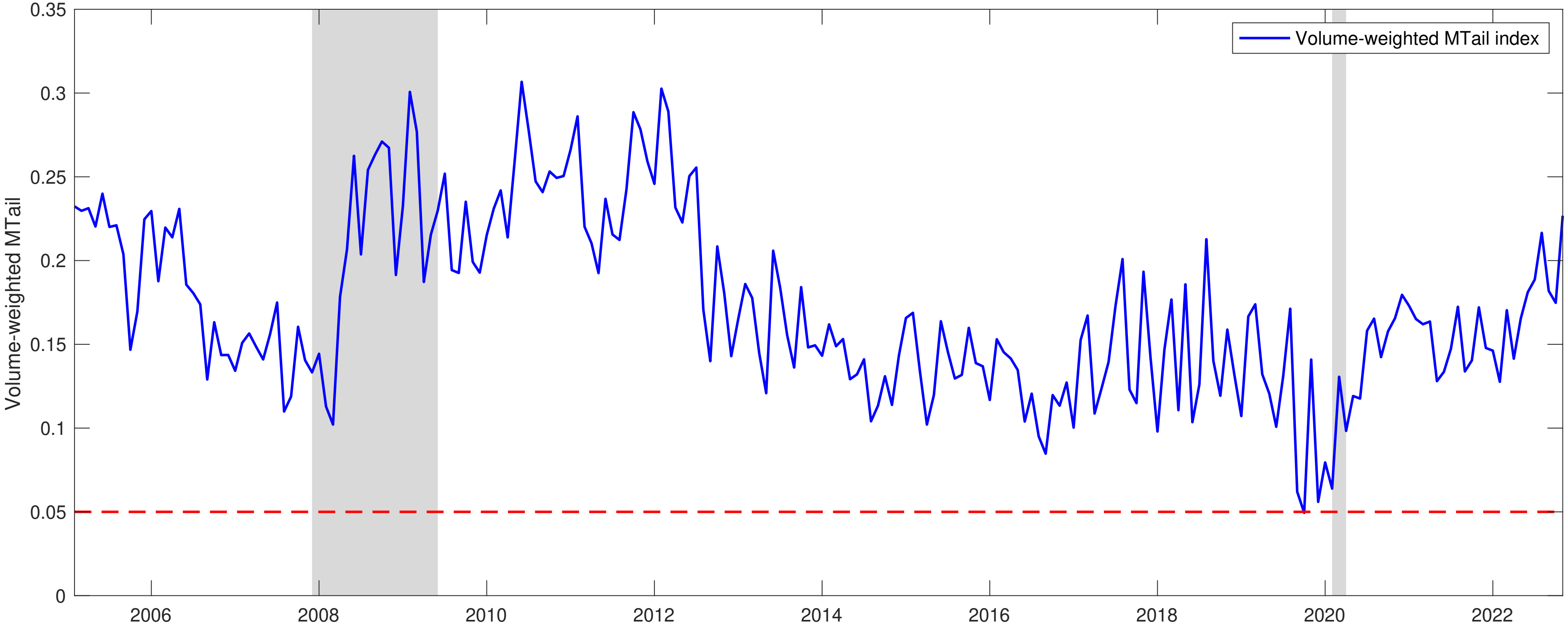

Table 1: **Summary statistics of commodity factors and the MTail index**

This table summarizes descriptive statistics of commodity risk factors and commodity multivariate tail risk (MTail) index. To construct commodity factors, we sort all commodity contracts into five quintile portfolios based on different pricing signals at the month end, and take long (short) positions in the quintiles predicted to appreciate (depreciate) in the following month. All portfolios are equally-weighted and re-balanced monthly with updated pricing signals. We use the third-nearest futures contracts due to liquidity concern. CMKT is the long-only equally-weighted cross-sectional average of all available commodity contracts. We consider three commodity factors, including the term structure (Basis), momentum (CMOM), and basis-momentum (Basis-Mom). For each factor, we report annualized mean returns, annualized standard deviations (S.D.) and Sharpe ratio (SR), skewness (Skew), kurtosis (Kurt), minimum (Min), 25th percentile (Q25), median (Med), 75th percentile (Q75), and maximum (Max) for each monthly (daily) factor return series in Panel A (B). The $t-$statistics is the Newey & West (1986) adjusted t-statistics. Panel C tabulates correlations of monthly commodity factors. The Pearson (Spearman) correlations are reported below (above) the diagonal. Panel D shows the summary statistics of the MTail index. The sample period is from January 2005 to October 2022.

Panel A: Monthly commodity factors

	Mean	$t-$Stat	S.D.	SR	Skew	Kurt	Min	Q25	Med	Q75	Max
CMKT	0.02	0.43	0.13	0.12	-0.72	8.27	-0.23	-0.02	0.00	0.02	0.15
Basis	0.14	3.12	0.18	0.77	-1.56	14.50	-0.36	-0.01	0.01	0.04	0.19
CMOM	0.18	3.76	0.20	0.87	0.15	4.35	-0.21	-0.02	0.01	0.05	0.22
Basis-Mom	0.13	4.65	0.14	0.96	0.21	5.51	-0.12	-0.01	0.01	0.03	0.19

Panel B: Daily commodity factors

	Mean	$t-$Stat	S.D.	SR	Skew	Kurt	Min	Q25	Med	Q75	Max
CMKT	0.01	0.41	0.10	0.12	-0.57	7.33	-0.04	0.00	0.00	0.00	0.03
Basis	0.13	3.51	0.13	1.00	-0.18	7.60	-0.06	0.00	0.00	0.01	0.06
CMOM	0.17	3.83	0.16	1.07	-0.19	5.33	-0.05	0.00	0.00	0.01	0.06
Basis-Mom	0.13	4.11	0.13	1.07	-0.10	4.56	-0.04	0.00	0.00	0.01	0.04

Panel C: Correlation between monthly factors

	CMKT	Basis	CMOM	Basis-Mom
CMKT		0.22	0.24	0.25
Basis	0.40		0.37	0.35
CMOM	0.26	0.42		0.32
Basis-Mom	0.33	0.42	0.33	

Panel D: Commodity tail risk index

	Mean	S.D.	Skew	Kurt	Min	Q25	Med	Q75	Max
MTail index	0.16	0.04	0.40	2.08	0.08	0.13	0.15	0.19	0.25

Table 2: **Descriptive statistics and correlation for stock variables**

This table reports the descriptive statistics (Panel A) and correlations (Panel B) for the commodity tail risk beta (β^{MTail}) and a set of firm-specific control variables, including the mean, standard deviation (S.D.), minimum (Min), 5th percentile (Q5), 25th percentile (Q25), median (Med), 75th percentile (Q75), 95th percentile (Q95), maximum (Max), skewness (Skew), and kurtosis (Kurt) for each variable. The variables include firm size (Size), book-to-market ratio (BM), momentum (MOM), market beta (Beta), reversal (REV), investment (IA), operating profitability (ROE), co-skewness (Coskew), illiquidity (ILLIQ), turnover (TURN), lottery demand (MAX), idiosyncratic volatility (IVOL), and the equity left tail risk (VaR). Details of firm-level variables are summarized in Appendix C. The summary statistics as the time-series averages of the cross-sectional means. In Panel B, the Pearson (below the diagonal) and Spearman (above the diagonal) correlation coefficients are the time-series averages at the end of each month of the cross-sectional correlations between these variables. The sample period is from January 2005 to October 2022.

Panel A: Descriptive statistics

	Mean	S.D.	Min	Q5	Q25	Med	Q75	Q95	Max	Skew	Kurt
β^{MTail}	-0.27	0.64	-5.01	-1.25	-0.61	-0.25	0.09	0.67	4.43	-0.57	20.56
Size	4.20	1.02	1.94	2.95	3.48	3.99	4.71	6.12	9.82	1.33	5.85
BM	0.41	0.27	-1.84	0.10	0.24	0.36	0.53	0.89	2.76	1.78	83.98
MOM	0.00	0.03	-0.10	-0.04	-0.01	0.00	0.02	0.05	0.17	0.73	5.61
Beta	1.08	0.31	-0.18	0.54	0.89	1.09	1.28	1.55	2.62	-0.04	5.85
REV	0.01	0.12	-0.39	-0.13	-0.05	-0.01	0.06	0.20	1.70	3.53	63.97
IA	0.36	2.86	-0.70	-0.14	0.02	0.11	0.26	0.97	71.11	17.14	363.35
ROE	0.02	0.31	-5.52	-0.10	0.01	0.03	0.07	0.14	2.04	-6.88	223.02
Coskew	-0.04	0.25	-0.73	-0.40	-0.22	-0.07	0.10	0.41	0.95	0.57	3.54
ILLIQ	0.47	1.39	0.00	0.03	0.14	0.29	0.56	1.24	44.53	17.68	539.67
TURN	0.02	0.01	0.00	0.00	0.01	0.01	0.02	0.04	0.15	2.83	17.79
MAX	0.03	0.02	0.00	0.01	0.02	0.03	0.04	0.06	0.20	2.79	51.70
IVOL	0.02	0.01	0.00	0.01	0.01	0.02	0.03	0.04	0.09	1.59	28.18
VaR	0.05	0.01	0.01	0.03	0.04	0.05	0.05	0.06	0.09	0.22	4.15

Panel B: Correlation matrix

	β^{MTail}	Size	BM	MOM	Beta	REV	IA	ROE	Coskew	ILLIQ	TURN	MAX	IVOL	VaR
β^{MTail}		0.04	0.05	-0.07	0.03	-0.02	0.02	0.04	-0.04	-0.04	-0.03	-0.04	-0.05	-0.07
Size	0.05		0.09	0.19	0.01	0.05	0.23	0.39	0.11	-0.70	-0.27	0.00	0.00	-0.24
BM	0.04	0.17		0.00	0.00	0.02	-0.04	-0.08	0.09	-0.04	-0.12	-0.14	-0.19	-0.33
MOM	-0.08	0.20	-0.02		-0.04	0.25	0.01	0.19	-0.07	-0.23	0.16	0.15	0.21	0.12
Beta	0.03	0.00	0.00	-0.03		-0.04	0.05	0.00	0.01	-0.14	0.33	0.20	0.09	0.52
REV	-0.02	0.05	0.00	0.29	-0.02		-0.01	0.03	-0.02	-0.10	0.13	0.09	0.17	-0.05
IA	-0.02	0.08	0.01	0.01	0.01	-0.01		0.29	-0.02	-0.23	-0.07	0.02	0.02	-0.03
ROE	0.02	0.13	0.01	0.07	0.02	0.01	0.02		-0.01	-0.30	-0.15	-0.02	-0.04	-0.19
Coskew	-0.03	0.13	0.12	-0.07	0.01	-0.02	0.00	-0.01		-0.06	-0.07	-0.05	-0.05	-0.08
ILLIQ	-0.03	-0.31	-0.09	-0.10	-0.14	-0.05	-0.02	-0.08	-0.02		-0.14	-0.01	-0.01	0.01
TURN	-0.02	-0.21	-0.10	0.20	0.22	0.24	-0.05	-0.03	-0.07	-0.11		0.49	0.48	0.53
MAX	-0.04	-0.02	-0.11	0.13	0.17	0.14	0.01	-0.01	-0.04	0.01	0.46		0.83	0.37
IVOL	-0.05	-0.05	-0.15	0.19	0.08	0.22	0.01	-0.02	-0.04	0.04	0.49	0.87		0.37
VaR	-0.07	-0.29	-0.33	0.14	0.52	-0.01	0.01	-0.07	-0.09	0.01	0.46	0.33	0.36	

Table 3: **Univariate portfolio of stocks sorts on β^{MTail}**

This table reports monthly excess returns and risk-adjusted returns for decile portfolios formed based on commodity tail risk beta β^{MTail}, where Low (High) includes stocks with the lowest (highest) β^{MTail} at the end of the previous month. For each decile portfolio, we report the one-month ahead mean excess returns (Ret-Rf), annualized standard deviation (S.D.) and Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt). The last column shows the return spread (H-L) between taking long (short) positions in the highest (lowest) β^{MTail} portfolios. Risk-adjusted returns (αs) are based on the CAPM, Fama-French 3-factor (FF3), Carhart 4-factor (Carhart), and Fama-French 5-factor (FF5) models. Panel A (B) summarizes equally- (value-) weighted portfolio results. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Equally-weighted portfolios	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Ret-Rf	-0.224	0.135	0.420	0.699	0.725	0.763	0.689	0.755	0.778	0.582	0.807***
	(-0.37)	(0.23)	(0.71)	(1.15)	(1.18)	(1.20)	(1.11)	(1.23)	(1.14)	(0.94)	(2.72)
S.D.	0.27	0.27	0.26	0.26	0.26	0.26	0.26	0.26	0.27	0.26	0.13
SR	-0.10	0.06	0.19	0.32	0.33	0.35	0.32	0.35	0.34	0.27	0.75
Skew	0.01	-0.06	-0.09	0.01	-0.04	0.00	-0.02	-0.04	0.09	0.06	0.46
Kurt	4.23	4.94	4.99	4.89	4.71	4.36	4.48	4.30	4.30	3.59	4.87
CAPM α	-0.571*	-0.219	0.078	0.355	0.379	0.413	0.345	0.413	0.415	0.242	0.813***
	(-1.91)	(-0.74)	(0.26)	(1.13)	(1.24)	(1.26)	(1.18)	(1.41)	(1.22)	(0.77)	(2.75)
FF3 α	-1.004***	-0.695***	-0.461***	-0.162*	-0.105	-0.101	-0.145	-0.052	-0.039	-0.051	0.953***
	(-6.51)	(-5.14)	(-3.67)	(-1.83)	(-1.02)	(-1.00)	(-1.38)	(-0.48)	(-0.24)	(-0.24)	(3.15)
Carhart α	-0.992***	-0.689***	-0.446***	-0.149	-0.079	-0.070	-0.114	-0.022	-0.009	-0.034	0.958***
	(-6.13)	(-4.96)	(-3.52)	(-1.64)	(-0.75)	(-0.75)	(-1.09)	(-0.22)	(-0.05)	(-0.15)	(3.11)
FF5 α	-0.909***	-0.565***	-0.327***	-0.024	0.040	0.024	0.004	0.061	0.110	0.058	0.968***
	(-6.79)	(-4.65)	(-2.78)	(-0.26)	(0.37)	(0.24)	(0.03)	(0.53)	(0.61)	(0.23)	(2.99)

Panel B: Value-weighted portfolios	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Ret-Rf	-0.815	-0.344	-0.184	-0.101	0.001	0.438	0.188	0.346	0.261	0.293	1.108***
	(-1.41)	(-0.61)	(-0.35)	(-0.19)	(0.00)	(0.84)	(0.35)	(0.59)	(0.44)	(0.48)	(2.73)
S.D.	0.25	0.24	0.23	0.23	0.23	0.22	0.22	0.22	0.22	0.25	0.16
SR	-0.39	-0.17	-0.10	-0.05	0.00	0.24	0.10	0.19	0.14	0.14	0.84
Skew	-0.28	-0.21	-0.12	-0.01	0.12	-0.13	0.31	0.21	0.09	-0.04	0.09
Kurt	4.56	5.65	5.98	5.48	5.88	4.63	5.23	4.90	3.65	3.27	3.77
CAPM α	-1.161***	-0.685***	-0.512***	-0.420**	-0.321**	0.128	-0.117	0.030	-0.046	-0.041	1.120***
	(-4.95)	(-3.48)	(-3.84)	(-2.17)	(-2.00)	(0.63)	(-0.59)	(0.19)	(-0.23)	(-0.14)	(2.68)
FF3 α	-1.246***	-0.813***	-0.591***	-0.536***	-0.367**	0.030	-0.159	0.043	-0.003	0.075	1.320***
	(-5.62)	(-4.73)	(-4.28)	(-3.02)	(-2.33)	(0.15)	(-0.84)	(0.28)	(-0.01)	(0.25)	(2.92)
Carhart α	-1.263***	-0.824***	-0.586***	-0.545***	-0.360**	0.048	-0.129	0.077	0.022	0.073	1.337***
	(-5.76)	(-4.80)	(-4.22)	(-3.17)	(-2.32)	(0.24)	(-0.68)	(0.46)	(0.10)	(0.25)	(2.93)
FF5 α	-1.255***	-0.721***	-0.538***	-0.500***	-0.342**	0.076	-0.164	0.033	0.098	0.132	1.388***
	(-6.74)	(-4.58)	(-3.77)	(-2.91)	(-1.98)	(0.36)	(-0.97)	(0.21)	(0.45)	(0.42)	(3.27)

Table 4: **Long-term portfolio returns**

This table reports the long-term performance of value-weighted decile portfolios formed based on commodity tail risk beta β^{MTail}, where Low (High) includes stocks with the lowest (highest) β^{MTail} at the end of the previous month. We report monthly average excess returns (Panel A) and risk-adjusted returns (αs) (Panel B) for each portfolio from two to 36 months after the portfolio formation. The last column shows the return spread (H-L) between taking long (short) positions in the highest (lowest) β^{MTail} portfolios. Risk-adjusted returns (αs) are based on the CAPM, Fama-French 3-factor (FF3), Carhart 4-factor (Carhart), and Fama-French 5-factor (FF5) models. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Excess returns

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
$t+2$	-0.525	-0.296	0.016	0.223	-0.063	0.201	0.398	0.317	0.350	0.336	0.861**
	(-0.87)	(-0.57)	(0.03)	(0.39)	(-0.12)	(0.35)	(0.76)	(0.56)	(0.60)	(0.55)	(2.21)
$t+3$	-0.609	-0.217	-0.017	0.189	-0.271	0.081	0.229	0.316	0.400	0.336	0.945**
	(-1.01)	(-0.38)	(-0.03)	(0.31)	(-0.47)	(0.16)	(0.45)	(0.56)	(0.69)	(0.55)	(2.53)
$t+4$	-0.540	-0.112	0.208	-0.080	-0.011	0.222	0.204	0.314	0.273	0.347	0.887**
	(-0.90)	(-0.19)	(0.34)	(-0.12)	(-0.02)	(0.44)	(0.39)	(0.57)	(0.47)	(0.55)	(2.38)
$t+5$	-0.610	-0.163	0.180	-0.042	0.145	-0.034	0.399	0.568	0.271	0.384	0.994***
	(-0.99)	(-0.29)	(0.30)	(-0.07)	(0.29)	(-0.07)	(0.81)	(1.00)	(0.45)	(0.60)	(2.76)
$t+6$	-0.473	-0.048	0.162	0.156	0.243	0.347	0.421	0.409	0.293	0.379	0.853**
	(-0.81)	(-0.08)	(0.28)	(0.28)	(0.42)	(0.64)	(0.80)	(0.73)	(0.49)	(0.59)	(2.26)
$t+12$	-0.201	0.090	0.171	0.164	0.236	0.230	0.350	0.821	0.554	0.493	0.694**
	(-0.32)	(0.15)	(0.28)	(0.30)	(0.47)	(0.43)	(0.65)	(1.31)	(0.99)	(0.79)	(2.02)
$t+18$	-0.110	0.114	0.345	0.320	0.173	0.429	0.598	0.611	0.454	0.555	0.665**
	(-0.16)	(0.18)	(0.60)	(0.55)	(0.30)	(0.77)	(1.05)	(1.03)	(0.77)	(0.90)	(2.00)
$t+24$	0.190	0.425	0.515	0.757	0.440	0.638	0.789	0.889	0.822	0.841	0.650**
	(0.27)	(0.68)	(0.90)	(1.22)	(0.71)	(1.08)	(1.23)	(1.51)	(1.29)	(1.39)	(1.99)
$t+30$	0.086	0.393	0.633	0.493	0.677	0.350	0.551	0.840	0.669	0.532	0.445
	(0.13)	(0.56)	(0.98)	(0.83)	(1.13)	(0.56)	(0.89)	(1.45)	(1.06)	(0.85)	(1.55)
$t+36$	0.590	0.378	0.418	0.712	0.666	0.734	0.801	0.872	0.542	0.418	-0.172
	(0.86)	(0.57)	(0.67)	(1.08)	(1.07)	(1.16)	(1.31)	(1.36)	(0.83)	(0.63)	(-0.55)

Panel B: Risk-adjusted returns

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
$t+2$	-1.025***	-0.629***	-0.404**	-0.246	-0.355**	-0.131	0.034	0.076	0.150	0.115	1.140***
	(-6.14)	(-3.85)	(-2.57)	(-1.63)	(-2.40)	(-0.64)	(0.19)	(0.43)	(0.69)	(0.40)	(2.81)
$t+3$	-1.033***	-0.557***	-0.394**	-0.114	-0.601***	-0.288*	0.041	0.063	0.184	0.151	1.183***
	(-5.86)	(-3.29)	(-2.29)	(-0.64)	(-3.73)	(-1.88)	(0.24)	(0.30)	(0.78)	(0.59)	(3.03)
$t+4$	-0.971***	-0.482***	-0.180	-0.456**	-0.340*	-0.076	0.021	0.107	0.036	0.168	1.139***
	(-5.21)	(-2.73)	(-1.15)	(-2.40)	(-1.82)	(-0.41)	(0.10)	(0.54)	(0.17)	(0.62)	(2.88)
$t+5$	-1.050***	-0.521***	-0.185	-0.429**	-0.111	-0.309*	0.105	0.365*	0.010	0.195	1.245***
	(-6.20)	(-3.35)	(-1.33)	(-2.52)	(-0.64)	(-1.84)	(0.52)	(1.71)	(0.04)	(0.78)	(3.43)
$t+6$	-0.975***	-0.544***	-0.264	-0.266	-0.065	-0.038	0.077	0.192	-0.026	0.135	1.110***
	(-5.35)	(-3.74)	(-1.47)	(-1.52)	(-0.27)	(-0.21)	(0.47)	(1.13)	(-0.14)	(0.60)	(3.39)
$t+12$	-0.778***	-0.356**	-0.307**	-0.356*	-0.176	-0.314*	-0.116	0.358**	0.141	0.042	0.820**
	(-5.35)	(-2.14)	(-2.25)	(-1.89)	(-1.10)	(-1.85)	(-0.74)	(1.97)	(0.71)	(0.16)	(2.55)
$t+18$	-0.768***	-0.377**	-0.064	-0.228	-0.341**	-0.066	0.077	0.109	0.015	0.031	0.799***
	(-5.31)	(-2.17)	(-0.32)	(-1.18)	(-2.06)	(-0.28)	(0.55)	(0.84)	(0.08)	(0.13)	(2.59)
$t+24$	-0.735***	-0.348	-0.206	0.049	-0.209	-0.012	0.102	0.232	0.079	0.128	0.863***
	(-3.64)	(-1.53)	(-0.94)	(0.26)	(-1.09)	(-0.06)	(0.58)	(1.52)	(0.43)	(0.61)	(2.89)
$t+30$	-0.588***	-0.256	-0.025	-0.150	0.211	-0.189	-0.016	0.331**	0.094	0.055	0.643**
	(-2.59)	(-1.17)	(-0.12)	(-0.83)	(0.92)	(-1.06)	(-0.10)	(1.97)	(0.58)	(0.29)	(2.18)
$t+36$	-0.113	-0.187	-0.151	0.166	0.156	0.152	0.261	0.199	-0.001	-0.083	0.030
	(-0.41)	(-1.20)	(-0.72)	(1.01)	(0.90)	(0.97)	(1.24)	(1.12)	(-0.01)	(-0.55)	(0.10)

Table 5: **Average portfolio characteristics**

This table reports the time-series averages of monthly firm-level characteristics for decile portfolios sorted by β^{MTail}. Decile 1 (Low) and decile 10 (High) contain stocks with the lowest and highest β^{MTail}, respectively. Firm-level characteristics include firm size (Size), book-to-market ratio (BM), momentum (MOM), market beta (Beta), short-term reversal (REV), annual growth of total assets (IA), quarterly operating profitability (ROE), co-skewness (Coskew), Amihud's illiquidity measure (ILLIQ), turnover (TURN), lottery demand (MAX), idiosyncratic volatility (IVOL), and the equity left-tail risk (VaR). The last column reports the differences for firm-level characteristics between extreme deciles (H-L). The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Size	4.349	4.208	4.181	4.171	4.178	4.209	4.230	4.283	4.351	4.515	0.166** (2.05)
BM	0.336	0.397	0.432	0.447	0.460	0.473	0.464	0.451	0.420	0.363	0.028 (1.61)
MOM	0.008	0.004	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.002	-0.006 (-0.57)
Beta	1.069	1.065	1.064	1.065	1.060	1.053	1.059	1.072	1.085	1.123	0.054*** (2.71)
REV	0.022	0.012	0.008	0.007	0.006	0.004	0.005	0.004	0.005	0.011	-0.011 (-0.61)
IA	0.599	0.334	0.495	0.566	0.342	0.313	0.250	0.274	0.350	0.724	0.125 (0.35)
ROE	-0.010	-0.004	0.000	0.003	-0.001	0.000	0.007	0.008	0.016	0.023	0.033*** (2.92)
Coskew	-0.015	-0.033	-0.033	-0.039	-0.042	-0.041	-0.044	-0.053	-0.051	-0.052	-0.037 (-1.29)
ILLIQ	0.453	0.475	0.503	0.498	0.488	0.497	0.500	0.461	0.455	0.419	-0.034 (-1.04)
TURN	0.018	0.017	0.016	0.016	0.016	0.015	0.015	0.015	0.016	0.018	0.000 (-0.14)
MAX	0.033	0.031	0.031	0.030	0.030	0.030	0.030	0.030	0.031	0.032	-0.001 (-0.14)
IVOL	0.021	0.020	0.019	0.019	0.018	0.018	0.018	0.018	0.019	0.020	-0.001 (-0.49)
VaR	0.048	0.045	0.044	0.044	0.043	0.043	0.043	0.043	0.044	0.045	-0.002 (-1.14)

Table 6: **Transition matrix**

This table summarizes six- and 12-month ahead transition probabilities for stocks sorted by commodity tail risk beta (β^{MTail}). After sorting stocks into decile portfolios in month t, we repeat the same procedure and summarize the average percentage that a stock in a decile portfolio (indicated by the row) in month t moves to another portfolio (indicated by the column) in month $t+6$ and $t+12$ in Panels A and B, respectively. The sample period is from January 2005 to October 2022.

Panel A: 6-month ahead transition probabilities

To	Low (%)	P2 (%)	P3 (%)	P4 (%)	P5 (%)	P6 (%)	P7 (%)	P8 (%)	P9 (%)	High (%)
From										
Low	52.9	24.7	11.2	5.5	2.8	1.4	0.8	0.4	0.2	0.1
P2	22.5	28.8	20.5	12.6	7.3	4.1	2.3	1.2	0.6	0.2
P3	10.2	18.6	23.0	18.6	12.7	7.9	4.7	2.5	1.2	0.5
P4	5.4	11.2	17.2	20.5	17.4	12.4	8.0	4.7	2.3	0.9
P5	3.1	6.8	11.4	16.1	19.4	16.9	12.4	8.0	4.2	1.7
P6	1.9	4.1	7.3	11.2	15.9	19.3	17.2	12.6	7.4	3.1
P7	1.1	2.5	4.5	7.4	11.4	16.3	20.3	18.3	12.4	5.8
P8	0.7	1.4	2.7	4.5	7.4	11.7	17.3	22.7	20.1	11.4
P9	0.4	0.8	1.5	2.5	4.3	7.1	11.8	19.1	28.2	24.3
High	0.2	0.4	0.6	1.1	1.8	3.2	5.7	10.9	23.7	52.4

Panel B: 12-month ahead transition probabilities

To	Low (%)	P2 (%)	P3 (%)	P4 (%)	P5 (%)	P6 (%)	P7 (%)	P8 (%)	P9 (%)	High (%)
From										
Low	35.1	23.1	15.0	9.9	6.5	4.3	2.8	1.7	1.0	0.5
P2	21.5	19.8	16.6	13.1	10.0	7.3	5.2	3.5	2.1	1.1
P3	13.6	15.6	15.8	14.4	12.3	9.9	7.6	5.5	3.5	1.9
P4	9.2	12.0	13.8	14.2	13.4	11.8	9.8	7.6	5.2	3.0
P5	6.4	9.1	11.4	12.9	13.5	13.1	11.8	9.9	7.4	4.6
P6	4.4	6.8	9.1	11.1	12.7	13.5	13.4	12.2	10.0	6.8
P7	3.1	5.0	7.1	9.1	11.2	13.0	14.2	14.3	13.0	10.1
P8	2.1	3.5	5.2	7.1	9.3	11.6	13.9	15.8	16.4	15.0
P9	1.4	2.4	3.6	5.1	7.1	9.5	12.5	15.9	19.8	22.8
High	0.8	1.3	2.1	3.1	4.6	6.7	9.7	14.4	22.3	34.9

Table 7: **Bivariate portfolio analysis**

This table summarizes the sequential bivariate portfolio analysis results based on a set of control variables and a stock's commodity tail risk beta (β^{MTail}). We first sort stocks into decile portfolios based on one of 13 control variables collated in Appendix C. Within each decile, stocks are further sorted into decile portfolios based on the β^{MTail}. All portfolios are re-balanced at the end of each month. Panel A (b) reports monthly excess returns for equal-weighted (value-weighted) portfolios. The penultimate column shows the monthly average return spreads between the highest- and lowest-β^{MTail} portfolios across each firm-specific characteristics, and the last column reports risk-adjusted returns (α) based on the Fama-French 5-factor model. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Equal-weighted bivariate portfolios												
	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L	FF5 α
Size	-0.032	0.175	0.395	0.596	0.689	0.681	0.660	0.676	0.788	0.695	0.728**	0.839***
	(-0.05)	(0.30)	(0.66)	(1.01)	(1.09)	(1.07)	(1.09)	(1.09)	(1.21)	(1.08)	(2.56)	(2.61)
BM	-0.145	0.239	0.395	0.613	0.688	0.845	0.642	0.781	0.697	0.585	0.730**	0.871***
	(-0.24)	(0.40)	(0.66)	(1.00)	(1.11)	(1.32)	(1.07)	(1.28)	(1.05)	(0.93)	(2.40)	(2.66)
MOM	-0.096	0.316	0.446	0.603	0.814	0.537	0.772	0.655	0.697	0.633	0.730***	0.838***
	(-0.16)	(0.52)	(0.70)	(0.99)	(1.30)	(0.86)	(1.28)	(1.05)	(1.14)	(1.03)	(2.75)	(3.12)
Beta	-0.185	0.215	0.327	0.562	0.692	0.682	0.724	0.614	0.769	0.547	0.732***	0.883***
	(-0.31)	(0.36)	(0.55)	(0.92)	(1.08)	(1.09)	(1.18)	(0.99)	(1.18)	(0.87)	(2.59)	(2.77)
REV	-0.206	0.187	0.471	0.634	0.826	0.697	0.666	0.809	0.825	0.597	0.803***	0.931***
	(-0.34)	(0.31)	(0.79)	(1.03)	(1.29)	(1.14)	(1.10)	(1.26)	(1.23)	(0.96)	(2.86)	(3.19)
IA	-0.249	0.216	0.427	0.570	0.804	0.725	0.687	0.745	0.816	0.580	0.829***	0.953***
	(-0.42)	(0.36)	(0.71)	(0.95)	(1.29)	(1.16)	(1.09)	(1.22)	(1.21)	(0.93)	(2.73)	(2.91)
ROE	-0.216	0.146	0.442	0.647	0.744	0.754	0.662	0.713	0.832	0.587	0.803***	0.920***
	(-0.35)	(0.25)	(0.74)	(1.05)	(1.22)	(1.20)	(1.08)	(1.16)	(1.23)	(0.94)	(2.69)	(2.79)
Coskew	-0.196	0.172	0.386	0.639	0.635	0.769	0.610	0.692	0.678	0.653	0.849***	0.985***
	(-0.32)	(0.28)	(0.65)	(1.03)	(1.03)	(1.20)	(0.98)	(1.11)	(1.07)	(1.00)	(2.89)	(3.03)
ILLIQ	-0.135	0.215	0.403	0.544	0.716	0.642	0.610	0.677	0.721	0.687	0.822***	0.904***
	(-0.22)	(0.36)	(0.66)	(0.86)	(1.16)	(1.04)	(0.99)	(1.08)	(1.10)	(1.08)	(3.03)	(2.97)
TURN	-0.109	0.126	0.418	0.625	0.700	0.614	0.664	0.723	0.665	0.617	0.726***	0.890***
	(-0.18)	(0.21)	(0.69)	(1.00)	(1.08)	(0.99)	(1.09)	(1.17)	(1.04)	(0.99)	(2.65)	(2.87)
MAX	-0.042	0.152	0.427	0.590	0.661	0.596	0.629	0.725	0.703	0.616	0.658**	0.793***
	(-0.07)	(0.25)	(0.69)	(0.95)	(1.08)	(0.96)	(1.00)	(1.15)	(1.10)	(1.00)	(2.47)	(2.94)
IVOL	-0.041	0.249	0.399	0.642	0.628	0.627	0.557	0.694	0.618	0.645	0.686***	0.837***
	(-0.07)	(0.41)	(0.65)	(1.03)	(0.99)	(0.99)	(0.91)	(1.10)	(0.98)	(1.05)	(2.71)	(3.07)
VaR	-0.056	0.127	0.496	0.490	0.582	0.621	0.473	0.719	0.632	0.475	0.531**	0.657**
	(-0.10)	(0.22)	(0.81)	(0.80)	(0.95)	(1.06)	(0.79)	(1.15)	(0.99)	(0.79)	(2.27)	(2.50)

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Panel B: Value-weighted bivariate portfolios												
	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L	FF5 α
Size	-0.043	0.154	0.376	0.564	0.676	0.659	0.629	0.621	0.761	0.640	0.683**	0.797**
	(-0.07)	(0.26)	(0.64)	(0.96)	(1.10)	(1.06)	(1.05)	(1.02)	(1.17)	(1.00)	(2.41)	(2.51)
BM	-0.708	-0.153	-0.136	-0.026	0.269	0.395	0.200	0.437	0.302	0.227	0.935***	1.106***
	(-1.21)	(-0.26)	(-0.25)	(-0.05)	(0.46)	(0.69)	(0.36)	(0.76)	(0.51)	(0.39)	(2.67)	(2.90)
MOM	-0.641	-0.221	0.014	0.116	0.397	0.200	0.280	0.105	0.228	0.258	0.899***	1.146***
	(-1.16)	(-0.40)	(0.02)	(0.19)	(0.7)	(0.36)	(0.53)	(0.18)	(0.42)	(0.43)	(2.88)	(3.47)
Beta	-0.578	-0.091	-0.057	0.100	0.271	0.563	0.481	0.430	0.389	0.343	0.922***	1.167***
	(-0.96)	(-0.16)	(-0.10)	(0.17)	(0.44)	(0.92)	(0.83)	(0.71)	(0.64)	(0.57)	(2.75)	(3.09)
REV	-0.730	-0.224	-0.032	0.111	0.210	0.360	0.293	0.547	0.446	0.422	1.152***	1.379***
	(-1.27)	(-0.39)	(-0.06)	(0.19)	(0.36)	(0.68)	(0.53)	(0.89)	(0.70)	(0.68)	(3.66)	(4.17)
IA	-0.740	-0.189	0.014	0.081	0.221	0.506	0.439	0.310	0.552	0.294	1.034***	1.250***
	(-1.29)	(-0.34)	(0.03)	(0.14)	(0.38)	(0.90)	(0.74)	(0.55)	(0.87)	(0.49)	(2.98)	(3.33)
ROE	-0.768	-0.197	-0.138	0.063	0.308	0.402	0.244	0.349	0.337	0.157	0.925***	1.153***
	(-1.28)	(-0.34)	(-0.25)	(0.11)	(0.49)	(0.68)	(0.42)	(0.61)	(0.51)	(0.25)	(2.77)	(3.09)
Coskew	-0.530	-0.160	0.095	0.180	0.217	0.562	0.377	0.462	0.398	0.425	0.955***	1.246***
	(-0.89)	(-0.26)	(0.16)	(0.31)	(0.37)	(0.92)	(0.64)	(0.75)	(0.63)	(0.67)	(2.60)	(3.06)
ILLIQ	-0.242	0.106	0.308	0.357	0.630	0.652	0.544	0.559	0.568	0.592	0.834***	0.900***
	(-0.42)	(0.18)	(0.53)	(0.62)	(1.07)	(1.12)	(0.90)	(0.99)	(0.94)	(0.97)	(2.94)	(2.80)
TURN	-0.675	-0.246	-0.114	0.037	0.231	0.133	0.415	0.375	0.175	0.218	0.893***	1.154***
	(-1.15)	(-0.42)	(-0.20)	(0.07)	(0.39)	(0.23)	(0.70)	(0.62)	(0.29)	(0.35)	(2.78)	(3.13)
MAX	-0.602	-0.229	0.008	0.125	0.269	0.336	0.588	0.294	0.422	0.290	0.893***	1.099***
	(-1.04)	(-0.41)	(0.01)	(0.23)	(0.46)	(0.57)	(1.02)	(0.49)	(0.72)	(0.47)	(2.79)	(3.49)
IVOL	-0.646	-0.159	-0.176	0.047	0.251	0.453	0.136	0.385	0.279	0.299	0.945***	1.207***
	(-1.10)	(-0.29)	(-0.31)	(0.08)	(0.40)	(0.77)	(0.25)	(0.61)	(0.48)	(0.49)	(2.93)	(3.64)
VaR	-0.614	-0.230	0.082	0.191	0.255	0.193	0.112	0.493	0.276	0.145	0.759***	1.004***
	(-1.06)	(-0.40)	(0.14)	(0.32)	(0.42)	(0.35)	(0.20)	(0.84)	(0.46)	(0.25)	(2.86)	(3.29)

Table 8: **Fama-MacBeth regressions**

This table summarizes Fama & MacBeth (1973) regression results. We run cross-sectional regressions of monthly excess stock returns (in percent) in month $t+1$ on the stock's commodity tail risk beta (β^{MTail}) and a set of lagged control variables, and report the time-series averages of the slope coefficients. Panel A (B) presents the results without (with) controlling for the industry effects. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Without controlling for the industry effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
β^{MTail}	0.548***	0.532***	0.485***	0.341***	0.370***	0.408***	0.404***	0.402***	0.395***	0.419***	0.356***	0.259**	0.277**	0.293***
	(3.05)	(2.99)	(2.85)	(2.67)	(2.77)	(3.06)	(3.03)	(3.03)	(3.00)	(3.16)	(2.89)	(2.19)	(2.47)	(2.80)
Size		-0.541***	-0.549***	-0.540***	-0.464***	-0.449***	-0.448***	-0.453***	-0.439***	-0.364**	-0.604***	-0.558***	-0.564***	-0.404***
		(-3.16)	(-3.32)	(-3.46)	(-3.09)	(-2.98)	(-2.98)	(-3.03)	(-2.95)	(-2.39)	(-3.87)	(-3.57)	(-3.62)	(-2.93)
BM			0.015	0.007	0.267	0.250	0.257	0.261	0.275	0.334	0.135	0.062	-0.008	0.008
			(0.04)	(0.02)	(0.78)	(0.74)	(0.76)	(0.77)	(0.82)	(1.00)	(0.41)	(0.19)	(-0.02)	(0.03)
MOM				-4.077	-3.896	-0.818	-0.906	-1.151	-1.471	-0.921	4.917	4.324	5.843	8.401**
				(-1.00)	(-1.01)	(-0.22)	(-0.24)	(-0.31)	(-0.39)	(-0.25)	(1.22)	(1.07)	(1.50)	(2.39)
Beta					-0.393	-0.445	-0.442	-0.439	-0.422	-0.262	0.362	0.481*	0.268	0.378
					(-1.10)	(-1.26)	(-1.25)	(-1.24)	(-1.18)	(-0.76)	(1.23)	(1.67)	(0.91)	(1.13)
REV						-1.873***	-1.868***	-1.837***	-1.772***	-1.673***	-0.032	0.054	0.340	0.675
						(-3.29)	(-3.28)	(-3.23)	(-3.18)	(-3.02)	(-0.06)	(0.10)	(0.63)	(1.16)
IA							-0.006	-0.007	-0.006	-0.006	-0.027	-0.025	-0.021	-0.027
							(-0.21)	(-0.25)	(-0.23)	(-0.21)	(-1.02)	(-0.95)	(-0.80)	(-1.07)
ROE								0.191	0.205	0.279	0.204	0.206	0.178	0.275
								(0.78)	(0.87)	(1.11)	(0.81)	(0.82)	(0.73)	(1.02)
Coskew									-0.259	-0.275	-0.310	-0.295	-0.289	-0.344
									(-1.27)	(-1.30)	(-1.47)	(-1.44)	(-1.43)	(-1.59)
ILLIQ										0.445***	0.172*	0.262**	0.292***	0.769**
										(3.88)	(1.71)	(2.53)	(2.82)	(2.47)
TURN											-0.553***	-0.448***	-0.425***	-0.357***
											(-11.53)	(-9.65)	(-9.46)	(-7.76)
MAX												-0.214***	0.076	0.054
												(-4.18)	(0.89)	(0.60)
IVOL													-0.549***	-0.563***
													(-4.54)	(-4.34)
VaR														-2.387
														(-0.26)
Intercept	0.755	3.036***	3.102***	3.060***	2.933***	2.818**	2.810**	2.817**	2.725**	2.069*	3.516***	3.748***	4.025***	3.067***
	(1.25)	(2.69)	(2.72)	(2.74)	(2.59)	(2.52)	(2.51)	(2.53)	(2.51)	(1.85)	(3.07)	(3.16)	(3.33)	(3.10)
R^2 (%)	0.58	2.65	3.47	4.32	5.77	6.21	6.25	6.38	6.57	6.88	8.07	8.67	8.98	9.63

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Panel B: Controlling for the industry effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
β^{MTail}	0.615***	0.612***	0.579***	0.436***	0.460***	0.490***	0.487***	0.485***	0.488***	0.513***	0.458***	0.349***	0.360***	0.373***
	(3.37)	(3.49)	(3.40)	(3.64)	(3.68)	(3.91)	(3.89)	(3.89)	(3.98)	(4.05)	(4.07)	(3.36)	(3.59)	(3.93)
Size		-0.591***	-0.596***	-0.577***	-0.504***	-0.491***	-0.490***	-0.495***	-0.478***	-0.396**	-0.651***	-0.594***	-0.592***	-0.429***
		(-3.22)	(-3.35)	(-3.43)	(-3.12)	(-3.03)	(-3.02)	(-3.07)	(-3.02)	(-2.44)	(-3.92)	(-3.59)	(-3.60)	(-2.97)
BM			0.009	0.002	0.247	0.230	0.237	0.239	0.255	0.321	0.152	0.067	0.003	0.016
			(0.03)	(0.01)	(0.79)	(0.74)	(0.76)	(0.77)	(0.82)	(1.03)	(0.49)	(0.22)	(0.01)	(0.06)
MOM				-4.836	-4.771	-1.641	-1.724	-1.968	-2.016	-1.463	4.527	3.966	5.277	8.090**
				(-1.27)	(-1.34)	(-0.47)	(-0.50)	(-0.57)	(-0.58)	(-0.42)	(1.21)	(1.07)	(1.46)	(2.46)
Beta					-0.398	-0.454	-0.452	-0.448	-0.428	-0.256	0.369	0.508*	0.310	0.450
					(-1.15)	(-1.34)	(-1.33)	(-1.32)	(-1.24)	(-0.76)	(1.32)	(1.89)	(1.11)	(1.43)
REV						-1.989***	-1.980***	-1.948***	-1.888***	-1.791***	-0.151	-0.053	0.221	0.536
						(-3.85)	(-3.83)	(-3.76)	(-3.71)	(-3.54)	(-0.30)	(-0.11)	(0.44)	(0.99)
IA							-0.001	-0.001	0.001	0.001	-0.020	-0.016	-0.013	-0.019
							(-0.03)	(-0.05)	(0.03)	(0.05)	(-0.73)	(-0.62)	(-0.48)	(-0.78)
ROE								0.151	0.155	0.228	0.176	0.174	0.146	0.250
								(0.61)	(0.64)	(0.89)	(0.69)	(0.69)	(0.59)	(0.94)
Coskew									-0.319*	-0.330*	-0.359*	-0.337*	-0.335*	-0.358*
									(-1.74)	(-1.72)	(-1.90)	(-1.90)	(-1.92)	(-1.87)
ILLIQ										0.478***	0.193*	0.296***	0.326***	0.802**
										(4.03)	(1.85)	(2.77)	(3.04)	(2.52)
TURN											-0.566***	-0.452***	-0.431***	-0.364***
											(-12.05)	(-9.81)	(-9.69)	(-8.16)
MAX												-0.233***	0.033	0.003
												(-4.78)	(0.44)	(0.04)
IVOL													-0.499***	-0.509***
													(-4.39)	(-4.20)
VaR														-2.963
														(-0.37)
Intercept	0.600	3.055**	3.100**	3.022**	2.954**	2.865**	2.859**	2.865**	2.759**	2.039*	3.505***	3.747***	3.977***	2.957***
	(0.92)	(2.47)	(2.49)	(2.48)	(2.37)	(2.31)	(2.30)	(2.32)	(2.31)	(1.66)	(2.78)	(2.88)	(3.00)	(2.79)
Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (%)	3.43	5.33	5.85	6.59	7.92	8.29	8.33	8.45	8.58	8.89	10.02	10.58	10.85	11.60

Table 9: **Spanning test**

This table summarizes average monthly returns and risk-adjusted returns of the commodity tail risk beta factor. At the end of each month, we independently separate all stocks into two groups based on market capitalization (Size) using the median value of the stock universe, and three commodity tail risk beta (β^{MTail}) groups using the 30th and 70th percentiles of β^{MTail}. We use the intersections of those groups and obtain six size-β^{MTail} combinations. The equal- (EW) and value-weighted (VW) β^{MTail} factors are constructed by taking the return differences of high- and low-β^{MTail} portfolios via equal- and value-weighting schemes, respectively. Risk-adjusted returns (αs) are based on the CAPM, the Fama-French 3-factor (FF3), Carhart 4-factor (Carhart), and Fama-French 5-factor (FF5) models. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

	Average return	CAPM α	FF3 α	Carhart α	FF5 α
EW β^{MTail} factor	0.594***	0.593***	0.673***	0.687***	0.677***
	(2.87)	(2.83)	(3.19)	(3.20)	(3.19)
VW β^{MTail} factor	0.611***	0.611***	0.707***	0.722***	0.722***
	(2.88)	(2.87)	(3.26)	(3.29)	(3.27)

Table 10: **Cross-sectional pricing tests: The commodity tail risk and other risk factors**

This table summarizes the second-stage Fama-MacBeth regression results for commodity risk factors on the cross section of equity portfolios. We consider four commodity risk factors: the commodity market (CMKT), basis (Basis), momentum (CMOM), and basis-momentum (BM) factors. We use 35 equity portfolios as test assets: 25 size and book-to-market sorted and 10 β^{MTail}-sorted portfolios. Across all specifications, we control the market, size, value, and momentum factors in the equity market. We report the estimated price of risk, root mean square error (RMSE), and cross-sectional R^2. The t-statistics are computed based on the Newey & West (1986) approach (in parentheses) and the Shanken (1992) correction (in square brackets). The sample period is from January 2005 to October 2022.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
γ_0	0.026	0.03	0.026	0.031	0.025	0.024	0.028	0.032	0.024	0.027	0.027	0.027
	(4.50)	(5.21)	(4.50)	(5.22)	(4.34)	(4.33)	(4.76)	(5.39)	(4.26)	(4.71)	(4.93)	(4.94)
	[3.93]	[4.36]	[3.77]	[4.24]	[1.79]	[1.71]	[3.19]	[3.76]	[3.66]	[3.39]	[2.09]	[1.97]
λ_{MTail}		0.011		0.010		0.008		0.010		0.010		0.008
		(3.28)		(3.01)		(2.63)		(2.93)		(3.08)		(2.53)
		[3.22]		[2.99]		[2.10]		[2.82]		[2.96]		[2.21]
λ_{CMKT}			0.005	0.006							0.008	0.009
			(0.77)	(0.86)							(1.19)	(1.31)
			[0.66]	[0.70]							[0.55]	[0.57]
λ_{Basis}					0.076	0.085					0.073	0.081
					(6.24)	(6.49)					(6.13)	(6.26)
					[3.18]	[2.86]					[3.21]	[2.86]
λ_{CMOM}							0.050	0.048			0.058	0.060
							(5.41)	(5.24)			(6.08)	(6.07)
							[3.18]	[3.08]			[2.41]	[2.21]
λ_{BM}									0.011	0.024	0.014	0.012
									(1.34)	(2.87)	(1.90)	(1.69)
									[1.06]	[1.90]	[0.76]	[0.63]
λ_{MKT}	-0.027	-0.032	-0.028	-0.033	-0.026	-0.024	-0.029	-0.033	-0.025	-0.028	-0.029	-0.028
	(-2.95)	(-3.46)	(-3.01)	(-3.54)	(-2.79)	(-2.71)	(-3.15)	(-3.61)	(-2.8)	(-3.12)	(-3.20)	(-3.16)
	[-3.07]	[-3.48]	[-3.06]	[-3.50]	[-1.59]	[-1.52]	[-2.70]	[-3.17]	[-2.86]	[-2.79]	[-1.91]	[-1.80]
λ_{SMB}	0.008	0.009	0.008	0.009	0.008	0.008	0.007	0.008	0.008	0.009	0.008	0.008
	(1.84)	(2.04)	(1.90)	(2.12)	(1.95)	(1.91)	(1.59)	(1.81)	(1.85)	(2.09)	(1.86)	(1.82)
	[1.87]	[2.09]	[1.92]	[2.16]	[1.84]	[1.77]	[1.56]	[1.80]	[1.88]	[2.13]	[1.72]	[1.65]
λ_{HML}	0.006	0.006	0.005	0.005	0.007	0.007	0.004	0.005	0.005	0.005	0.007	0.007
	(1.87)	(2.12)	(1.64)	(1.86)	(2.39)	(2.39)	(1.27)	(1.56)	(1.70)	(1.66)	(2.28)	(2.36)
	[1.65]	[1.84]	[1.40]	[1.56]	[1.67]	[1.61]	[1.11]	[1.35]	[1.48]	[1.41]	[1.66]	[1.66]
λ_{MOM}	-0.014	0.002	-0.016	0.000	0.004	0.002	-0.018	-0.002	-0.014	0.004	0.000	-0.002
	(-1.62)	(0.27)	(-1.83)	(0.02)	(0.52)	(0.23)	(-2.01)	(-0.27)	(-1.60)	(0.52)	(0.01)	(-0.28)
	[-1.60]	[0.25]	[-1.71]	[0.02]	[0.26]	[0.11]	[-1.60]	[-0.22]	[-1.54]	[0.43]	[0.00]	[-0.13]
RMSE	0.29	0.21	0.28	0.21	0.11	0.10	0.24	0.17	0.28	0.20	0.10	0.09
R^2	0.57	0.67	0.56	0.67	0.84	0.83	0.63	0.72	0.56	0.68	0.83	0.83

Table 11: **Economic channel analysis**

This table summarizes results of the predictability tests of commodity tail risk index (MTail) on macroeconomic variable and indices of economic outlook. We estimate an ARMA model as follows: $y_{t+1} = \alpha_y + \beta_y \Delta\text{MTail}_{t-3:t} + \theta_1 y_t + \theta_2 \epsilon_t + \epsilon_{t+1}$, where y_{t+1} is the growth rate of dependent variables at time $t+1$, $\Delta\text{MTail}_{t-3:t}$ is the difference between MTail values at time t and $t-3$, and y_t and ϵ_t are first-order autoregressive and moving-average terms, respectively. Panel A reports results for macroeconomic variables as the dependent variable (Δy_{t+1}): the consumer price inflation index (CPI), producer price index (PPI), and industrial production (IP). Panel B summarizes results for economic outlook indices as the forecasted variable: the purchasing managers' index (PMI), consumer confidence index (CCI), and consumer expectation index (CEI). LLF is the log-likelihood function value, and AIC is the Akaike information criterion. Standard errors are reported in parentheses, *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Macroeconomic variables

	α_y	θ_1	θ_2	β_y	LLF	AIC
CPI	-0.000	0.799***	-0.675***		795	-1582
	(0.001)	(0.077)	(0.062)			
CPI + MTail	-0.000	0.811***	-0.712***	-0.047**	797	-1585
	(0.001)	(0.062)	(0.051)	(0.022)		
PPI	-0.001	0.631***	0.312***		762	-1516
	(0.002)	(0.080)	(0.092)			
PPI + MTail	-0.001	0.614***	0.351***	-0.064**	765	-1519
	(0.002)	(0.079)	(0.106)	(0.028)		
IP	0.101***	0.970***	-0.270***		570	-1131
	(0.026)	(0.018)	(0.094)			
IP + MTail	0.101***	0.969***	-0.250**	-0.160**	573	-1135
	(0.025)	(0.019)	(0.104)	(0.073)		

Panel B: Economic outlook indices

	α_y	θ_1	θ_2	β_y	LLF	AIC
PMI	-0.001***	0.594**	-0.928***		366	-724
	(0.001)	(0.236)	(0.077)			
PMI + MTail	-0.002***	0.618***	-1.000***	-0.276**	371	-732
	(0.000)	(0.136)	(0.000)	(0.111)		
CCI	-0.002	-0.423	0.457		443	-878
	(0.002)	(0.502)	(0.433)			
CCI + MTail	-0.002	-0.428	0.450	-0.260**	446	-883
	(0.002)	(0.480)	(0.416)	(0.117)		
CEI	-0.002	0.773**	-0.788**		423	-839
	(0.002)	(0.379)	(0.340)			
CEI + MTail	-0.001	0.953***	-1.000***	-0.319**	428	-845
	(0.001)	(0.024)	(0.000)	(0.138)		

Table 12: **Robustness: Portfolio analysis based on volume-weighted β_{VW}^{MTail}**

This table reports monthly excess returns and risk-adjusted returns for decile portfolios formed based on volume-weighted commodity tail risk beta β_{VW}^{MTail}, where Low (High) includes stocks with the lowest (highest) β_{VW}^{MTail} at the end of the previous month. For each decile portfolio, we report the one-month ahead mean excess returns (Ret-Rf), annualized standard deviation (S.D.) and Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt). The last column shows the return spread (H-L) between taking long (short) positions in the highest (lowest) β_{VW}^{MTail} portfolios. Risk-adjusted returns (αs) are based on the CAPM, Fama-French 3-factor (FF3), Carhart 4-factor (Carhart), and Fama-French 5-factor (FF5) models. Panel A (B) summarizes equally- (value-) weighted portfolio results. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Equally-weighted portfolios											
	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Ret-Rf	-0.154	0.305	0.282	0.570	0.688	0.778	0.720	0.715	0.866	0.551	0.705***
	(-0.25)	(0.52)	(0.49)	(0.92)	(1.12)	(1.29)	(1.10)	(1.16)	(1.36)	(0.87)	(2.73)
S.D.	0.27	0.27	0.26	0.26	0.26	0.26	0.26	0.26	0.27	0.27	0.12
SR	-0.07	0.14	0.13	0.26	0.32	0.36	0.33	0.33	0.39	0.25	0.73
Skew	0.00	-0.02	-0.17	-0.06	-0.07	0.05	-0.09	-0.05	0.12	0.18	0.90
Kurt	4.26	4.90	4.84	4.95	4.83	4.72	4.35	4.12	4.12	3.91	5.73
CAPM α	-0.504*	-0.039	-0.061	0.220	0.346	0.437	0.369	0.366	0.514	0.200	0.703***
	(-1.67)	(-0.13)	(-0.24)	(0.73)	(1.10)	(1.40)	(1.21)	(1.25)	(1.53)	(0.64)	(2.71)
FF3 α	-0.914***	-0.508***	-0.540***	-0.269***	-0.145	-0.074	-0.103	-0.090	0.033	-0.206	0.707***
	(-6.21)	(-4.19)	(-4.37)	(-3.06)	(-1.23)	(-0.77)	(-0.90)	(-0.81)	(0.25)	(-1.12)	(2.85)
Carhart α	-0.908***	-0.497***	-0.526***	-0.250***	-0.123	-0.050	-0.081	-0.063	0.065	-0.170	0.738***
	(-5.97)	(-4.02)	(-3.94)	(-3.04)	(-1.07)	(-0.57)	(-0.67)	(-0.53)	(0.51)	(-0.93)	(2.95)
FF5 α	-0.789***	-0.386***	-0.399***	-0.090	0.010	0.070	0.034	0.007	0.114	-0.099	0.690***
	(-6.48)	(-3.54)	(-3.29)	(-1.05)	(0.09)	(0.64)	(0.27)	(0.06)	(0.77)	(-0.49)	(2.74)

Panel B: Value-weighted portfolios											
	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Ret-Rf	-0.772	-0.367	-0.344	0.127	0.038	0.300	0.260	0.570	0.450	0.242	1.014***
	(-1.33)	(-0.69)	(-0.68)	(0.22)	(0.07)	(0.59)	(0.45)	(0.99)	(0.77)	(0.38)	(3.03)
S.D.	0.25	0.23	0.22	0.24	0.22	0.21	0.23	0.23	0.24	0.26	0.15
SR	-0.37	-0.19	-0.19	0.06	0.02	0.17	0.14	0.30	0.23	0.11	0.83
Skew	-0.17	-0.39	-0.62	-0.03	0.07	-0.19	0.53	0.29	0.11	0.32	0.32
Kurt	4.73	5.77	6.06	5.37	5.06	5.26	5.35	4.55	3.85	4.09	3.63
CAPM α	-1.120***	-0.683***	-0.650***	-0.213	-0.282	-0.001	-0.063	0.249	0.122	-0.103	1.017***
	(-5.77)	(-3.74)	(-4.00)	(-1.49)	(-1.37)	(-0.01)	(-0.35)	(1.33)	(0.70)	(-0.40)	(2.96)
FF3 α	-1.200***	-0.831***	-0.722***	-0.250*	-0.322*	-0.017	0.000	0.341*	0.176	-0.085	1.115***
	(-6.94)	(-4.59)	(-4.12)	(-1.83)	(-1.73)	(-0.11)	(0.00)	(1.76)	(0.94)	(-0.33)	(3.08)
Carhart α	-1.212***	-0.831***	-0.730***	-0.245*	-0.301*	-0.014	0.006	0.342*	0.186	-0.072	1.140***
	(-6.77)	(-4.50)	(-4.17)	(-1.78)	(-1.76)	(-0.09)	(0.03)	(1.78)	(0.97)	(-0.27)	(3.00)
FF5 α	-1.113***	-0.624***	-0.615***	-0.180	-0.352**	0.019	-0.019	0.323*	0.164	-0.016	1.098***
	(-7.01)	(-3.69)	(-3.72)	(-1.36)	(-1.96)	(0.11)	(-0.09)	(1.72)	(0.85)	(-0.06)	(2.95)

Table 13: **Robustness: Chinese-specific asset pricing model**

This table reports monthly excess returns and risk-adjusted returns for decile portfolios formed based on the commodity tail risk beta (β^{MTail}) estimated with respect to the China-specific asset pricing model of Liu et al. (2019):

$$\mathbb{E}_t\left[R_{i,t+1}\right] = \alpha_{i,t} + \beta_{i,t}^{MTail} \cdot MTail_t + \boldsymbol{\beta}_{i,t}^{F} \cdot \mathbb{E}_t\left[\mathbf{F}_{t+1}\right],$$

where $\mathbf{F}$ is a vector of four China-specific equity risk factors: the market (MKT^{CH}), size (SMB^{CH}), EP-based value (VMG), and turnover (PMO) factors. We follow Liu et al. (2019) to exclude stocks in the bottom 30% of firm size cross-sectionally. Low (High) includes stocks with the lowest (highest) β^{MTail} at the end of the previous month. For each decile portfolio, we report the one-month ahead mean excess returns (Ret-Rf). The last column shows the return spread (H-L) between taking long (short) positions in the highest (lowest) β^{MTail} portfolios. Risk-adjusted returns (αs) are based on the Fama-French 3-factor (FF3), Carhart 4-factor (Carhart), Chinese 4-factor (CH4), and Fama-French 5-factor (FF5) models. Panel A (B) summarizes equally- (value-) weighted portfolio results. The Newey & West (1986) adjusted t-statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to December 2021.

Panel A: Equal-weighted portfolios

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Ret-Rf	-0.363	-0.039	0.008	0.443	0.496	0.481	0.592	0.430	0.547	0.539	0.902***
	(-0.54)	(-0.06)	(0.01)	(0.65)	(0.78)	(0.75)	(0.91)	(0.66)	(0.81)	(0.82)	(2.69)
FF3 α	-1.215***	-0.939***	-0.889***	-0.455***	-0.398***	-0.419***	-0.310***	-0.468***	-0.366**	-0.231	0.984***
	(-6.70)	(-6.42)	(-7.54)	(-3.15)	(-3.42)	(-4.15)	(-2.62)	(-3.56)	(-2.55)	(-0.94)	(2.88)
Carhart α	-1.204***	-0.926***	-0.874***	-0.419***	-0.348***	-0.387***	-0.267*	-0.430***	-0.335**	-0.218	0.986***
	(-6.38)	(-5.98)	(-6.87)	(-3.08)	(-2.77)	(-3.47)	(-1.85)	(-2.95)	(-2.24)	(-0.89)	(2.89)
CH4 α	-1.091***	-0.792***	-0.725***	-0.321**	-0.310***	-0.268**	-0.162	-0.327**	-0.225	-0.065	1.027***
	(-6.70)	(-5.97)	(-6.33)	(-2.08)	(-2.62)	(-2.48)	(-1.32)	(-2.16)	(-1.17)	(-0.21)	(2.65)
FF5 α	-0.709***	-0.590***	-0.666***	-0.352**	-0.313***	-0.248**	-0.195	-0.310*	-0.182	0.147	0.856**
	(-3.48)	(-3.84)	(-4.47)	(-2.50)	(-2.76)	(-2.12)	(-1.48)	(-1.95)	(-1.11)	(0.50)	(2.01)

Panel B: Value-weighted portfolios

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Ret-Rf	-0.615	-0.212	-0.038	0.108	0.414	0.286	0.993	0.243	0.523	0.270	0.885**
	(-0.92)	(-0.35)	(-0.07)	(0.21)	(0.79)	(0.53)	(1.61)	(0.41)	(0.85)	(0.42)	(2.20)
FF3 α	-1.224***	-0.756***	-0.545***	-0.329*	-0.011	-0.228	0.408**	-0.283*	-0.057	-0.159	1.065**
	(-5.49)	(-5.07)	(-3.56)	(-1.91)	(-0.06)	(-1.31)	(1.96)	(-1.85)	(-0.28)	(-0.55)	(2.57)
Carhart α	-1.255***	-0.740***	-0.525***	-0.303*	0.034	-0.190	0.457**	-0.269*	-0.040	-0.182	1.073***
	(-5.43)	(-4.83)	(-3.47)	(-1.91)	(0.19)	(-1.09)	(2.03)	(-1.70)	(-0.18)	(-0.67)	(2.60)
CH4 α	-0.916***	-0.644***	-0.650***	-0.768***	-0.310*	-0.532***	0.167	-0.357*	-0.013	0.259	1.175**
	(-3.20)	(-3.62)	(-3.31)	(-4.09)	(-1.70)	(-2.75)	(0.81)	(-1.90)	(-0.07)	(0.83)	(2.24)
FF5 α	-1.169***	-0.756***	-0.471***	-0.336*	-0.104	-0.234	0.525**	-0.277*	0.009	-0.046	1.123**
	(-5.44)	(-5.19)	(-3.04)	(-1.92)	(-0.59)	(-1.31)	(2.38)	(-1.71)	(0.04)	(-0.14)	(2.54)

Table 14: **Robustness: Institutional ownership**

This table summarizes results for sequential bivariate portfolio analysis based on a stock's institutional ownership and its commodity tail risk beta (β^{MTail}). We first sort stocks into quintile portfolios based on their institutional ownership (InstOwn). Within each portfolio stocks are further allocated to quintiles based on their β^{MTail}. All portfolios are re-balanced monthly. For each portfolio we obtain one-month ahead excess returns. The last column shows the return differential between long positions in the highest β^{MTail} stocks and short positions in the lowest β^{MTail} stocks. Panel A (B) summarizes results for equally-weighted (value-weighted) portfolios. The Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

Panel A: Equally-weighted portfolios

	Low β^{MTail}	2	3	4	High β^{MTail}	High-Low
Low InstOwn	-0.081	0.597	0.582	0.663	0.747	0.828***
	(-0.13)	(0.99)	(0.88)	(0.99)	(1.03)	(2.61)
2	-0.091	0.336	0.681	0.720	0.758	0.849***
	(-0.14)	(0.52)	(1.06)	(1.10)	(1.11)	(2.98)
3	-0.213	0.668	0.646	0.537	0.560	0.773**
	(-0.36)	(1.03)	(1.01)	(0.85)	(0.84)	(2.50)
4	0.049	0.631	0.658	0.724	0.661	0.611**
	(0.08)	(1.05)	(1.04)	(1.19)	(1.00)	(2.27)
High InstOwn	0.126	0.606	1.011*	0.850	0.624	0.498*
	(0.22)	(0.97)	(1.78)	(1.47)	(1.09)	(1.77)

Panel B: Value-weighted portfolios

	Low β^{MTail}	2	3	4	High β^{MTail}	High-Low
Low InstOwn	-0.260	0.344	0.399	0.539	0.545	0.805***
	(-0.41)	(0.57)	(0.60)	(0.80)	(0.77)	(2.59)
2	-0.233	0.200	0.606	0.594	0.652	0.885***
	(-0.37)	(0.32)	(0.95)	(0.92)	(0.97)	(3.06)
3	-0.339	0.524	0.516	0.434	0.455	0.793**
	(-0.57)	(0.81)	(0.82)	(0.69)	(0.68)	(2.47)
4	-0.085	0.500	0.540	0.595	0.512	0.596**
	(-0.14)	(0.86)	(0.87)	(0.99)	(0.78)	(2.21)
High InstOwn	0.009	0.466	0.891	0.811	0.584	0.575**
	(0.02)	(0.75)	(1.61)	(1.43)	(1.02)	(2.00)

Table 15: **Robustness: Additional tests**

This table summarizes results from a battery of additional robustness tests. In Panels A and B, we consider two alternative models to estimate the monthly commodity tail risk beta (β^{MTail}): $\mathbb{E}_t\left[R_{i,t+1}\right] = \alpha_{i,t} + \beta^{MTail}_{i,t} \cdot MTail_t + \boldsymbol{\beta}^F_{i,t} \cdot \mathbb{E}_t\left[\mathbf{F}_{t+1}\right]$, where $\mathbf{F}$ is a set of equity risk factors. In specification (1), we set $\mathbf{F} = [\text{MKT}, \text{SMB}, \text{HML}, \text{RMW}, \text{CMA}]$. In specification (2), we set $\mathbf{F} = [\text{MKT}, \text{SMB}, \text{HML}, \text{UMD}, \text{IML}]$. Panel C reports univariate portfolio analysis by excluding stocks in the bottom 30% of firm size cross-sectionally, or in the ST/PT states, or in the finance industry. Panels D and E tabulate results when a rolling window of 96 months and 120 months, respectively, are used to estimate β^{MTail}. In terms of the estimation methodology for MTail, Panels F and G report results when we consider alternative thresholds $p = 2.5\%$ and $p = 10\%$ for left-tail events, respectively. High (low) includes stocks with the highest (lowest) β^{MTail} at the end of a month. For each decile portfolio, we report the one-month ahead mean excess returns (Ret-Rf). The last column shows the high-minus-low (H-L) spread for portfolios with long positions in the highest β^{MTail} stocks and short positions in the lowest β^{MTail} stocks. The risk-adjusted returns based on the Carhart 4-factor and Fama-French 5-factor models are also reported. All portfolios are value-weighted. The Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	H-L
Panel A: Alternative model specification (1)											
Ret-Rf	-0.212	0.174	0.367	0.415	0.614	0.450	0.529	0.518	0.555	0.604	0.816***
	(-0.35)	(0.30)	(0.62)	(0.70)	(1.02)	(0.73)	(0.88)	(0.83)	(0.90)	(0.94)	(2.78)
Carhart α	-0.881***	-0.541***	-0.388***	-0.358***	-0.146	-0.302***	-0.226*	-0.241**	-0.199	-0.003	0.878***
	(-5.35)	(-4.38)	(-3.72)	(-3.55)	(-1.45)	(-3.67)	(-1.83)	(-2.30)	(-1.62)	(-0.01)	(2.96)
FF5 α	-0.799***	-0.407***	-0.314**	-0.223**	-0.046	-0.217**	-0.095	-0.146	-0.126	0.084	0.884***
	(-5.59)	(-4.10)	(-2.46)	(-2.32)	(-0.42)	(-2.09)	(-0.84)	(-1.26)	(-0.92)	(0.33)	(2.70)
Panel B: Alternative model specification (2)											
Ret-Rf	-0.568	-0.042	0.039	0.169	-0.010	0.280	0.182	0.123	0.293	0.259	0.827**
	(-0.91)	(-0.07)	(0.07)	(0.29)	(-0.02)	(0.51)	(0.35)	(0.24)	(0.51)	(0.41)	(2.24)
Carhart α	-0.932***	-0.457**	-0.327**	-0.217	-0.334**	-0.026	-0.140	-0.209	-0.050	0.018	0.949**
	(-4.79)	(-2.52)	(-2.13)	(-1.33)	(-2.05)	(-0.17)	(-0.66)	(-0.95)	(-0.25)	(0.07)	(2.57)
FF5 α	-0.933***	-0.424**	-0.311**	-0.198	-0.317*	-0.105	-0.089	-0.170	0.011	0.110	1.043***
	(-5.40)	(-2.16)	(-1.98)	(-1.10)	(-1.94)	(-0.61)	(-0.43)	(-0.84)	(0.05)	(0.39)	(2.78)
Panel C: Stocks in bottom 30%, ST/PT status, or finance industry excluded											
Ret-Rf	-0.698	-0.320	-0.135	-0.151	0.009	0.600	0.232	0.339	0.075	0.307	1.004**
	(-1.09)	(-0.56)	(-0.24)	(-0.29)	(0.02)	(1.10)	(0.41)	(0.60)	(0.12)	(0.48)	(2.11)
Carhart α	-1.053***	-0.809***	-0.574***	-0.530***	-0.353*	0.261	-0.051	0.089	-0.139	0.198	1.252**
	(-4.11)	(-4.24)	(-3.54)	(-3.39)	(-1.85)	(1.08)	(-0.25)	(0.47)	(-0.51)	(0.61)	(2.41)
FF5 α	-1.037***	-0.627***	-0.567***	-0.474***	-0.321	0.332	-0.116	0.104	-0.099	0.230	1.267**
	(-4.68)	(-3.35)	(-3.39)	(-2.88)	(-1.61)	(1.26)	(-0.62)	(0.62)	(-0.37)	(0.68)	(2.54)
Panel D: Estimation window length = 96 months											
Ret-Rf	-0.354	-0.183	-0.216	0.183	0.414	0.464	0.926	0.946	0.741	0.591	0.945***
	(-0.54)	(-0.31)	(-0.35)	(0.30)	(0.66)	(0.81)	(1.52)	(1.63)	(1.32)	(0.98)	(2.74)
Carhart α	-0.783***	-0.621**	-0.649**	-0.363*	-0.041	-0.054	0.356*	0.488***	0.274	0.260	1.043***
	(-2.89)	(-2.44)	(-2.56)	(-1.71)	(-0.18)	(-0.25)	(1.74)	(2.91)	(1.47)	(1.29)	(3.33)
FF5 α	-0.757***	-0.600**	-0.554**	-0.262	0.013	0.103	0.384*	0.521***	0.311*	0.280	1.037***
	(-3.03)	(-2.50)	(-2.46)	(-1.24)	(0.06)	(0.51)	(1.86)	(3.08)	(1.75)	(1.35)	(3.53)
Panel E: Estimation window length = 120 months											
Ret-Rf	-0.598	-0.174	0.263	0.289	0.526	0.222	0.744	0.043	0.366	0.205	0.803**
	(-0.82)	(-0.26)	(0.38)	(0.42)	(0.80)	(0.33)	(1.12)	(0.06)	(0.56)	(0.28)	(2.20)
Carhart α	-0.739***	-0.475*	-0.223	-0.134	-0.062	-0.195	0.133	-0.290	-0.043	-0.105	0.635***
	(-2.67)	(-1.72)	(-0.96)	(-0.61)	(-0.25)	(-0.84)	(0.57)	(-1.13)	(-0.20)	(-0.41)	(2.81)
FF5 α	-0.692**	-0.372	-0.161	-0.082	0.018	-0.103	0.218	-0.173	-0.062	-0.023	0.668***
	(-2.48)	(-1.29)	(-0.68)	(-0.32)	(0.07)	(-0.45)	(0.82)	(-0.69)	(-0.26)	(-0.09)	(2.76)
Panel F: The threshold for left-tail events = 2.5%											
Ret-Rf	-0.704	-0.524	-0.117	-0.092	0.323	0.363	-0.058	0.344	0.407	0.089	0.793**
	(-1.16)	(-0.93)	(-0.22)	(-0.17)	(0.62)	(0.73)	(-0.10)	(0.61)	(0.69)	(0.14)	(1.96)
Carhart α	-1.153***	-1.006***	-0.613***	-0.525***	-0.072	-0.030	-0.419**	0.067	0.184	-0.093	1.060**
	(-4.49)	(-5.37)	(-3.77)	(-3.21)	(-0.51)	(-0.21)	(-2.41)	(0.34)	(0.99)	(-0.33)	(2.20)
FF5 α	-1.111***	-1.008***	-0.502***	-0.504***	-0.023	-0.016	-0.405**	0.068	0.196	-0.061	1.050**
	(-4.78)	(-6.61)	(-2.83)	(-3.14)	(-0.15)	(-0.11)	(-2.23)	(0.37)	(1.00)	(-0.22)	(2.28)
Panel G: The threshold for left-tail events = 10%											
Ret-Rf	-0.802	-0.315	-0.111	-0.011	0.050	0.251	0.262	0.278	0.328	0.124	0.926**
	(-1.32)	(-0.53)	(-0.20)	(-0.02)	(0.09)	(0.44)	(0.46)	(0.52)	(0.57)	(0.21)	(2.40)
Carhart α	-1.198***	-0.716***	-0.527***	-0.452***	-0.330**	-0.175	-0.118	0.018	0.056	-0.200	0.997**
	(-4.95)	(-3.50)	(-3.24)	(-2.60)	(-2.15)	(-0.94)	(-0.89)	(0.10)	(0.28)	(-0.82)	(2.28)
FF5 α	-1.155***	-0.599***	-0.434***	-0.398**	-0.334**	-0.188	-0.118	-0.026	0.042	-0.143	1.012***
	(-5.40)	(-3.10)	(-2.67)	(-2.36)	(-1.99)	(-0.89)	(-0.78)	(-0.15)	(0.23)	(-0.62)	(2.61)

Table 16: **Robustness: Industry-level evidence**

In this table, we divide stocks into nine industries based on the CSRC industry code, including Mining, Manufacturing, Retail & Wholesale, Transportation, IT, Finance, Real estate, Utilities, and Other. Stocks in each industry are sorted into quartile portfolios based on the monthly commodity tail risk beta (β^{MTail}) and Low (High) portfolios include those with the lowest (highest) β^{MTail} at the end of a month. We report the one-month ahead mean excess returns, and H-L is the high-minus-low spread for portfolios that take long positions in the highest β^{MTail} stocks and short positions in the lowest β^{MTail} stocks. Risk-adjusted returns are computed for based on the Carhart 4-factor and Fama-French 5-factor model (FF5) models. The Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to October 2022.

	Low	P2	P3	High	H-L	Carhart α	FF5 α
Mining	-0.737	0.452	-0.109	0.152	0.889**	0.896**	1.095**
	(-1.07)	(0.65)	(-0.17)	(0.21)	(2.17)	(2.29)	(2.43)
Manufacturing	0.021	0.612	0.738	0.642	0.621**	0.613**	0.735***
	(0.04)	(0.99)	(1.19)	(1.00)	(2.52)	(2.57)	(2.85)
Retail & Wholesale	-0.570	0.275	0.736	0.303	0.873**	0.868**	0.828**
	(-0.93)	(0.45)	(1.12)	(0.44)	(2.38)	(2.29)	(2.22)
Transportation	-0.435	0.339	0.352	0.740	1.176**	1.113**	0.961***
	(-0.75)	(0.48)	(0.50)	(1.06)	(2.45)	(2.29)	(2.76)
IT	0.455	0.893	1.211	1.411	0.956**	0.963**	0.940**
	(0.47)	(1.13)	(1.52)	(1.63)	(2.14)	(2.24)	(1.99)
Finance	-0.026	0.058	0.742	0.528	0.554**	0.590**	0.711***
	(-0.03)	(0.10)	(1.10)	(0.72)	(1.98)	(2.20)	(2.84)
Real estate	-0.163	0.471	0.317	0.348	0.511	0.438	0.383
	(-0.26)	(0.69)	(0.49)	(0.49)	(1.46)	(1.24)	(1.12)
Utilities	-0.122	0.550	0.344	0.208	0.330	0.434	0.211
	(-0.19)	(0.87)	(0.61)	(0.35)	(0.93)	(1.29)	(0.74)
Other	-0.001	0.066	0.375	0.586	0.587**	0.685**	0.710**
	(0.00)	(0.11)	(0.60)	(0.86)	(2.06)	(2.15)	(2.14)

Appendix A The multivariate tail risk estimation

Let $r_{i,s}^d$ and $x_{1,s}^d, \ldots, x_{N,s}^d$ denote, respectively, the daily returns of asset i and N systematic risk factors over the estimation period, containing the recent 250 trading days ($s = 1, \ldots, 250$). We collect these two groups of return series into a $(N+1) \times 1$ vector $(\boldsymbol{Y}_s)_{s=1,\ldots,250}$ and assume that these $N+1$ marginal distributions follow the GARCH(1,1) model of the form:

$$Y_{f,s} = \mu_f + \sigma_{f,s} U_{f,s}, \tag{A.1}$$

$$\sigma_{f,s}^2 = \omega_{f,0} + \omega_{f,1} \left(\sigma_{f,s-1} U_{f,s-1}\right)^2 + \omega_{f,2} \sigma_{f,s-1}^2, \tag{A.2}$$

where $f = 1, \ldots, N+1$, $U_{f,s}$ is the independent and identically distributed residuals, and μ_f, $\omega_{f,0}$, $\omega_{f,1}$, $\omega_{f,2} \in \mathbb{R}$. To apply the maximum likelihood estimation method for this model, we further restrict that $\omega_{f,0}, \omega_{f,1}, \omega_{f,2} > 0$ and $\omega_{f,1} + \omega_{f,2} < 1$. Following Christoffersen et al. (2012), we assume that the distribution of innovations follows the skewed$-t$ distribution of Hansen (1994). Hence, the conditional distribution of $U_{f,s}$ can be represented by parametric functions of $\mathcal{F}_{s-1}$-measurable parameters, where $\mathcal{F}_{s-1}$ represents the information set available at time $s-1$ (Fan & Patton, 2014). Based on this distributional assumption, the transformation of $U_{f,s}$ is completed by the probability integral transforms:

$$\hat{u}_{f,s} = F_{f,s}\left(U_{f,s}\right), \qquad \hat{u}_{f,s} \sim \text{Uniform}[0,1], \tag{A.3}$$

where $\hat{u}_{f,s}$ is the white-noise series and $F_{f,s}$ denotes the conditional cumulative distribution functions (CDFs) of $U_{f,s}$.

With transformed marginal return series $\hat{u}_{f,s}$ and the copula approach, we non-parametrically estimate the left-tail dependence structure between asset i and factor returns, MTail, and rewrite Equation (1) as follows:

$$\text{MTail}_{i,t}^{\boldsymbol{X}} = \frac{\sum_{s \in \mathcal{D}} \mathbb{1}\left(\{\hat{u}_{1,s} \leq q_1\}\right) \cdot \mathbb{1}\left(\bigcup_{j=2}^{N+1} \{\hat{u}_{j,s} \leq q_j\}\right)}{\sum_{s \in \mathcal{D}} \mathbb{1}\left(\bigcup_{j=2}^{N+1} \{\hat{u}_{j,s} \leq q_j\}\right)}, \tag{A.4}$$

where q_f denotes the upper p-quantile of $(\hat{u}_{f,s})_{s \in \mathcal{D}}$, $f = 1, \ldots, N+1$, and $\mathcal{D}$ is the number of returns in valid trading days for all marginal series. In particular, the denominator of Equation (A.4) measures the sum of days in which a lower-tail event occurs for at least one of these systematic risk factors over the rolling window estimation period. The numerator indicates the total number of days on which asset i and one (or more) of risk factors realize a left-tail event simultaneously over the rolling window estimation period. Hence, a higher value of MTail indicates that the asset i has a higher crash sensitivity under a multi-factor setting, and vice versa. We set $p = 5\%$ for calculating the q_f in Equation (A.4). Thus MTail captures the conditional probability of an extreme return realization which is below or at the corresponding 5%-quantile of commodity i's return distribution given that at least one commodity factor realizes a return observation below or at the 5%-quantile.

Appendix B Commodity risk factors

To construct the multivariate commodity tail risk measure, we adopt the three-factor pricing model featuring the commodity market, basis, and momentum factor of Bakshi et al. (2019), which nests the two-factor model of Yang (2013). We also include the basis-momentum factor proposed by Boons & Prado (2019) to complete the factor space. We use portfolio sorting and systematic long-short strategies to construct these factors in Chinese futures markets. In particular, at the month end, we sort all commodities into five quintile portfolios based on different pricing characteristics, and take long (short) positions in commodities quintile portfolios predicted to appreciate (depreciate) in the following month. All portfolios are equally-weighted and re-balanced monthly with updated pricing signals.

Commodity market (CMKT): Bakshi et al. (2019) find that a model without featuring an average factor fails to explain the time-series variation in commodity futures returns. The commodity market factor (CMKT) is obtained as the long-only equally-weighted cross-sectional average of all available commodity contracts at time t.

Term structure (Basis): The basis in commodity markets is defined as the price difference between spot and different-maturity contracts. Following Fuertes et al. (2010), Xu & Wang (2021), and Yang (2013), we apply the roll-yield to measure the slope of the futures curve of commodity k at time t as follows:

$$Basis_{k,t} = \log\left(P_{k,t}^{(3)}\right) - \log\left(P_{k,t}^{(4)}\right), \tag{A.5}$$

where $P_{k,t}^{(3)}$ and $P_{k,t}^{(4)}$ are prices for the third-nearest and fourth-nearest contracts for commodity k at time t, respectively. The term structure (basis) strategy buys (sells) contracts with the highest (lowest) roll-yield sorted quintile portfolios.

Commodity momentum (CMOM): The momentum effect emerges from the relation between an asset's current returns and its recent performance history (Asness et al., 2013). Specifically, we use the prior twelve months as the formation period for each commodity futures to construct the commodity momentum factor as follows:

$$CMOM_{k,t} = \left(\frac{1}{12}\right)\sum_{j=0}^{11} r_{k,t-j}, \tag{A.6}$$

where $r_{k,t-j}$ represents returns to the third-nearest contracts of commodity k in month $t-j$. Based on this $CMOM_{k,t}$ signal, we first sort commodities into quintile portfolios at the end of month t. We buy (sell) portfolios containing past winners (losers) and hold this long-short portfolio for one month. We also follow Bakshi et al. (2019) to use cumulative futures returns in past twelve months and construct the characteristic as follows:

$$CMOM_{k,t}^{Cum} = \prod_{j=0}^{11}(1 + r_{k,t-j}) - 1. \tag{A.7}$$

Empirical results from using alternative momentum formation procedures are qualitatively the same.

Basis-Momentum (Basis-Mom): To capture the slope and curvature of the futures term structure, Boons & Prado (2019) find that the basis-momentum as a new return predictor outperforms other characteristics in predicting commodity futures returns. The economic rationale of basis-momentum is based on the impaired market-clearing ability of speculators and financial intermediaries. Combining the basis and momentum factors, the basis-momentum (Basis-Mom) is defined as the difference between momentum in third- and fourth-nearby futures contracts:

$$Basis\text{-}Mom_{k,t} = \prod_{j=0}^{11}\left(1 + r_{k,t-j}^{(3)}\right) - \prod_{j=0}^{11}\left(1 + r_{k,t-j}^{(4)}\right), \tag{A.8}$$

where $r^{(3)}_{k,t-j}$ and $r^{(4)}_{k,t-j}$ represent the third- and fourth-nearest contract returns of commodity k in month $t-j$. The Basis-Mom factor is constructed by taking a long (short) position in commodities with high (low) basis-momentum characteristics.

Appendix C Firm-level variables

In this appendix, we define the firm-level variables used in the empirical analysis.

Firm size (Size): Fama & French (1992) find that the firm size significantly impacts the stock's expected returns. We compute the firm size as the natural logarithm of the market value of equity (in 100 million of RMB) at the end of each month.

Book-to-market ratio (BM): Following Liu et al. (2019), we calculate the book-to-market ratio as the book value of common equity (total shareholders' equity excluding minority interests) divided by the market value of equity (daily close price multiplied by the total shares outstanding). In particular, at the end of June in each calendar year, we estimate the BM ratio as total shareholders' equity for the fiscal year ending in last calendar year divided by the market equity at the end of December in the previous year. We assume that the book value of shareholder equity is available six-month later for each fiscal year.

Momentum (MOM): We follow Jegadeesh & Titman (1993) to construct the momentum factor as a stock's cumulative returns during the past 11-month period after skipping one month, controlling for the medium-term momentum effect. We calculate the momentum in month t as the cumulative returns of a stock over the 11-month period ending one month before the portfolio formation month, i.e., from month $t-12$ to $t-1$.

Market beta (Beta): Following Fama & French (1992), we estimate the market beta for each individual stock via the following regression:

$$R_{i,d} = \alpha_i + \beta_{1,i} MKT_d + \varepsilon_{i,d}, \tag{A.9}$$

where $R_{i,d}$ is the excess daily returns of stock i on day d, and MKT_d is the daily market factor. In particular, at the end of each month, we estimate the market beta with daily returns over the prior twelve months from month $t-11$ to month t.

Reversal (REV): We follow Jegadeesh (1990) to define the reversal for each stock as the excess stock returns over the previous month.

Growth of assets (IA): Cooper et al. (2008) find that firms with a higher growth rate of total assets earn lower future returns. We define the investment-to-asset ratio as the annual growth rate of total assets. In particular, at the end of June in year t, we calculate the change in total book asset from the fiscal year ending in two years before (year $t-2$) to the prior fiscal year (year $t-1$) divided by the lagged total book assets.

Return-on-equity (ROE): Following Liu et al. (2019), we define the return-on-equity ratio as the net profit excluding non-recurring gains and losses divided by the total shareholders' equity excluding minority interests. In particular, at the end of each month, we compute the ROE ratio as the quarterly net profit excluding non-recurring gains and losses divided by the one-quarter-lagged book value of equity.

Co-skewness (Coskew): Harvey & Siddique (2000) find that systematic (conditional) skewness explains the cross-section of expected stock returns and commands a risk premium. We define the Coskew as the monthly co-skewness of monthly excess returns of each stock i with monthly excess market returns in month t as follows:

$$\text{Coskew}_{i,t} = \frac{\mathbb{E}\left[\epsilon_{i,t} R_{m,t}^2\right]}{\sqrt{\mathbb{E}\left[\epsilon_{i,t}^2\right] \mathbb{E}\left[R_{m,t}^2\right]}}, \tag{A.10}$$

where $\epsilon_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t})$ is the residual term from regressing the stock's monthly excess returns ($R_{i,t}$) on the monthly contemporaneous excess market returns ($R_{m,t}$) over the prior five years.

Illiquidity (ILLIQ): Amihud (2002) finds that illiquid stocks command an expected return premium. We calculate a stock's illiquidity in month t as follows:

$$\text{ILLIQ}_{i,t} = \text{Mean}\left[\frac{|R_{i,d}|}{\text{Volume}_{i,d}}\right], \tag{A.11}$$

where $|R_{i,d}|$ is stock i's absolute return on day d and $Volume_{i,d}$ is the stock's dollar trading volume on the same day. To calculate the monthly $ILLIQ_{i,t}$, we take the average of the daily illiquidity ratio within the month t. The Amihud (2002)'s ILLIQ measure is scaled by 10^6.

Turnover (TURN): Following Liu et al. (2019), we measure the turnover as the average daily share turnover over the past twelve months for each month. A stock's daily turnover is computed as the daily trading volume divided by the total shares outstanding.

Lottery demand (MAX): Following Bali et al. (2011), we measure the demands for lottery stocks using the maximum daily returns (MAX) in a given month. Because of the price limit rule in Chinese stock markets, the prices of each stock can only change by a maximum of 10% from the last closing price in a single trading day. Hence, we follow Bali et al. (2017) and Hou et al. (2023) to compute the maximum daily returns as the average of the five highest daily returns of stock i in the given month t.

Idiosyncratic volatility (IVOL): Ang, Hodrick, et al. (2006) document a negative relationship between stock's expected returns and the idiosyncratic volatility. We define the idiosyncratic volatility of stock i on day d in month t as the standard deviation of daily residual returns in one month from the following regression:

$$R_{i,d} = \alpha_i + \beta_{1,i} MKT_d + \beta_{2,i} SMB_d + \beta_{3,i} HML_d + \varepsilon_{i,d}, \tag{A.12}$$

where $R_{i,d}$ is the excess daily returns of stock i on day d, $\varepsilon_{i,d}$ is the daily residuals, MKT_d, SMB_d, and HML_d are the daily market, size, and value factors. The IVOL of stock i in month t is computed as follows:

$$\text{IVOL}_{i,t} = \sqrt{\text{Var}\left(\varepsilon_{i,d}\right)}. \tag{A.13}$$

Value-at-Risk (VaR): Following Atilgan et al. (2020), we use the Value-at-Risk (VaR) to measure the equity left-tail risk. In particular, as the end of month t, the VaR is estimated as the 5th percentile of the daily stock returns over the past one year. We multiply this measure by -1 for the ease of interpretation. Thereby, higher values of VaR indicate greater levels of equity left-tail risk. Moreover, we also consider the Expected Shortfall (ES) as an alternative proxy for the equity tail risk. We calculate the ES as the average of daily observations that are smaller than or equal to the 5th percentile of the daily returns for each stock during the past year. We find that the empirical results from using this alternative measure of the equity tail risk are qualitatively the same.

Table A.1: **Summary statistics for commodity futures**

This table summarizes descriptive statistics of third-nearest contracts across 65 commodities traded in the Chinese futures markets. We categorize all commodities into three sectors: grains, agriculture, & oilseeds, metals, and energies & industrial materials. Annualized average returns, standard deviation, skewness (Skew), kurtosis (Kurt), maximum (Max), minimum (Min), first-order autocorrelation ($\rho(1)$), volume, i.e., the average number of contracts (lots) traded per month, open interest (OI), i.e., the average number of daily open interest (lots) per month, the start month (Start), and the number of valid trading months (Obs) of each commodity futures contract are reported. The sample period is from January 2003 to October 2022.

Sectors	**Contracts**	**Code**	**Mean**	**SD**	**Skew**	**Kurt**	**Max**	**Min**	$\rho(1)$	**Volume**	**OI**	**Start**	**Obs**
	No.1 Soybean	A	0.06	0.16	0.13	4.62	0.16	-0.18	0.08	83692	94836	200301	238
	Apple	AP	0.03	0.28	0.17	3.61	0.19	-0.24	0.10	68808	46402	201712	59
	No.2 Soybean	B	0.06	0.16	-0.42	4.19	0.12	-0.19	0.01	4158	3997	200412	215
	Corn	C	0.01	0.10	-0.15	3.14	0.08	-0.08	0.13	141084	302845	200409	218
	Cornstarch	CS	0.02	0.15	-0.09	3.24	0.11	-0.12	0.06	64628	89750	201412	95
	Egg	JD	-0.11	0.21	-0.65	4.63	0.15	-0.21	0.07	54451	52967	201311	108
	Japonica Rice	JR	-0.04	0.15	0.92	6.34	0.19	-0.11	-0.21	3	21	201311	108
	Late Rice	LR	-0.04	0.15	-3.08	21.39	0.07	-0.29	0.06	129	218	201407	100
	Common Wheat	PM	-0.01	0.11	0.84	5.08	0.11	-0.07	-0.15	2	11	201201	130
	Early Rice	RI	-0.03	0.11	0.58	5.28	0.13	-0.10	-0.09	11929	11082	200904	163
Grains, Agriculture, & Oilseeds	Sugar	SR	-0.02	0.19	0.55	6.88	0.27	-0.18	-0.01	271596	219919	200601	202
	Strong Wheat	WH	-0.06	0.11	-0.64	6.18	0.11	-0.17	-0.05	25996	37764	200303	236
	Hard Wheat	WT	-0.05	0.11	0.61	10.91	0.16	-0.12	0.08	8594	14233	200301	118
	Jujube	CJ	-0.01	0.26	0.98	5.90	0.25	-0.19	0.02	11701	11540	201904	43
	Peanut Kernel	PK	-0.03	0.18	0.05	2.39	0.10	-0.10	-0.23	21448	20794	202102	21
	Polished Rice	RR	-0.08	0.08	-1.68	9.86	0.04	-0.11	-0.16	4462	7002	201908	39
	Live Hog	LH	-0.14	0.30	-0.77	3.64	0.14	-0.25	-0.04	4721	16907	202101	22
	Soybean Meal	M	0.11	0.20	0.19	3.78	0.19	-0.21	0.10	370395	457049	200301	238
	Rapeseed Oil	OI	0.02	0.21	-0.53	9.50	0.29	-0.30	0.13	49824	69742	200706	185
	Palm Olein	P	0.03	0.27	-0.68	6.07	0.22	-0.38	0.26	109546	84955	200710	181
	Rapeseed Meal	RM	0.11	0.20	0.20	2.88	0.16	-0.12	0.06	405228	236322	201212	119
	Rapeseed	RS	0.01	0.14	-1.45	11.44	0.11	-0.23	0.29	2198	1092	201212	119
	Soybean Oil	Y	0.03	0.21	-0.53	6.80	0.25	-0.27	0.08	165414	184756	200601	202
	Silver	AG	-0.06	0.24	0.12	5.23	0.25	-0.23	-0.05	188691	109142	201205	126
	Aluminum	AL	0.00	0.16	-0.13	4.32	0.15	-0.14	0.15	45161	80749	200301	238
	Gold	AU	0.03	0.17	-0.50	5.03	0.12	-0.21	-0.14	38278	48410	200801	178
	Copper	CU	0.11	0.26	-1.40	13.41	0.29	-0.53	0.14	115902	109583	200301	238
	Iron Ore	I	0.21	0.36	-0.23	2.97	0.27	-0.28	0.01	342179	280448	201310	109
	Nickel	NI	0.08	0.25	-0.31	2.72	0.18	-0.19	0.10	188442	99090	201503	92
	Lead	PB	-0.01	0.17	0.44	7.92	0.25	-0.19	-0.09	3261	6878	201103	140
Metals	Steel Rebar	RB	0.04	0.23	-0.14	3.69	0.19	-0.24	0.02	567205	419114	200903	164
	Ferrosilicon	SF	0.02	0.36	-0.56	10.33	0.43	-0.43	-0.15	33170	28507	201408	99
	Silicon Manganese	SM	0.11	0.31	0.28	5.85	0.34	-0.29	0.07	31799	30328	201408	99
	Tin	SN	0.05	0.22	-1.04	6.33	0.13	-0.27	0.36	7264	7514	201503	92
	Wire Rod	WR	0.04	0.20	0.55	5.82	0.25	-0.17	-0.04	332	515	200903	163
	Zinc	ZN	-0.01	0.25	-1.84	12.74	0.18	-0.47	0.00	128257	93259	200703	188
	Copper Cathode	CU	0.09	0.22	0.44	4.14	0.18	-0.13	-0.17	5412	4753	202011	24
	Stainless Steel	SS	0.12	0.24	0.42	2.62	0.18	-0.10	0.07	12914	19639	201909	38

(Continued next page.)

Sectors	Contracts	Code	Mean	SD	Skew	Kurt	Max	Min	$\rho(1)$	Volume	OI	Start	Obs
	Fuel Oil	FU	-0.01	0.30	-1.14	9.00	0.31	-0.51	0.21	100626	43764	200408	219
	Methanol	MA	-0.06	0.27	-0.66	5.49	0.23	-0.32	0.01	294500	187156	201110	133
	Crude Oil	SC	0.09	0.35	-1.14	4.84	0.18	-0.35	0.28	19678	13734	201803	56
	Plywood	BB	-0.04	0.32	-1.75	10.51	0.20	-0.49	0.03	1841	1218	201312	107
	Bitumen	BU	-0.08	0.31	-0.74	6.22	0.21	-0.42	0.07	149114	108889	201310	109
	Cotton	CF	-0.05	0.20	0.22	6.71	0.26	-0.26	0.10	103438	108522	200406	221
	Cotton Yarn	CY	-0.06	0.20	0.21	2.99	0.15	-0.13	-0.12	1850	1536	201708	63
	Fiberboard	FB	0.01	0.31	0.51	6.96	0.33	-0.36	0.00	1657	1843	201312	106
	Flat Glass	FG	0.06	0.24	0.14	5.04	0.28	-0.21	0.06	150575	97709	201212	119
	Hot-Rolled Coil	HC	0.10	0.25	-0.07	2.88	0.19	-0.21	0.11	102061	116781	201403	104
	Coke	J	0.05	0.33	0.38	3.90	0.31	-0.25	0.09	66972	43885	201104	139
	Coking Coal	JM	0.13	0.33	0.06	3.94	0.25	-0.30	0.15	66143	51783	201303	116
Energies & Industrial materials	LLDPE	L	0.00	0.26	-2.90	24.70	0.18	-0.60	-0.02	118981	87515	200707	184
	Polypropylene	PP	0.05	0.22	0.47	4.01	0.19	-0.17	-0.09	144476	122193	201402	105
	Natural Rubber	RU	-0.06	0.31	-0.23	4.22	0.27	-0.40	0.13	151138	68383	200301	238
	PTA	TA	-0.03	0.27	-0.89	9.54	0.30	-0.45	0.14	248115	236976	200612	191
	PVC	V	0.01	0.21	-0.01	6.53	0.26	-0.26	0.03	61461	54009	200905	162
	Thermal Coal	ZC	0.12	0.27	0.72	10.74	0.42	-0.31	0.00	52925	51593	201309	110
	Liquefied Petroleum Gas	PG	0.37	0.34	-0.14	3.38	0.26	-0.22	-0.06	9098	13301	202003	32
	Low Sulfur Fuel Oil	LU	0.35	0.31	-0.40	2.55	0.17	-0.17	0.01	45352	48985	202006	29
	Polyester Staple Fiber	PF	0.07	0.26	0.42	4.70	0.23	-0.17	-0.28	56068	68712	202010	25
	Urea	UR	0.17	0.28	-0.19	3.13	0.20	-0.17	-0.13	28666	22658	201908	39
	TSR 20	NR	-0.10	0.24	-0.11	3.26	0.16	-0.17	-0.08	10048	18554	201908	39
	Ethenylbenzene	EB	0.09	0.40	-0.92	7.38	0.30	-0.43	-0.12	25409	24245	201909	38
	Ethylene Glycol	EG	-0.11	0.33	-0.30	5.08	0.24	-0.34	-0.17	104916	81921	201812	47
	Softwood Kraft Pulp	SP	0.04	0.22	0.09	3.19	0.15	-0.15	0.18	63756	59454	201811	48
	Soda Ash	SA	0.07	0.35	0.53	3.24	0.24	-0.19	-0.10	167383	92395	201912	35