Cross-sectoral crash risk and expected commodity futures returns

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Abstract

This study examines the pricing of equity cross-sectoral crash (CSC) risk in the cross section of commodity futures returns. Theoretically, commodity futures with higher exposure to the CSC risk are expected to offer lower subsequent returns as they hedge against the CSC risk. We first construct a CSC risk measure by averaging the pairwise left-tail dependence across 17 sectors in the US market, which allows us to better capture granular sector-level shocks often washed out at the aggregate level. We find that the return spread between commodity futures with the lowest and highest loading of the CSC risk is 1.04% per month and significant at the 1% level. This result can be rationalized as shocks to the CSC risk precede impaired economic activities in the future. Overall, our paper sheds light on the pricing of commodity futures with a novel stock market crash risk factor.

JEL classification: G12; G13; C58.

Keywords: Sectoral crash risk; Nonlinear left-tail dependence; Commodity futures; Cross-sectional return predictability.

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1 Introduction

We examine the impact of equity cross-sectoral crash risk on the cross section of US commodity futures returns under the rare disaster framework. Rare disaster events, such as equity market crashes, are crucial for understanding asset returns and shown to account for a number of financial market puzzles, including the equity premium puzzle and volatility puzzle (Barro, 2006; Farhi & Gabaix, 2016; Gabaix, 2012; Wachter, 2013). In the seminal work of Rietz (1988), the author argues that high equity premiums are compensations to investors for bearing the risk of rare disaster events as market crashes result in severe wealth destruction and unfavourable shifts in consumption opportunities.[1] Existing studies have documented a substantial implication of rare disaster events in determining asset prices (see, for example, Bollerslev & Todorov, 2011; Fan et al., 2022; Gabaix, 2012; Gao et al., 2019). However, the relationship between extreme equity market downturns and commodity futures markets has received little attention.

When faced with the prospect of disaster events, investors naturally reallocate their investment from equity to alternative asset classes (Faias & Zambrano, 2022) and are willing to hold assets with higher resilience (Gabaix, 2012). Given the inflation hedging role of commodities, commodity returns are expected to have low or even negative correlation with traditional asset classes such as the equity and yield diversification benefits (Daskalaki et al., 2017; Erb & Harvey, 2006; Geman, 2005; Geman & Kharoubi, 2008; Gorton & Rouwenhorst, 2006; Skiadopoulos, 2013). However, over the past decades, institutional investors, including commodity index traders and fund managers, have notably increased their exposure to commodity futures to exploit historically low correlations between equity and commodities. This leads to a fundamentally changed nature of price fluctuations for commodity futures contracts (Basak & Pavlova,

[1] It is important to distinguish the crash risk from downside risk of Roy (1952). Ang, Chen, & Xing (2006) propose the downside beta as assets' exposure to aggregate market returns when these returns are below the average level and document a significant downside risk premium. Similarly, Lettau et al. (2014) develop a downside risk capital asset pricing model to understand the cross sectional returns of many asset classes. The crash risk is conceptually different as it emphasizes extreme left-tail events (Chabi-Yo et al., 2018; Kelly & Jiang, 2014; van Oordt & Zhou, 2016).

2016; Cheng & Xiong, 2014; Henderson et al., 2015), known as the *Financialization of commodities* in the literature (Goldstein & Yang, 2022; Singleton, 2014; Tang & Xiong, 2012). This important development has put the traditional diversification benefit of commodities in doubt (Daskalaki & Skiadopoulos, 2011; Hu et al., 2024).

We join this discussion by focusing on the *relative* safeness of commodity futures and exploring whether, in the cross section, commodity futures still possess the time-varying hedging ability. In particular, we construct a dynamic measure for extreme equity market downturns and test if commodities with lower loadings on the equity crash risk would be discounted more heavily and offer higher expected returns than those with higher crash risk loadings. Our paper builds on the intuition that, if the returns of commodity futures contracts rise when the cross-sectoral crash risk increases, commodity futures can be regarded as an effective hedge against the equity crash risk, and risk-averse investors are more willing to pay higher prices for holding these contracts.

Our measure for extreme equity market downturns is in the spirit of Faias & Zambrano (2022). This study utilizes the information contained in the cross-sectoral left-tail dependence to predict the equity risk premium (ERP). It finds that incorporating sectoral tail dependence leads to a greater improvement of the ERP prediction than by adding the variance risk premium of Bollerslev et al. (2009), a traditional predictive variable characterizing investor risk aversion (Bakshi & Madan, 2006; Bekaert et al., 2023). The economic rationale is that joint sectoral downturns strongly indicate an upcoming systematic consumption disaster event.

The empirical success of the sectoral tail dependence measure in capturing time-varying disaster events in the equity market can be attributed to two features. First, the industry-level information. According to the multi-index model of Moskowwitz & Grinblatt (1999), asset returns are considered to contain an industry-specific component orthogonal to the market- or firm-level components. The industry effect has been identified by researchers and practitioners as a key factor in constructing equity portfolio, and empirically tested in the asset pricing framework (Asness et al., 2000, 2014; Bali et al., 2006). Hoberg & Phillips (2018) and Hong et al. (2007) argue that industry portfolio returns are able to predict stock market movements because of investors' limited information processing ability leading to a lead-lag relation between industry and market portfolios. Cohen & Frazzini (2008) show that industry interdependence matters for return predictability due to economic links between firms. Hence, the industry-specific information, especially the negative news pertaining to left-tail events, is instrumental in describing movements in extreme asset returns. Second, the disaggregated nature. Compared with aggregated univariate tail variables, such as the fear index of Bollerslev & Todorov (2011) and extreme value dependence of Poon et al. (2004), non-aggregated sectoral information better reflects sector heterogeneity as different pro-cyclical industry shocks are often neglected or washed out at the aggregate level (Holly & Petrella, 2012; Horvath, 2000; Menzly & Ozbas, 2010; Veldkamp & Wolfers, 2007). The sectoral-level tail measure also has the advantage of capturing joint distributions of sector returns at a more granular level. Taken together, the cross-sectoral tail dependence measure contains rich information and exhibits superior pricing performance in the existing literature.

In the empirical exercises, we adopt a copula-based semi-parametric left-tail dependence approach in constructing the cross-sectoral tail measure. Each month, we compute the bivariate left-tail dependence for a pair of sectors by combining the GARCH(1,1) model with a non-parametric copula. This approach is able to account for the volatility clustering effect without imposing a restrictive form on the pairwise sector dependence (Chabi-Yo et al., 2022). We then take the arithmetic mean of dependence estimates across all sector pairs to obtain the joint cross-sectoral crash (CSC) risk measure. Our measure draws substantial information from pairwise sector connections and thus differs conceptually from the existing tail behaviour indicators in the literature (see Agarwal et al., 2017; Faias & Zambrano, 2022; Harvey & Siddique, 2000; Kelly & Jiang, 2014; Ruenzi et al., 2020; Weigert, 2016, for example).

Our study makes an important empirical contribution to the literature by showing that the equity CSC risk is priced in the cross section of commodity futures returns with a significant risk premium. Using data for 17 US sectors and 31 commodity futures traded at four North American exchanges between January 1990 and May 2022, we build long-short portfolios by sorting commodity futures contracts into quintiles based on their exposure to the CSC risk, i.e., their CSC betas. We find that the one-month ahead returns of these quintile portfolios exhibit a decreasing pattern as high CSC beta portfolios underperform low CSC beta portfolios by 1.04% per month (t-statistic = 3.27), and this predictability is persistent over the next three months. To investigate whether the hedging role of commodity futures is weakened due to the financialization of commodities, we perform a subsample analysis focusing on the post-financialization period and still observe significant predictive performance of the CSC risk in the subsample.

We obtain consistent results by running the Fama & MacBeth (1973) cross-sectional regressions at the *commodity level* and simultaneously controlling for a large set of commodity characteristics. Moreover, we show that the significant return differential cannot be spanned by existing commodity risk factors or cross-sectional return predictors. For example, we implement the three-factor commodity asset pricing model of Bakshi et al. (2019) and find that the monthly return spreads between portfolios with long (short) position in the CSC beta-sorted bottom (top) quintile are economically large at 0.9% per month and statistically significant at the 1% level (t-statistic = 3.05). This substantial sectoral crash risk premium indicates that commodity futures with a greater exposure to the CSC risk earn significantly lower subsequent returns compared with their counterparts with a smaller exposure. Finally, we perform a range of robustness checks in terms of the investability and empirical design of the strategy by considering the turnover adjustment, transaction cost, alternative estimates of CSC betas, and an alternative construction of the CSC index. Our baseline results remain qualitatively the same.

We construct a CSC beta factor as the long-short return spread by buying low CSC beta commodities and shorting high CSC beta commodities. To examine the asset pricing performance of the CSC beta factor and its risk premium, we implement the Fama-MacBeth two-stage regressions and generalized method of moments (GMM) estimations. We find that the CSC plays an important role in explaining commodity futures portfolio returns. The risk premium is highly significant at the 1% level and close to the average monthly returns of the CSC beta factor. Compared with well-documented risk factors such as basis, the CSC beta factor bears the most significant risk premium. Moreover, pricing models augmented with the CSC beta factor exhibit improved explanatory power. We also show that the pricing ability of our CSC beta factor remains highly significant when controlling for existing disaster and downside risk factors, such as the tail index of Kelly & Jiang (2014), global tail risk of Gao et al. (2019), left tail jump risk of Bollerslev et al. (2015), news-implied rare disaster index of Manela & Moreira (2017), and downside risk factor of Lettau et al. (2014). These results underscore the incremental information in the CSC beta factor and suggest that investors would demand compensation for holding commodity futures that cannot effectively hedge the CSC risk.

What is the economic interpretation of the significant CSC risk premium? It is natural to explore whether heightened CSC risk indeed captures bad states of the economy as suggested in the literature. Exploiting this avenue, we find that empirically the CSC risk is linked to the aggregate economic prospect. We show that the output (industrial production) and employment decline significantly following a positive shock to the CSC risk. In other words, increased CSC risk predicts impaired economic activities, or bad states of the world, in the near future. These results suggest that the CSC risk matters to the marginal utility of investors and underlies its ability in impacting equilibrium prices.

Our paper is closely related to Fan et al. (2022), which explores the pricing of equity tail risk in the cross section of currency returns. We differ from Fan et al. (2022) in that we focus on commodity futures as an important asset class, especially given its financialization in the past two decades. Furthermore, our tail risk measure draws upon an extensive literature on the role of industry-specific information in asset pricing, contrary to Fan et al. (2022) which utilize an index option-based measure of equity tail risk.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents theoretical motivation and develops our testable hypothesis. Section 4 describes data and outlines the construction of CSC risk measure. In Section 5, we discuss empirical results and robustness checks on the pricing of CSC risk in commodity futures returns. Section 6 provides a possible economic mechanism of the results. Finally, Section 7 concludes.

2 Related literature

Our research belongs to the literature on asset pricing with the rare disaster framework. Gabaix (2012) finds that macro-finance puzzles, such as the equity premium puzzle and yield curve slope puzzle, can be explained by the time-varying rare disaster risk. Bollerslev & Todorov (2011) argue that the compensation for rare events largely accounts for average equity risk premia in the US. Gao et al. (2019) show that the beta loading on a global *ex ante* tail risk concern index negatively drives variations of cross-sectional returns in multiple asset classes. Fan et al. (2022) provide a rare disaster risk-based explanation of exchange rate puzzles. In commodity futures markets, Zhang (2021) uncovers a significant time-series predictability of the news-implied rare disaster concern for the returns of index commodity futures. Our paper contributes to this strand of the literature by showing that the exposure of commodity futures to the cross-sectoral crash risk is an important determinant of cross-sectional return variations.

Meanwhile, our study speaks to the literature on the relation between equity and commodity markets. Bakshi et al. (2019) show that innovations of equity volatility are the economic fundamentals underlying commodity risk factors. Fernandez-Perez et al. (2017) consider commodity risk factors as sources of intertemporal risk in the equity market, whereas Fernandez-Perez et al. (2023) study the cross-asset time-series momentum strategy across crude oil and international stock markets. An extensive literature explores the diversification role of commodities for equity risk. For example, Gorton & Rouwenhorst (2006) show that commodity futures provide effective diversification for equity portfolios and Brooks & Prokopczuk (2013) conclude that commodities act as a useful diversifier of equity returns and volatility. Additional evidence supporting the hedging role of commodities includes Bessler & Wolff (2015), Bhardwaj et al. (2016), Daskalaki et al. (2017), Gagnon et al. (2020), and Rubbaniy et al. (2022). However, Daskalaki & Skiadopoulos (2011) and Nguyen et al. (2020) argue that such diversification role is weakened by the financialization of commodities. Our study adds to this debate by showing that commodity futures still possess time-varying hedging capability in the cross section.

Our study is also related to the literature on the crash risk in commodity markets, including Ammann et al. (2023), Bianchi (2018), Enilov et al. (2023), Fernandez-Perez et al. (2018), Lu et al. (2024), Mehlitz & Auer (2021), Iqbal et al. (2023), and Qiao & Han (2023), among others. For instance, Fernandez-Perez et al. (2018) highlight the role of skewness in commodity markets; Ammann et al. (2023) estimate the option-implied commodity tail risk and explore drivers behind its cross-sectional pricing ability; whereas Enilov et al. (2023) and Qiao & Han (2023) analyze the tail behaviour patterns and tail risk contagion across commodity markets during the COVID-19 pandemic, respectively. Our study differs from these as we focus on understanding the role of sectoral tail risk in the pricing of cross-sectional commodity futures returns.

Finally, our paper contributes to the emerging literature on the cross-sectional pricing of commodity futures returns by proposing a novel cross-sectoral crash risk factor. Existing studies have provided a large set of return predictors in commodity futures markets, including basis (Bakshi et al., 2019; Koijen et al., 2018; Szymanowska et al., 2014; Yang, 2013), momentum (Asness et al., 2013; Bianchi et al., 2015; Miffre & Rallis, 2007), basis-momentum (Boons & Prado, 2019), skewness (Fernandez-Perez et al., 2018), open interest (Hong & Yogo, 2012), and relative basis (Gu et al., 2023), among others. We extend this strand of the literature by proposing a new commodity risk factor and examining its predictive performance. Our findings thus have important economic and practical implications for risk management, asset allocation, and portfolio diversification.

3 Theoretical motivation

Existing theoretical studies have recognized the link between dynamic disaster risk and asset prices (Gabaix, 2012; Seo & Wachter, 2018; Wachter, 2013). Similar to Gabaix (2012), we assume a representative agent with utility $\mathbb{E}_0\left[\sum_{t=0}^{\infty} e^{-\rho t}\frac{C_t^{1-\gamma}-1}{1-\gamma}\right]$, where C_t is a consumption endowment, γ is the coefficient of relative risk aversion, and ρ is the rate of time preference. At time $t+1$, a disaster occurs with probability p_t. The process of the endowment can be described as follows:

$$\frac{C_{t+1}}{C_t} = e^{g_c} \times \begin{cases} B_{t+1} & \text{if a disaster happens at } t+1, \\ 1 & \text{if no disaster happens at } t+1, \end{cases} \tag{1}$$

where g_c is the growth rate of the economy in normal times, and $B_{t+1} > 0$ is a random variable. The pricing kernel is the marginal utility of consumption $M_t = e^{-\rho t}C_t^{-\gamma}$ and follows the process:

$$\frac{M_{t+1}}{M_t} = e^{-\rho-\gamma g_c} \times \begin{cases} B_{t+1}^{-\gamma} & \text{if a disaster happens at } t+1, \\ 1 & \text{if no disaster happens at } t+1. \end{cases} \tag{2}$$

In disaster times, the payoff of asset i is expected to be destroyed. Gabaix (2012) models the time variation in the asset's recovery rate by introducing the resilience (H_{it}) of asset i during disaster times as follows:

$$H_{it} = p_t \mathbb{E}_t^D\left[F_{i,t+1}^{RC} B_{t+1}^{-\gamma} - 1\right], \tag{3}$$

where $\mathbb{E}_t^D$ is the expected value conditioning on a disaster happening at time $t+1$, and $F_{i,t+1}^{RC} > 0$ is the asset-specific recovery rate. Intuitively, when an asset is expected to perform well during disaster times with a high value of $F_{i,t+1}^{RC}$, the resilience of this asset is high. Investors are more optimistic (pessimistic) and willing to pay higher (lower) prices for holding assets with higher (lower) resilience H_{it}. In the cross section, assets with a higher level of resilience carry lower risk premiums. This intuition implies a negative relation between resilience and the expected returns to assets (see Proposition 1 of Gabaix 2012). We examine this theoretical implication in commodity futures markets and develop our testable prediction: *Commodity futures with higher* *(lower) exposures to time-varying disaster risk offer lower (higher) average expected returns.*

We follow Faias & Zambrano (2022) to characterize the time-varying rare disaster states. In a two-sector economy, we consider the bivariate returns (X, Y) for the two sectors with corresponding marginal cumulative distribution functions F_X and F_Y. The probability of equity markets entering a disaster state is identified as the probability of both sectors falling below a lower bound threshold (s):

$$P^D(s) = \Pr\left[X < F_X^{-1}(s) \mid Y < F_Y^{-1}(s)\right]. \tag{4}$$

If $P^D(s)$ approaches a limit that is not equal to zero as s approaches zero from the right, X and Y are asymptotically dependent in the lower tail (Chabi-Yo et al., 2018) with a lower tail dependence defined as: $\lim_{s\to 0^+} P^D(s)$.

4 Data and variables

We use 17 sectors in the US equity markets to construct the CSC risk measure at the daily frequency. We collect these daily data from Kenneth R. French's data library for the period from 1989 to 2022. The details and summary statistics of sectors are outlined in Appendix A. Historical prices for the S&P 500 index and Goldman Sachs Commodity Index are obtained from the Bloomberg, and the time series of VIX is downloaded from the FRED.

We consider 31 commodity futures contracts traded at four North American exchanges: CBOT, CME, ICE, and NYMEX. We collect daily settlement prices, trading volume, and open interest from January 1990 to May 2022 from the Bloomberg. We group the futures contracts into five categories: energies (crude oil Brent, crude oil WTI, gasoline, gasoline unleaded, gasoline blendstock, heating oil, and natural gas), metals (copper, gold, palladium, platinum, and silver), softs (butter, cocoa, coffee, milk, orange juice, lumber, and sugar), grains (corn, cotton, Kansas wheat, oats, rough rice, soybean meal, soybean oil, soybean, and wheat), and livestock (feeder cattle, lean hogs, and live cattle). Our data coverage is comparable to those used in Bakshi et al. (2019) and Gu et al. (2023). For trader's long and short positions data, we collect weekly Commitment of Trade (COT) reports from the US Commodity Futures Trading Commission.

Since futures contracts have pre-determined expiration dates and are thinly traded when they are close to expiration, we follow the convention to hold the front-end contracts until one month before maturity and then roll over to the second-nearest contracts, similar to Boons & Prado (2019), Fernandez-Perez et al. (2018), and Han & Kong (2022). We calculate the return of commodity k on day d as $R_{k,d} = \frac{F_{k,d}-F_{k,d-1}}{F_{k,d-1}}$, where $F_{k,d}$ is the futures price of commodity k on day d for the front-end contract and $F_{k,d-1}$ is the price of the same contract on day $d-1$. We then compound the daily return series to obtain monthly returns.

Table 1 reports the summary statistics of all commodity futures. Consistent with Bakshi et al. (2019) and Sakkas & Tessaromatis (2020), investment in individual commodities is unattractive as their annualized mean returns are all below 10% and 13 out of 31 commodities yield negative average returns. Moreover, 21 out of 31 commodities have the first-order autocorrelation coefficients below 0.1, indicating that the daily return series of most commodity futures are serially uncorrelated.

4.1 Cross-sectoral crash risk

Without imposing a restrictive functional form on the dependence structure between sectors, we follow Chabi-Yo et al. (2022) and implement a semi-parametric method for estimating the bivariate left-tail dependence (BLTD) between a pair of sectors. It is defined as follows:

$$\text{BLTD}_{i,j} := \mathbb{P}[T_p[R_i] \mid T_p[R_j]] = \mathbb{P}[R_i \leq Q_p[R_i] \mid R_j \leq Q_p[R_j]], \tag{5}$$

where R_i and R_j represent returns of sectors i and j, respectively. We define crash 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, $R_j \leq Q_p[R_j]$ stands for the crash events in sector j. Hence, $\mathbb{P}[T_p[R_i] \mid T_p[R_j]]$ denotes the conditional probability that sector i realizes crash events given that another sector j also takes on an extreme realization at or below its p-quantile. The value of $\text{BLTD}_{i,j}$ tends to be high (low) if sector i is more (less) likely to exhibit extreme realizations simultaneously with sector j, suggesting higher (lower) left-tail dependence of a given joint distribution.

To compute BLTD for each pair of sectors in month t, we use a rolling window of the most recent 250 trading days to ensure sufficient observations and stable estimates (Ang & Chen, 2002). We combine a parametric GARCH(1,1) model to describe marginal sector return distributions and a non-parametric approach for modelling the left-tail dependence. Specifically, let $r^d_{i,s}$ and $r^d_{j,s}$ denote, respectively, the daily returns of sectors i and j over the recent 250-day estimation period ($s = 1, \ldots, 250$). We collect these two return series into a vector $(\boldsymbol{R}_s)_{s=1,\ldots,250}$ and fit two marginal distributions to the GARCH(1,1) model of the form:

$$R_{f,s} = \mu_f + \sigma_{f,s}\Phi_{f,s}, \qquad f = i \text{ or } j \tag{6}$$

$$\sigma^2_{f,s} = \omega_{f,0} + \omega_{f,1}(\sigma_{f,s-1}\Phi_{f,s-1})^2 + \omega_{f,2}\sigma^2_{f,s-1}, \tag{7}$$

where $\Phi_{f,s}$ stands for independent and identically distributed residuals, and $\mu_f, \omega_{f,0}, \omega_{f,1}, \omega_{f,2} \in \mathbb{R}$. 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). Thus, the conditional distribution of $\Phi_{f,s}$ 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 $\Phi_{f,s}$ is completed by the probability integral transforms:

$$\hat{u}_{f,s} = F_{f,s}(\Phi_{f,s}), \qquad \hat{u}_{f,s} \sim \text{Uniform}[0, 1], \tag{8}$$

where $\hat{u}_{f,s}$ denotes the white-noise series and $F_{f,s}$ is the conditional cumulative distribution functions (CDFs) of $\Phi_{f,s}$. With transformed marginal return series $\hat{u}_{f,s}$, we re-write Eq.(5) as follows:

$$\text{BLTD}_{i,j,t} = \frac{\sum_{s\in\mathcal{D}} \mathbb{1}(\{\hat{u}_{i,s} \le q_i\}) \cdot \mathbb{1}(\{\hat{u}_{j,s} \le q_j\})}{\sum_{s\in\mathcal{D}} \mathbb{1}(\{\hat{u}_{j,s} \le q_j\})}, \tag{9}$$

where q_f is the upper p-quantile of $(\hat{u}_{f,s})_{s\in\mathcal{D}}$, $f = i$ or j, and $\mathcal{D}$ is the number of returns for all series. In particular, the denominator of Eq.(9) is the sum of days in which a left-tail event occurs for sector j over the rolling window estimation period, whereas the numerator is the total number of days on which sectors i and j simultaneously realize a left-tail event during the same period. Hence, a higher BLTD value indicates a stronger left-tail comovement between sectors i and j, and vice versa. As we set $p = 5\%$ in Eq.(9), the BLTD measures the conditional probability of an extreme return realization which is at or below the corresponding 5%-quantile of sector i's return distribution given that sector j realizes a return at or below its 5%-quantile.

To construct the joint cross-sectoral crash risk index, we follow Faias & Zambrano (2022) and use the cross-sectional arithmetic mean of the BLTD estimates as follows:

$$\text{CSC}_t = \begin{pmatrix} N \\ 2 \end{pmatrix}^{-1} \sum_{i<j} \text{BLTD}_{i,j,t}, \tag{10}$$

where N is the total number of pairwise combinations.

Figure 1 shows the dynamics of the cross-sectoral crash risk index, which is stationary without a clear trend but able to capture major economic events during the sample period. At the beginning of the sample, high values of the crash risk index could be attributed to the long-lasting impact of the 1987 stock market crash and the Gulf War in 1991. Since then, the index exhibits spikes between 1997 and 1998, which is probably associated with the Asian financial crisis and the Russian government debt default, respectively. During the Great Recession of 2007-09, we observe a notable spike that captures heightened left-tail dependence during market downturns. Another pronounced spike is observed in 2010, which corresponds to the onset of the European debt crisis. A final spike in 2020 is around the episode of the COVID-19 pandemic.

4.2 *Commodity factor portfolios*

We construct ten commodity factor portfolios as sorting variables, including the basis (Bakshi et al., 2019; Szymanowska et al., 2014; Yang, 2013), momentum (Bakshi et al., 2019; Miffre & Rallis, 2007), basis-momentum (Boons & Prado, 2019), relative basis (Gu et al., 2023), hedging pressure (Kang et al., 2020), liquidity (Szymanowska et al., 2014), volatility (Dhume, 2010; Szymanowska et al., 2014), skewness (Fernandez-Perez et al., 2018), value (Asness et al., 2013), and open interest (Hong & Yogo, 2012; Szymanowska et al., 2014). Each month, we sort all commodities into five quintile portfolios based on these variables, and take long (short) positions in extreme quintile portfolios predicted to appreciate (depreciate) in the following month. All portfolios are equally-weighted and re-balanced monthly with updated signals. We also construct the average commodity factor (AVG) as the long-only equally-weighted cross-sectional average of all available commodity contracts' returns following Bakshi et al. (2019). Detailed descriptions for constructing these variables are provided in Appendix B.

5 Empirical analysis

To evaluate whether the US CSC risk is priced in the cross section of commodity futures returns, we sort futures contracts into quintile portfolios based on their lagged exposure to the CSC risk. To do so, we run the following regression with a rolling window of 60 months:

$$R_{k,t} = \alpha_i + \beta_{\mathrm{CSC},k}\Delta\mathrm{CSC}_t + \beta_{\mathrm{MKT},k}\mathrm{MKT}_t + \beta_{\mathrm{CMKT},k}\mathrm{CMKT}_t + \beta_{\mathrm{VIX},k}\Delta\mathrm{VIX}_t + \varepsilon_{k,t}, \tag{11}$$

where $R_{k,t}$ denotes excess returns of commodity futures k and $\Delta\mathrm{CSC}_t$ is the change in the joint CSC risk, both in month t. In this regression, MKT_t denotes the US stock market returns in month t and captures changes in demand caused by changes in expectations about the US economic growth, and CMKT_t is the commodity market index in month t proxied by the GSCI commodity index, which accounts for changes in the investment set pursued by commodity futures investors. Motivated by Fan et al. (2022) and Henderson et al. (2015), we control for the contemporaneous relation between commodity futures prices and innovations to the VIX found in Cheng et al. (2015) by including the contemporaneous log change in the VIX (ΔVIX_t). The CSC betas (β_{CSC}) from this regression are used for the portfolio analysis below.

5.1 Univariate portfolio sorts

At the end of month t, we sort all commodity futures into equally-weighted quintile portfolios based on the pre-ranking CSC beta (β_{CSC}) to calculate one-month and one-quarter ahead portfolio returns. The return spreads, low-minus-high (L-H), are obtained by taking long and short positions in portfolios with the lowest and highest β_{CSC}, respectively.

Table 2 Panel A provides summary statistics of one-month ahead portfolio returns. We find that portfolios with the lowest CSC beta yield significantly higher returns than those with the highest CSC beta. For example, the returns of portfolio 1 (P1, low CSC beta) and portfolio 5 (P5, high CSC beta) are 0.53% and -0.51% per month, respectively. Intuitively, commodity futures that effectively hedge the CSC risk, i.e., those with high CSC beta, deliver significantly lower returns than their counterparts as investors are willing to pay higher prices for these commodity futures. Hence, the long-short strategy of buying P1 and selling P5 generates an average return spread of 1.04% on a monthly basis with a t-statistic of 3.27 and an annualized Sharpe ratio of 0.60. More importantly, the significant return differential is attributable to both long and short legs as the average returns of P1 and P5 are comparable in magnitude. In Panel B, we report CSC beta-sorted portfolio returns over the next quarter. The returns of P1 and P5 are 1.23% and -1.34% during the subsequent quarter, respectively, and the long-short strategy delivers a significant average return of 2.57% per quarter (t-statistic= 2.64) and an annualized Sharpe ratio of 0.85. Thus the negative relation between CSC beta and future commodity returns is not a one-month affair.

The dynamics of the beta estimates for all five portfolios are displayed in Figure 2. We observe a significant cross-sectional variation in β_{CSC}. It is interesting to note that P1 and P5 consistently have negative and positive CSC betas, respectively, over time and exhibit clearly distinct characteristics in terms of hedging the cross-sectoral crash risk. Figure 3 Panel A shows the cumulative returns of CSC beta-sorted quintile portfolios. We can see that P1 consistently outperforms P5 and the dispersion increases over the sample period. Thus the negative cross-sectional relation between CSC beta and commodity futures returns persists over time. Panel B compares the CSC factor, which is constructed by taking long (short) positions in commodities with the lowest (highest) CSC beta, with the AVG factor. We find that investing in the CSC factor is more attractive, as it yields a cumulative return about 3.5 times higher than investing in the AVG factor.

A rapidly growing strand of literature highlights the financialization of commodities and documents a tightening correlation between equity and commodity markets (see Basak & Pavlova, 2016; Da et al., 2024; Delatte & Lopez, 2013; Singleton, 2014; Tang & Xiong, 2012, for instance). This is relevant for our study as the financialization could weaken the hedging ability of commodity futures. Hence, we conduct a subsample analysis using January 2004 as the starting time for the financialization of commodities (Tang & Xiong, 2012) and summarize the results in Table 2 Panel C. We find that average portfolio returns over the next month still show a decreasing trend from P1 to P5, and the long-short trading strategy generates an average return of 1.02% per month with a t-statistic of 2.42 and an annualized Sharpe ratio of 0.55. These results are comparable in magnitude to those in Panel A although the economic significance somewhat reduces. They confirm that the hedging role of commodity futures remains after the financialization of commodities.

Another potential concern is that the returns of extreme quintile portfolios could be driven by a small number of commodities, which are persistently allocated to P1 and P5. To address this issue, we plot the average frequency of each commodity being assigned to P1 and P5 in the formation month in Figure 4. We find that, although individual commodities have different chances of being allocated to the extreme portfolios, the frequencies of being in P1 or P5 are below 50% except in two cases. Hence, their ability to hedge the cross-sectoral crash risk varies over time, and the predictive relation we explore in this study is not constrained to any specific commodity futures contracts.

In summary, our first set of empirical results shows a significant and strong negative relation between commodity futures' CSC risk exposure and their future returns. Such predictability persists over a longer post-formation horizon, remains after the financialization of commodities, and is not driven by specific futures products.

5.2 CSC exposure and commodity futures characteristics

To better understand the composition of CSC beta-sorted portfolios, we summarize average commodity characteristics based on the Fama & MacBeth (1973) cross-sectional regressions. In particular, we run the following nested econometric specification with a set of commodity characteristics, one at a time:

$$\beta_{k,t}^{CSC} = \varphi_{0,t} + \varphi_{1,t}\mathbf{\Omega}_{k,t} + \varepsilon_{k,t}, \tag{12}$$

where $\beta_{k,t}^{CSC}$ is the CSC beta of commodity k in month t, and $\mathbf{\Omega}_{k,t}$ is a vector of commodity-specific control variables, including basis, momentum, basis-momentum, relative basis, hedging pressure, liquidity, volatility, skewness, value, and open interest. We summarize the time-series average of the slope coefficients of the CSC beta on these commodity characteristics in Table 3.

We note that Model (2) reports a negative and significant slope coefficient for momentum, suggesting that commodities with high CSC beta, which generate low excess returns, have low momentum. This is consistent with the evidence in Bakshi et al. (2019) and Asness et al. (2013) that commodities with low momentum characteristics generate lower expected returns. Moreover, the average slope coefficient for liquidity is positive and significant at the 10% level, indicating that commodities with low CSC beta, which generate high excess returns, have low liquidity, i.e., they tend to be illiquid, which are in line with the illiquidity premium of Amihud (2002). Overall, the CSC beta is hardly correlated with well-known commodity-level control variables except for momentum and liquidity, and we obtain expected signs for the slope coefficients for these two variables.

5.3 Fama-MacBeth regressions

We next conduct the Fama & MacBeth (1973) regressions to examine the predictive power of CSC beta on future commodity returns by simultaneously controlling for a set of well-known commodity variables. In particular, we run the cross-sectional regression of commodity futures returns in month $t+1$ on their CSC beta and control variables in month t as follows:

$$R_{k,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{\text{CSC},k,t} + \lambda_{2,t}\boldsymbol{\Omega}_{k,t} + \varepsilon_{k,t+1}, \tag{13}$$

where $R_{k,t+1}$ is the futures returns for commodity k in month $t+1$, and $\beta_{\text{CSC},k,t}$ is the CSC beta estimated via Eq.(11) in month t. In the most general specification, we include ten commodity asset pricing characteristics defined in Section 4.2 as control variables. We compute the Newey & West (1986) adjusted t-statistics for the time-series average of the cross-sectional regression coefficient estimates to address the concern for potential autocorrelation.

Table 4 Model (1) shows the coefficient estimate from the univariate regression in which the commodity futures returns are regressed on the CSC beta. We observe that the coefficient is negative and highly significant at the 1% level (t-statistic $= -3.05$). Consistent with our univariate portfolio analysis in Section 5.1, this indicates a strong negative relation between the commodity CSC beta and future returns, i.e., the CSC beta significantly and negatively predicts commodity futures returns. From Models (2) to (11), we augment the univariate regression by adding one additional control variable at a time. We find that after controlling for all commodity characteristics, the negative relation still holds: the coefficient estimates for β_{CSC} are all negative and statistically significant with t-statistics ranging from -2.14 to -2.98. For instance, in Model

(11), the most comprehensive specification, the coefficient estimate for β_{CSC} is negative at -0.74 and significant at the 5% level. Hence, the return predictability of the CSC beta is economically important and statistically significant with or without control variables.

5.4 Spanning tests

Now we examine whether the returns to the CSC beta factor, computed as the return difference between P1 and P5 for the cross section of commodity futures returns, can be spanned by existing commodity factors such as those summarized in Section 4.2. Table 5 reports summary statistics (Panel A) and correlation matrix (Panel B) for these 11 variables and our CSC beta factor. In Panel A, we note that seven factors: basis, momentum, basis-momentum, relative basis, hedging pressure, liquidity, and skewness, individually generate significant returns. Meanwhile, the correlations between the CSC beta factor returns and these variables are low, indicating that the CSC beta factor is unlikely to be spanned by these commodity factors.

We perform the time series spanning tests by regressing the CSC beta factor returns on the contemporaneous returns to these 11 commodity variables and summarize the results in Panel A of Table 6. Model (1) is the two-factor model of Yang (2013) featuring the average and basis factors. Model (2) represents the two-factor model of Boons & Prado (2019) in which they replace the basis factor with the basis-momentum factor. Model (3) corresponds to the three-factor model of Bakshi et al. (2019) that considers the average, basis, and momentum factors. Results for these three specifications indicate that excess returns to the CSC beta factor are economically important at around 1% on a monthly basis and highly significant. In specifications (4) and (5), after controlling for the hedging pressure and relative basis factors separately, the CSC beta factor returns remain economically large at 0.9% and 0.8% per month, respectively, and statistically significant with a t-statistic of 3.04 and 2.72, respectively. In the final specification (6), we simultaneously include all 11 commodity risk factors. It is interesting to observe that the risk-adjusted returns of the CSC beta factor are still significant at the 5%

level and economically important with a comparable magnitude. Moreover, the factor model only explains a small proportion of the total variation in CSC beta factor returns as indicated by the low adjusted R^2 at 4.1%. Overall, results in Table 6 Panel A indicate that the profitability of the CSC beta factor cannot be fully spanned by existing commodity risk factors.

In Panel B, we also regress the CSC beta factor on a set of equity risk factors, including market (MKT-Rf), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors of Fama & French (2015), momentum factor (JT) of Jegadeesh & Titman (1993), investment-to-assets (IA) and return on equity (ROE) factors of Hou et al. (2015), expected growth factor (EG) of Hou et al. (2021), betting against beta factor (BAB) of Frazzini & Pedersen (2014), intermediary capital risk factor (HKM) of He et al. (2017), and liquidity (PS) factor of Pástor & Stambaugh (2003).[2] We find that all slope coefficients for the intercept term are positive and significant at the 1% level thus none of common equity risk factors can span our CSC beta factor.

5.5 Asset pricing tests with the CSC beta factor

In this section, we examine the cross-sectional asset pricing performance of the CSC beta factor via Fama & MacBeth (1973) two-stage regressions. In the first stage, we estimate the monthly time-series regressions to obtain each commodity futures portfolio's exposure to risk factors as follows:

$$r_{p,t} = \beta_{0,t} + \beta_{CSC\text{-}\beta,t} CSC\text{-}\beta_t + \boldsymbol{\beta}_{F,t} \boldsymbol{F}_t + \eta_{p,t}, \tag{14}$$

where $r_{p,t}$ is the excess returns of commodity portfolio p, $CSC\text{-}\beta$ is the cross-sectoral crash beta risk factor, and $\boldsymbol{F}_t$ is a set of existing commodity risk factors, including basis, momentum, basis-momentum, relative basis, skewness, and average factors. In the second stage, we run

[2] Fama-French five factors and JT data are from Kenneth R. French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. IA, ROE, and EG series are obtained from: http://global-q.org/index.html. PS data is obtained from Lubos Pastor's website: https://faculty.chicagobooth.edu/lubos-pastor/data. BAB series is collected from: https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly. HKM series is obtained from Zhiguo He's website: https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/.

cross-sectional regressions with coefficient estimates for risk factors as follows:

$$\bar{r}_p = \gamma_0 + \lambda_{CSC\text{-}\beta}\hat{\beta}_{CSC\text{-}\beta,p} + \boldsymbol{\lambda}_F\hat{\boldsymbol{\beta}}_{F,p} + \epsilon_p, \tag{15}$$

where $\bar{r}_p$ is the sample average of excess returns of portfolio p, $\lambda_{CSC\text{-}\beta}$ and $\boldsymbol{\lambda}_F$ are risk premium for the CSC beta and other factors, respectively, $\hat{\beta}_{CSC\text{-}\beta,p}$ and $\hat{\boldsymbol{\beta}}_{F,p}$ are portfolio beta loadings estimated from the first stage, γ_0 is the intercept, i.e., the excess zero-beta rate, and ϵ_p is the pricing error of portfolio p.[3] To compare model efficiency, we compute the cross-sectional R^2 as follows:

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{p=1}^{N}\hat{\epsilon}_p^2}{\mathrm{Var}\left(\bar{R}_p\right)}. \tag{16}$$

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

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\bar{r}_{p,t} - \hat{\bar{r}}_{p,t}\right)^2}, \tag{17}$$

where $\hat{\bar{r}}_p = \hat{\gamma}_0 + \hat{\lambda}_{CSC\text{-}\beta}\hat{\beta}_{CSC\text{-}\beta,p} + \hat{\boldsymbol{\lambda}}_F\hat{\boldsymbol{\beta}}_{F,p}$ is the model implied average excess portfolio returns. We consider 35 portfolios constructed by sorting commodity futures on characteristics as test assets, including five basis, five momentum, five basis-momentum, five CSC beta, five relative basis, five hedging pressure, and five skewness portfolios.

Table 7 reports the second-stage regression results, including estimated risk premium and standard errors calculated based on both the Newey & West (1986) approach (in parentheses) and Shanken (1992) correction (in square brackets). We can see that, across different models, the estimated risk premium for the CSC beta factor ($\lambda_{CSC\text{-}\beta}$) is positive, ranging from 0.011 to 0.013 per month, and highly significant at the 1% level. These estimates are close to the monthly average return of the CSC beta factor at 0.010 as shown in Table 2, thus, the estimated price of risk is approximately equal to the full sample average monthly returns.

Specifically, Models (1) and (2) are single-factor models with either the CSC beta factor or the basis momentum factor. Between them, Model (1) improves the R^2 from 0.13 to 0.29 and

[3] We also estimate Eq.(15) without the intercept term, i.e., assuming no common mispricing in the cross section of returns, and obtain qualitatively the same results.

reduces the RMSE from 0.15 to 0.12, indicating improved goodness of fit. Model (4) is the two-factor model of Boons & Prado (2019) with the average market and basis-momentum factors. When comparing the performance of Models (3) and (4), we find that replacing the BMom factor with our CSC beta factor in Model (3) leads to a rise in explanatory power from 0.12 to 0.27 and the average factor becomes insignificant, indicating that the CSC beta factor subsumes the average factor and exhibits greater pricing ability. When we form a two-factor model with the CSC beta and basis momentum in Model (5), the explanatory power increases substantially to 0.45 and the RMSE drops to 0.09. More importantly, this two-factor model also outperforms the three-factor model of Bakshi et al. (2019) in Model (7). The final *kitchen sink* model of (14) with all factors accounts for 0.62 of the cross-sectional variations in commodity futures portfolio returns and the pricing error decreases to 0.05. Overall, these results highlight the pricing ability of the CSC beta factor in explaining the cross section of commodity futures returns and show that this novel factor significantly outperforms some well-documented commodity risk factors.

In addition to the Fama-MacBeth two-stage regressions, we also implement the GMM estimation of Hansen (1982) to estimate the stochastic discount factor (SDF) with pricing errors as an identify weight matrix.[4] In Table 8, we report GMM-based heteroskedasticity and autocorrelation-consistent (HAC) standard errors (Burnside, 2011) for factor loading b and risk premium λ, as well as the Hansen-Jagannathan (HJ) distance Hansen & Jagannathan (1997), which calculates the normalized maximum pricing errors and associated p-values for the null H_0 : HJ distance = 0. We use the same set of test assets and pricing factors as in Table 7. Consistent with Fama-MacBeth regression results, both $b_{CSC\text{-}\beta}$ and $\lambda_{CSC\text{-}\beta}$ are positive and highly significant across all models, offering additional evidence that the CSC beta factor contains incremental information relative to existing commodity risk factors. For models with the CSC beta factor, the HJ distances are either insignificant or marginally significant at the 10%

[4] The SDF is $m_{t+1} = 1 - b'(f_{t+1} - \mu)$. Here b is the vector of factor loadings and μ is the mean of pricing factors (f_{t+1}). Combining the linear SDF with the Euler equation $(E_t\left[m_{t+1} r_{p,t+1}\right] = 0)$, we obtain a beta pricing model in which the excess returns of portfolio p equal to the quantity of risk (β_p) times the price of risk associated with factors (λ_t), i.e., $E_t\left[r_{p,t+1}\right] = \beta_{p,t}\lambda_t$. Here $\lambda_t = \Sigma_f b$ in which Σ_f is the covariance matrix of the factors.

level, indicating that the null hypothesis of zero HJ distance cannot be rejected at the 5% level. Moreover, the explanatory power of models with the CSC beta factor is higher than that of their competing models. For example, the two-factor Model (5) with the CSC beta and basis momentum factors has a cross-sectional R^2 of 0.48, higher than that of the three-factor model of Bakshi et al. (2019) in Model (7) at 0.31. Hence, we obtain consistent evidence based on the GMM that the CSC beta factor contains unique information which helps price the cross section of commodity futures portfolios.

5.6 Alternative disaster and downside risk factors

We further investigate the pricing ability of the CSC beta factor in comparison with popular disaster and downside risk factors in the literature. The first variable is the change in tail risk index (TR) in equity markets of Kelly & Jiang (2014), which is shown to exhibit significant predictive power for stock returns and negatively predicts economic outcomes. Second, we consider three option-based disaster risk measures, i.e., the change in *ex ante* global tail risk concern (GRIX) of Gao et al. (2019) based on out-of-the-money options written on multiple global assets, left jump variation (LJV) of Bollerslev et al. (2015) as a proxy for market fears, and change in the VIX. The LJV is estimated from option prices and captures the left jump tail risk, which is an important source of the market variance risk. Third, we use the change in the news-implied rare disaster index (NVIX) of Manela & Moreira (2017) to capture time-varying rare disaster risk. Finally, as the CSC crash risk originates from the equity market, we consider four equity factors, including the downside risk factor of Lettau et al. (2014), equity return volatility (RVol) of Ang, Hodrick, et al. (2006), equity return skewness (RSkew) of Bali et al. (2016), and coskewness (CoSkew) of Harvey & Siddique (2000).[5] In all cross-sectional tests, we control for the three-factor model of Bakshi et al. (2019).

We perform the Fama & MacBeth (1973) regressions with these nine risk factors as control

[5] Data for TR, GRIX, and NVIX are obtained from Chen et al. (2023). The LJV is collected from Lai Xu's website https://sites.google.com/site/laixuduke/home. The RVol, RSkew, and CoSkew are constructed by Jensen et al. (2023) and obtained from https://jkpfactors.com/.

variables one at a time and summarize the results in Table 9. Consistent with our previous findings, the estimated risk premiums for the CSC beta factor continue to be positive and significant at the 5% level across different specifications with alternative control variables. This provides additional supporting evidence that the CSC beta factor contains incremental explanatory power for commodity futures returns beyond existing disaster and downside risk factors.

5.7 Robustness checks

Turnover and transaction costs

Our first robustness check examines the impact of transaction cost on the performance of the long-short CSC beta strategy. We calculate the turnover rate (TO) of the long-short CSC beta portfolio as the time-series average of all re-balanced trades incurred as follows:

$$TO = \frac{1}{T-1}\sum_{t=1}^{T-1}\sum_{k=1}^{N_k}\left(|w_{k,t+1} - w_{k,t^*}|\right), \tag{18}$$

where $w_{k,t}$ is the portfolio weight allocated to commodity k in month t, $w_{k,t^*} = w_{k,t} \times (1 + r_{k,t+1})$ is the portfolio weight assigned to the same commodity for month $t+1$, and $r_{k,t+1}$ is the return of commodity k from month t to $t+1$. The TO takes into account the performance of commodity k over the holding period and ranges between 0 (i.e., no re-balancing) and 2 (i.e., all positions are re-balanced). And the net return of the strategy is expressed as follows:

$$\tilde{R}_{P,t+1} = \sum_{k=1}^{N_k}\widetilde{w}_{k,t}R_{k,t+1} - TC\sum_{k=1}^{N_k}|\widetilde{w}_{k,t} - \widetilde{w}_{k,t-1^*}|, \tag{19}$$

where $\tilde{R}_{P,t+1}$ is the return of the long-short CSC beta strategy in month $t+1$, and $R_{k,t+1}$ denotes returns to commodity k with its estimated weight in portfolio $\widetilde{w}_{k,t}$ in month t. We set the proportional transaction cost (TC) to 8.6 basis points (bps) as estimated by Marshall et al. (2012). We also calculate the break-even proportional transaction cost (in bps) which leads to zero net return.

Table 10 Panel A summarizes the results. We find that the average monthly turnover of the long-short CSC beta portfolio is 0.30. After subtracting the proportional transaction cost from gross returns, the net return of this strategy remains highly significant at the 1% level (t-statistic = 3.06). Moreover, the implied proportional transaction cost that makes the long-short CSC beta portfolio unprofitable is strikingly high at 508 bps on average. These results indicate that the CSC beta strategy delivers considerable returns and a high Sharpe ratio even after controlling for the transaction costs.

Alternative estimates of CSC beta

We examine the predictive performance of CSC beta according to a more comprehensive pricing model. We revise Eq.(11) by adding several commodity risk factors as follows:

$$\begin{aligned} R_{k,t} &= \alpha_i + \beta_{\mathrm{CSC},k}\Delta\mathrm{CSC}_t + \beta_{\mathrm{MKT},k}\mathrm{MKT}_t + \beta_{\mathrm{VIX},k}\Delta\mathrm{VIX}_t \\ &\quad + \beta_{\mathrm{AVG},k}\mathrm{AVG}_t + \beta_{\mathrm{Basis},k}\mathrm{Basis}_t + \beta_{\mathrm{MOM},k}\mathrm{MOM}_t + \beta_{\mathrm{BMom},k}\mathrm{BMom}_t + \varepsilon_{k,t}. \end{aligned} \tag{20}$$

In this way we control for the three risk factors of the Bakshi et al. (2019) model and basis-momentum factor in Boons & Prado (2019). We re-construct commodity quintile portfolios following the same procedure as in the baseline analysis to obtain alternative estimates of CSC betas. Table 10 Panel B summarizes the results. Consistent with the baseline results, commodities with the lowest CSC betas deliver significantly higher returns than their counterparts with the highest CSC betas. The long-short portfolios generate returns that are economically large at 1.10% per month and statistically significant with t-stat= 2.86, indicating that our baseline findings are robust to this alternative construction of CSC betas. Furthermore, when we employ a longer estimation window of 90 months to estimate CSC betas, we find that results shown in Panel C continue to exhibit a significant negative relation between CSC betas and expected commodity futures returns. In summary, these alternative changes in constructing the CSC beta do not impact the important role that CSC risk plays in the cross-sectional predictability of commodity futures returns.

Alternative CSC index

In our final robustness test, we consider an alternative measure of the CSC index. In particular, we use 30 US equity sectors to estimate the cross-sectoral crash dependence.[6] In unreported results, we find that the correlation between these two CSC indices is 0.98. We re-estimate Eq.(11) based on this alternative index and perform the univariate portfolio analysis. Table 10 Panel D shows that the baseline results are robust with respect to this alternative CSC index.

6 Dissecting the CSC risk premium

According to the intertemporal CAPM of Merton (1973), the CSC risk premium may arise because shocks to the CSC risk impact future investment and consumption opportunities. So we investigate the impact of CSC risk on aggregate economic outcomes. Following Bloom (2009) and Kelly & Jiang (2014), we estimate a vector autoregression (VAR) of the following form:

$$Y_t = A_0 + \sum_{p=1}^{\mathbf{P}} A_p Y_{t-p} + \mathbf{B}e_t, \quad \mathbf{B}e_t \sim (0, \Omega), \tag{21}$$

where Y_t is a 7×1 vector of variables in month t:

$$Y_t = \begin{bmatrix} \text{CSC}_t \\ \text{Federal funds rate}_t \\ \log(\text{Average hourly earnings}_t) \\ \log(\text{Consumer price index}_t) \\ \text{Hours}_t \\ \log(\text{Employment}_t) \\ \log(\text{Industrial production}_t) \end{bmatrix}. \tag{22}$$

In this system, in addition to CSC_t, we include the Federal funds rate, log average hourly earnings, log consumer price index, average hours, log employment, and log industrial production.[7]

[6] They are food, beer & liquor, tobacco, recreation, printing, consumer goods, apparel, healthcare, chemicals, textiles, construction, steel, fabricated products, electrical equipment, automobiles, carry, mines, coal, oil, utilities, communication, services, business equipment, paper, transportation, wholesale, retail, meals, finance, and others. These data are obtained from Kenneth R. French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7] All these macroeconomic data are obtained from the FRED: https://fred.stlouisfed.org/.

Moreover, A_0 is a 7×1 vector of constants, A_p is a 7×7 matrix of parameters for lag length p, $\mathbf{B}e_t$ is a vector of reduced form innovations assumed to follow a normal distribution with the covariance matrix $\Omega = \mathbf{BB}'$; and e_t denotes a vector of uncorrelated structural shocks with zero mean and unit variance. The Schwartz's Bayesian information criterion suggests a lag length of $p = 2$ for this VAR.

Figure 5 displays the dynamic responses of macroeconomic aggregates to CSC shocks. Panel (a) shows that the employment exhibits a significant and long-lasting decline as a response to a CSC risk shock, and Panel (b) depicts the impulse response of the industrial production. It is clear that a shock to CSC risk gives rise to a negative impact on the industrial production, as it does on employment. These results highlight that an increase in CSC risk precedes significant and prolonged contraction in aggregate economic activities. Hence, an increase in the CSC risk is associated with the deterioration of future investment and consumption opportunities and influences the marginal utility of investors, thus its ability to determine equilibrium asset prices.[8]

7 Conclusion

This study explores the asset pricing implication of the US cross-sectoral crash risk in commodity futures markets. To better describe the rare disaster risk in the equity market, we extract more granular sector-level information via a semi-parametric left-tail dependence modelling framework. Our results indicate that the US cross-sectoral crash risk matters in pricing commodity futures returns and bears a significant risk premium: commodities with greater exposure to the CSC risk underperform their counterparts with less exposure by 1.04% on a monthly basis indicating that commodity futures that hedge the crash risk offer lower subsequent risk premium.

[8] Heightened rare disaster risk also implies a high equity risk premium, i.e., a positive relation between cross-sectoral crash risk and expected stock market returns. We take this to the data and test the in- and out-of-sample predictive ability of the CSC risk for stock market returns. We find that the CSC risk is significantly positively related to future stock returns over multiple horizons and has out-of-sample predictability. This evidence suggests that the CSC risk serves as an effective measure of time-varying rare disaster risk and is positively related to market discount rates. See Appendix C for detailed descriptions of empirical methodology and results.

Such cross-sectional predictability is persistent for the next quarter and robust with respect to a wide range of control variables in both commodity futures and equity markets. Moreover, cross-sectional asset pricing tests show that the CSC beta factor bears a highly significant and positive risk premium and plays an important role in pricing the cross section of commodity futures returns.

To understand the significant CSC risk premium, we explore the potential economic channel. By estimating the monthly VAR, we investigate the dynamic relation between shocks to the CSC risk and aggregate economic activities. The impulse response analysis shows that output and employment are sensitive to the CSC risk such that a positive shock to the CSC risk precedes impaired economic conditions. These results give rise to the strong asset pricing implications of the cross-sectoral crash risk in commodity futures markets. Our study sheds new light on the relation between commodity futures and equity markets and dissects the role of equity crash risk in explaining expected returns to commodity futures in the rare disaster framework.

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Figure 1: **Time series of cross-sectoral crash risk**

This figure displays the time series of joint cross-sectoral crash risk (CSC) based on the average of pairwise left-tail dependence for 17 sectors in the US market. The sample period is from January 1990 to May 2022.

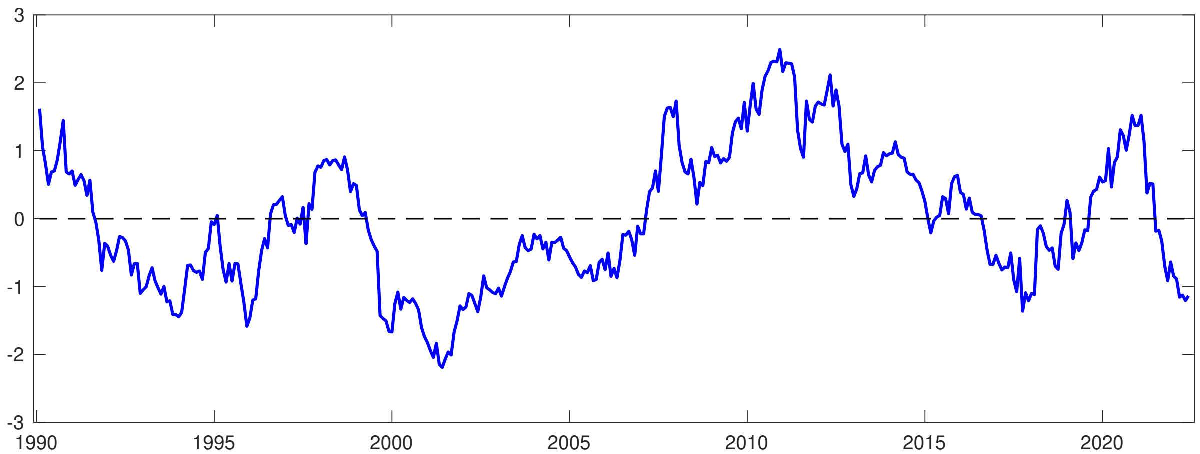

Figure 2: **Time series of cross-sectoral crash risk betas for commodity futures portfolios**

This figure shows the time series of the beta estimates of CSC beta-sorted commodity futures portfolios. P1 (P5) includes commodity futures with the lowest (highest) CSC beta. The sample period is from December 1994 to May 2022.

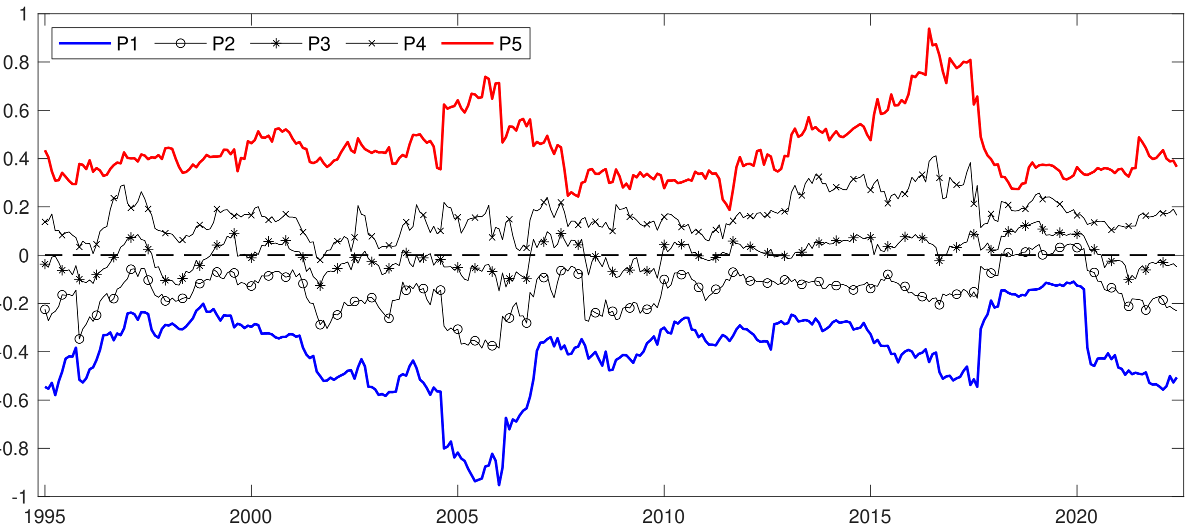

Figure 3: **Cumulative returns of CSC beta-sorted portfolios and the CSC beta factor returns**

Panel A shows the time series of cumulative returns of CSC beta-sorted commodity futures portfolios. P1 (P5) is the portfolio with the lowest (highest) CSC beta estimates. Panel B displays the dynamics of cumulative returns of the CSC beta factor constructed as the difference between returns for extreme CSC betas portfolios (P1-P5) in red. For comparison, we also plot cumulative returns of the market portfolio defined as the cross-sectional average of all available commodities in blue. The sample period is from January 1995 to May 2022.

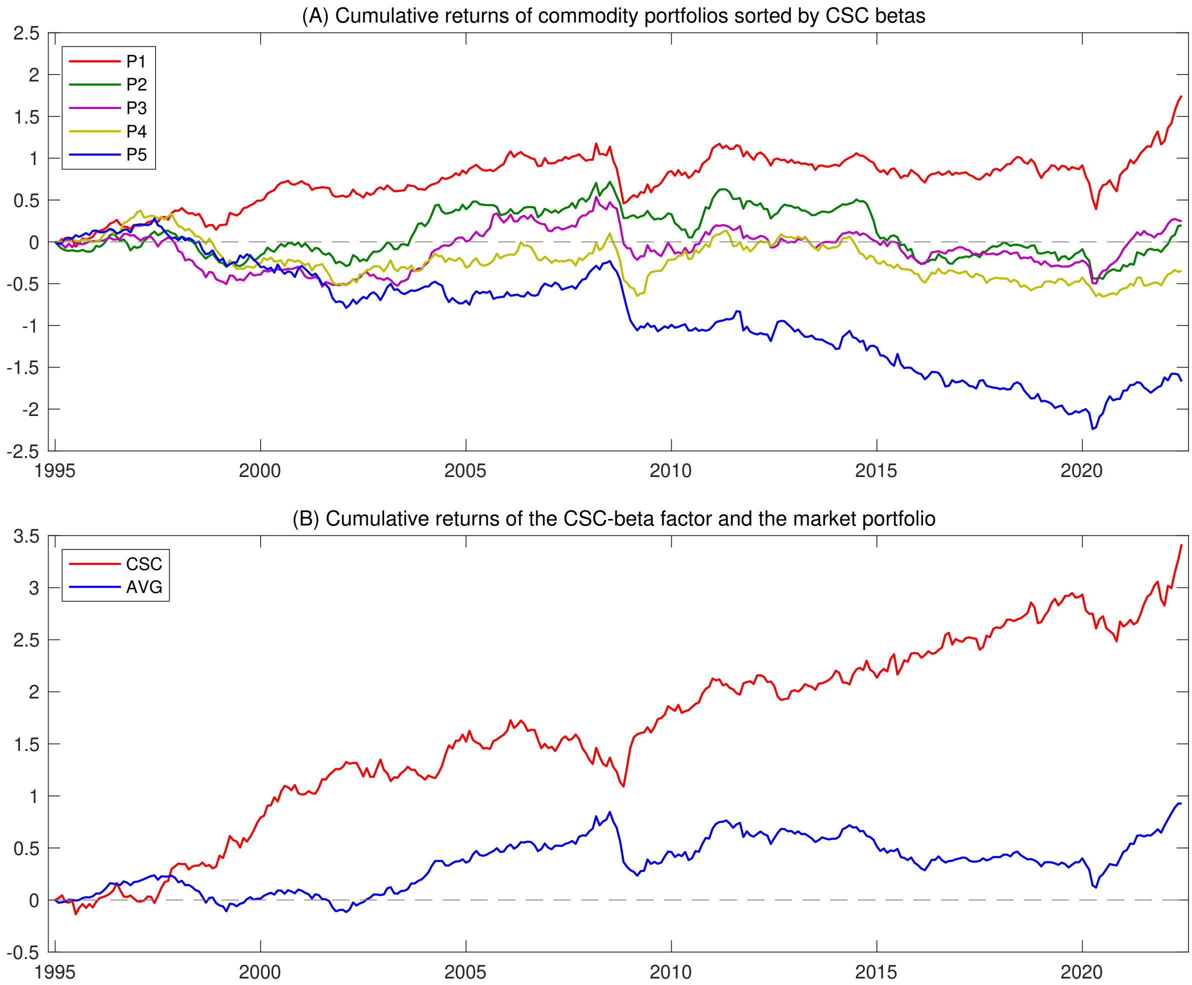

Figure 4: **Frequency of commodity futures in extreme CSC beta-sorted portfolios**

This figure shows the proportion (%) of months that each commodity futures is allocated to extreme quintile portfolios. P1 and P5 are portfolios with the lowest and highest CSC beta-sorted commodity futures contracts. The sample period is from January 1995 to May 2022.

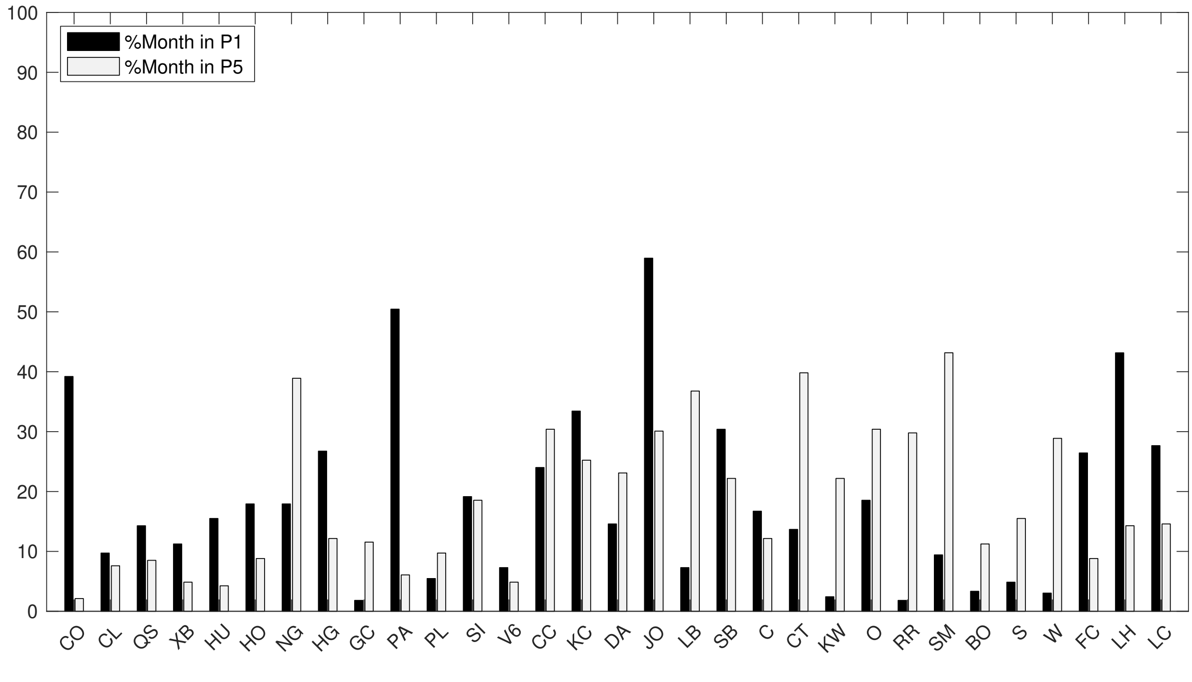

Figure 5: **Impact of CSC risk on macroeconomic aggregates**

This figure shows the impact of cross-sectoral crash risk (CSC) shocks on macroeconomic aggregates. We estimate the monthly vector autoregressive model, including the CSC index, log employment, log industrial production, Federal Funds Rate, log average hourly earnings, log consumer price index, and average hours. Panels (a) and (b) display the responses of employment and industrial production to CSC shocks, respectively. The solid line is the impulse response and shaded area indicates 95% confidence interval. The sample period is from January 1990 to May 2022.

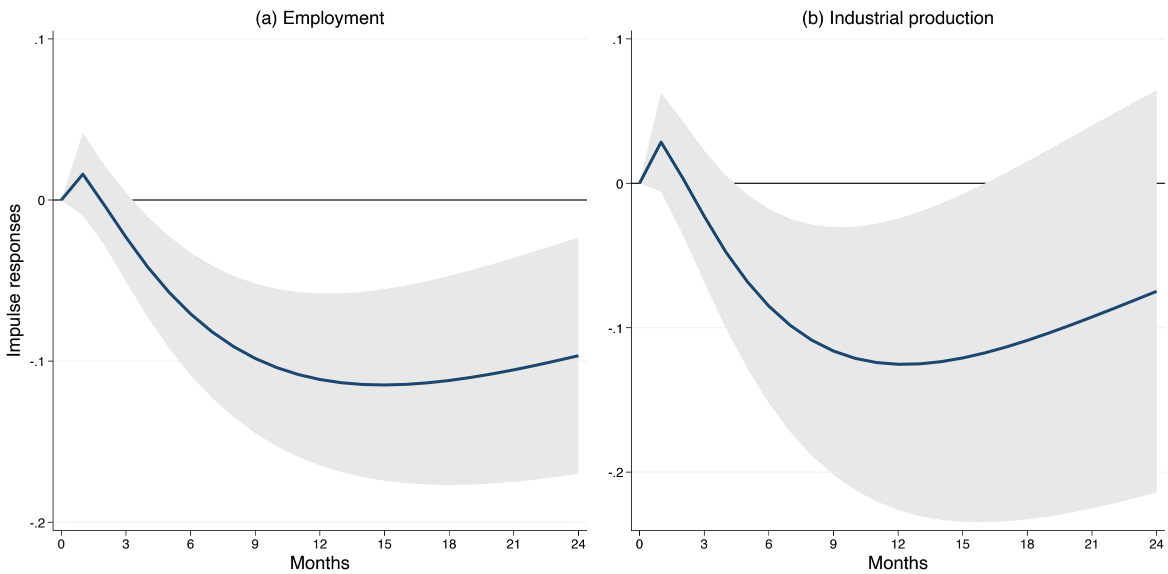

Table 1: **Summary statistics of commodity futures**

This table reports the summary statistics of front-month futures contracts across 31 commodities, including annualized mean returns (Mean), standard deviations (S.D.), skewness (Skew), kurtosis (Kurt), maximum (Max), minimum (Min), first-order autocorrelation coefficient ($\rho(1)$), volume (Vol, the average number of contracts traded per month), open interest (OI, the average number of daily open interest per month), start month (Start), and the number of valid trading months (Obs) of commodity futures contracts. The sample period is from January 1990 to May 2022.

	Code	**Mean**	**S.D.**	**Skew**	**Kurt**	**Max**	**Min**	$\rho(1)$	**Vol**	**OI**	**Start**	**Obs**
Panel A: Energies												
Crude Oil Brent	CO	0.06	0.34	-0.82	8.72	0.42	-0.63	0.24	86015	186027	199001	389
Crude Oil WTI	CL	0.04	0.36	-0.65	9.32	0.48	-0.68	0.21	109344	133727	199001	389
Gasoline	QS	0.05	0.33	-0.34	4.80	0.34	-0.40	0.22	44682	97013	199001	389
Gasoline Unleaded	XB	0.05	0.41	0.29	4.81	0.42	-0.39	-0.05	16645	7535	199001	204
Gasoline Blendstock	HU	0.04	0.40	-2.76	21.21	0.29	-0.90	0.17	43544	84571	200510	200
Heating Oil	HO	0.04	0.32	-0.23	4.39	0.31	-0.38	0.18	25008	58201	199001	389
Natural Gas	NG	-0.16	0.46	0.06	3.62	0.42	-0.39	0.05	41261	89969	199004	386
Panel B: Metals												
Copper	HG	0.04	0.25	-0.54	7.69	0.29	-0.45	0.06	28170	68774	199001	389
Gold	GC	0.02	0.15	-0.05	4.33	0.15	-0.20	-0.11	87425	174636	199001	389
Palladium	PA	0.07	0.32	-0.29	5.23	0.39	-0.41	0.02	1869	12756	199001	389
Platinum	PL	0.02	0.21	-0.90	7.20	0.23	-0.38	0.06	6119	29842	199001	389
Silver	SI	0.01	0.28	-0.10	4.23	0.26	-0.33	-0.07	32783	77165	199001	389
Panel C: Softs												
Butter	V6	-0.01	0.26	0.18	5.60	0.33	-0.28	0.21	20	1027	200509	201
Coccoa	CC	-0.04	0.28	0.09	3.54	0.30	-0.29	-0.20	9400	61750	199001	389
Coffee	KC	-0.07	0.35	0.57	4.68	0.42	-0.37	-0.05	11505	66741	199001	389
Milk	DA	0.02	0.28	0.30	6.25	0.40	-0.33	0.16	243	3535	199601	316
Orange Juice	JO	-0.05	0.32	0.34	4.97	0.45	-0.30	-0.10	1359	14616	199001	389
Lumber	LB	-0.02	0.37	0.11	5.29	0.43	-0.47	0.09	519	3079	199001	389
Sugar	SB	0.00	0.29	-0.22	3.95	0.27	-0.35	0.14	33261	230391	199001	389
Panel D: Grains												
Corn	C	-0.06	0.26	0.04	4.12	0.26	-0.26	0.06	90300	427940	199001	389
Cotton	CT	-0.03	0.26	-0.15	3.55	0.21	-0.26	-0.02	8640	59077	199001	389
Kansas Wheat	KW	-0.03	0.27	0.16	4.04	0.31	-0.27	-0.01	12508	71426	199001	389
Oats	O	-0.01	0.30	0.24	4.01	0.30	-0.31	0.05	758	6547	199001	388
Rough Rice	RR	-0.07	0.25	0.25	5.46	0.39	-0.26	-0.02	541	6033	199001	388
Soybean Meal	SM	0.07	0.25	0.09	4.12	0.26	-0.25	0.01	23376	80525	199001	389
Soybean Oil	BO	0.00	0.24	-0.13	4.86	0.24	-0.29	-0.04	26945	97075	199001	389
Soybean	S	0.04	0.23	-0.33	4.19	0.19	-0.25	-0.01	58728	181173	199001	389
Wheat	W	-0.08	0.27	0.09	4.10	0.32	-0.28	-0.06	37973	150751	199001	389
Panel E: Livestocks												
Feeder Cattle	FC	0.01	0.15	-0.37	3.97	0.13	-0.17	-0.02	2411	12530	199001	389
Lean Hogs	LH	-0.07	0.27	-0.40	4.14	0.26	-0.30	-0.04	10140	54291	199001	389
Live Cattle	LC	0.01	0.14	-0.54	6.03	0.15	-0.24	-0.05	14257	74091	199001	389

Table 2: **Univariate portfolio sorts**

This table reports the CSC beta and summary statistics of CSC beta-sorted commodity futures portfolio returns. P1 (P5) are portfolios with the lowest (highest) CSC beta and L-H is the zero-cost spread portfolio. We summarize monthly mean excess returns (Ret-Rf) for the next month (Panel A) and next quarter (Panel B), annualized standard deviations (S.D.) and the Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt). Panel C reports the same summary statistics for the post-financialization period. The Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1995 to May 2022, and the post-financialization period is from January 2004 to May 2022.

Panel A: Next-month returns						
	P1	P2	P3	P4	P5	L-H
β_{CSC}	-0.400	-0.150	0.000	0.164	0.440	-0.840***
						(-18.32)
Ret-Rf	0.531	0.060	0.075	-0.106	-0.507	1.039***
	(1.55)	(0.18)	(0.23)	(-0.37)	(-1.64)	(3.27)
S.D.	0.189	0.172	0.163	0.166	0.178	0.206
SR	0.338	0.042	0.055	-0.076	-0.342	0.604
Skew	-0.243	-0.485	-0.507	-0.180	-0.346	-0.026
Kurt	5.797	4.523	6.378	4.544	4.690	3.844
Panel B: Next-quarter returns						
	P1	P2	P3	P4	P5	L-H
Ret-Rf	1.226	0.864	-0.140	-0.333	-1.342	2.568***
	(1.24)	(0.89)	(-0.15)	(-0.42)	(-1.52)	(2.64)
S.D.	0.348	0.325	0.294	0.293	0.316	0.361
SR	0.422	0.319	-0.057	-0.136	-0.510	0.854
Skew	-0.343	-0.362	-0.351	-0.570	0.037	0.384
Kurt	7.270	5.098	3.993	4.877	4.830	4.527
Panel C: Next-month returns post financialization						
	P1	P2	P3	P4	P5	L-H
β_{CSC}	-0.407	-0.144	0.012	0.187	0.455	-0.862***
						(-13.19)
Ret-Rf	0.509	0.004	0.236	-0.044	-0.514	1.023**
	(1.07)	(0.01)	(0.57)	(-0.13)	(-1.25)	(2.42)
S.D.	0.213	0.185	0.177	0.173	0.189	0.222
SR	0.288	0.003	0.160	-0.031	-0.326	0.553
Skew	-0.255	-0.624	-0.627	-0.233	-0.444	-0.003
Kurt	5.096	4.621	6.396	5.027	4.927	3.817

Table 3: **Average commodity characteristics**

This table reports the time-series averages of slope estimates for monthly cross-sectional regressions of the CSC beta (β_{CSC}) on a set of commodity-level characteristics, including the basis, momentum (MOM), basis-momentum (BMom), relative basis (RB), hedging pressure (HP), liquidity (LIQ), volatility (VOL), skewness (Skew), value, and open interest (OI). The Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1995 to May 2022.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Basis	0.061									
	(1.45)									
MOM		-1.192**								
		(-2.41)								
BMom			-1.514							
			(-0.66)							
RB				-0.020						
				(-0.99)						
HP					-0.035					
					(-0.60)					
LIQ						0.023*				
						(1.93)				
VOL							0.002			
							(0.55)			
Skew								0.038		
								(1.11)		
Value									0.045	
									(0.43)	
OI										0.016
										(0.92)
Intercept	-0.002	0.009	0.002	0.012	0.011	0.005	0.010	0.013	-0.050	0.016*
	(-0.23)	(0.86)	(0.17)	(1.26)	(0.71)	(0.57)	(1.10)	(1.33)	(-0.47)	(1.90)

Table 4: **Fama-MacBeth regression results**

This table summarizes commodity-level Fama & MacBeth (1973) regression results. We run cross-sectional regressions of monthly excess commodity returns (in percentage) in month $t+1$ on the CSC beta (β_{CSC}) and a set of lagged control variables and report the time-series averages of slope coefficients obtained from the cross-sectional regressions. The control variables include the basis, momentum (MOM), basis-momentum (BMom), relative basis (RB), hedging pressure (HP), liquidity (LIQ), volatility (VOL), skewness (Skew), value, and open interest (OI). The Newey & West (1986) adjusted t-statistics are reported in parentheses. R^2 (%) is the average cross-sectional R^2. The sample period is from January 1995 to May 2022.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	-0.115	-0.018	-0.083	0.054	0.141	-0.028	0.009	-0.028	0.001	-1.394	-0.596
	(-0.49)	(-0.08)	(-0.40)	(0.24)	(0.62)	(-0.11)	(0.04)	(-0.11)	(0.00)	(-1.09)	(-0.42)
β_{CSC}	-0.980***	-0.971***	-0.882***	-0.862***	-0.684**	-0.716**	-0.752**	-0.837***	-0.644**	-0.646**	-0.737**
	(-3.05)	(-2.93)	(-2.97)	(-2.98)	(-2.37)	(-2.50)	(-2.48)	(-2.71)	(-2.14)	(-2.22)	(-2.29)
Basis		-0.598	-0.778	-0.413	-2.465**	-1.981*	-1.918*	-1.283	-1.285	-1.592	-1.719
		(-1.26)	(-1.43)	(-0.70)	(-2.54)	(-1.93)	(-1.85)	(-1.17)	(-1.18)	(-1.55)	(-1.60)
MOM			14.100**	12.171**	11.997**	7.928	6.857	7.037	9.085	10.937	8.469
			(2.57)	(2.23)	(2.26)	(1.35)	(1.17)	(1.13)	(1.63)	(1.61)	(1.08)
BMom				32.520	11.983	20.561	19.964	25.657	17.551	24.325	27.452
				(1.35)	(0.51)	(1.01)	(0.94)	(1.23)	(0.84)	(1.12)	(0.99)
RB					2.380***	2.145***	2.125***	1.624**	1.799**	2.118**	1.741**
					(3.36)	(2.76)	(2.76)	(2.26)	(2.47)	(2.65)	(2.01)
HP						1.001*	1.009*	1.134*	0.627	0.699	0.897
						(1.83)	(1.80)	(1.85)	(1.05)	(1.17)	(1.46)
LIQ							-0.002	-0.003	-0.002	-0.002	-0.002
							(-1.40)	(-1.61)	(-1.35)	(-1.40)	(-1.23)
VOL								-0.040	-0.049	-0.044	-0.036
								(-1.04)	(-1.23)	(-1.22)	(-0.92)
Skew									-1.028***	-0.888***	-0.804**
									(-3.27)	(-2.66)	(-1.96)
Value										1.383	0.522
										(1.15)	(0.39)
OI											0.009**
											(2.00)
R^2 (%)	2.43	4.56	9.84	12.11	14.61	14.27	13.12	12.94	15.54	19.16	21.17

Table 5: **Summary statistics for commodity factors**

This table reports the summary statistics of commodity risk factors. To construct these factors, we sort all commodity futures contracts into quintile portfolios based on different pricing signals at the month end, and take long (short) positions in the quintile portfolios predicted to appreciate (depreciate) in the following month. All portfolios are equally-weighted and re-balanced monthly with updated pricing signals. AVG is the long-only equally-weighted cross-sectional average of all available commodity contracts. We also the term structure (Basis), momentum (MOM), basis-momentum (BMom), relative basis (RB), hedging pressure (HP), liquidity (LIQ), volatility (VOL), skewness (Skew), value, and open interest (OI). For each factor, we report annualized mean returns (Mean), 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) in Panel A, and t-stat is the Newey & West (1986) adjusted t-statistics. Panel B reports the Pearson (below the diagonal) and Spearman (above the diagonal) correlations. The sample period is from January 1990 to May 2022.

Panel A: Summary statistics for commodity factors

	Mean	t-stat	SD	SR	Skew	Kurt	Min	Q25	Median	Q75	Max
AVG	0.03	1.10	0.12	0.23	-0.73	6.85	-0.20	-0.02	0.00	0.02	0.12
Basis	0.06	2.12	0.16	0.39	0.11	3.41	-0.14	-0.02	0.01	0.04	0.20
MOM	0.09	2.03	0.25	0.36	0.04	3.96	-0.23	-0.04	0.01	0.05	0.31
BMom	0.07	1.83	0.20	0.34	0.01	4.64	-0.26	-0.03	0.01	0.04	0.23
RB	0.07	2.68	0.16	0.42	0.07	3.59	-0.14	-0.02	0.00	0.03	0.16
HP	0.07	1.77	0.18	0.37	0.03	3.26	-0.16	-0.03	0.00	0.04	0.15
LIQ	0.05	1.90	0.16	0.33	0.05	3.68	-0.14	-0.02	0.00	0.03	0.21
VOL	-0.01	-0.26	0.18	-0.04	-0.03	4.39	-0.20	-0.03	0.00	0.03	0.18
Skew	0.09	2.61	0.20	0.46	-0.20	4.00	-0.21	-0.02	0.01	0.04	0.20
Value	-0.01	-0.39	0.21	-0.07	0.00	3.39	-0.21	-0.04	0.00	0.04	0.18
OI	0.03	0.76	0.20	0.15	0.08	5.67	-0.27	-0.03	0.00	0.03	0.21

Panel B: Correlation

	β_{CSC}	AVG	Basis	MOM	BMom	RB	HP	LIQ	VOL	Skew	Value	OI
β_{CSC}		0.04	0.00	0.03	-0.07	0.11	0.07	0.08	0.01	0.09	0.05	-0.02
AVG	0.10		0.04	-0.01	-0.01	-0.07	0.16	-0.27	0.16	0.05	-0.19	0.00
Basis	0.05	0.09		-0.08	0.08	-0.30	0.14	-0.11	-0.07	0.01	0.03	-0.02
MOM	0.07	-0.02	-0.08		0.25	0.09	0.19	0.00	0.18	0.10	-0.37	-0.15
BMom	-0.05	-0.02	0.03	0.35		0.10	0.04	0.03	0.07	0.15	-0.04	0.09
RB	0.06	-0.06	-0.32	0.09	0.08		0.04	0.37	0.12	0.12	-0.05	-0.02
HP	0.04	0.18	0.14	0.17	0.05	0.09		-0.07	0.06	0.14	-0.15	0.04
LIQ	0.05	-0.26	-0.11	-0.06	-0.02	0.37	-0.08		-0.04	-0.04	0.13	-0.01
VOL	0.05	0.18	-0.14	0.20	0.12	0.09	0.10	-0.11		0.03	-0.26	-0.03
Skew	0.14	0.11	0.03	0.08	0.11	0.13	0.19	0.01	0.15		-0.15	0.00
Value	0.05	-0.21	0.05	-0.42	-0.07	-0.05	-0.15	0.17	-0.29	-0.17		-0.01
OI	-0.09	0.01	-0.07	-0.13	0.10	0.02	0.08	0.02	0.04	0.03	-0.02	

Table 6: **Time-series spanning tests**

This table reports risk-adjusted returns and factor loadings by regressing CSC beta factor returns on a set of commodity asset pricing models (Panel A) and equity risk factors (Panel B). The Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1995 to May 2022.

Panel A: Commodity asset pricing models						
Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.010***	0.010***	0.009***	0.009***	0.008***	0.008**
	(2.98)	(3.26)	(3.05)	(3.04)	(2.72)	(2.33)
AVG	0.155	0.160	0.157	0.157	0.157	0.201*
	(1.44)	(1.42)	(1.48)	(1.35)	(1.50)	(1.86)
Basis	0.056		0.063	0.063	0.104	0.091
	(0.65)		(0.73)	(0.69)	(1.28)	(1.07)
MOM			0.061	0.061	0.082	0.128
			(0.77)	(0.77)	(1.08)	(1.53)
BMom		-0.044			-0.089	-0.108
		(-0.58)			(-1.24)	(-1.52)
RB					0.117	0.070
					(1.53)	(0.95)
HP				-0.001		-0.023
				(-0.01)		(-0.17)
LIQ						0.069
						(0.77)
VOL						0.058
						(0.65)
Skew						0.140*
						(1.82)
Value						0.161
						(1.59)
OI						-0.060
						(-1.06)
Adj R^2	0.007	0.007	0.009	0.006	0.016	0.041

Panel B: Equity risk factors

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Intercept	0.010***	0.010***	0.011***	0.011***	0.010***	0.010***	0.010***	0.012***	0.012***	0.012***	0.010***	0.011***	0.013***
	(2.95)	(3.15)	(3.18)	(3.49)	(3.11)	(3.26)	(3.08)	(3.60)	(3.52)	(3.45)	(2.96)	(3.18)	(3.44)
MKT-Rf	0.058												0.020
	(0.80)												(0.13)
SMB		0.037											-0.168
		(0.32)											(-1.02)
HML			-0.066										-0.133
			(-0.47)										(-0.64)
RMW				-0.267***									0.094
				(-2.88)									(0.38)
CMA					0.089								0.043
					(0.48)								(0.10)
JT						-0.021							0.133
						(-0.28)							(1.64)
IA							0.110						0.338
							(0.52)						(0.77)
ROE								-0.296***					-0.424**
								(-2.86)					(-2.03)
EG									-0.267*				-0.173
									(-1.92)				(-0.77)
BAB										-0.187*			-0.133
										(-1.95)			(-1.16)
HKM											0.022		-0.015
											(0.41)		(-0.14)
PS												-0.048	-0.043
												(-0.52)	(-0.49)
Adj R^2	0.192	0.039	0.139	1.559	0.103	0.032	0.176	2.166	1.146	1.540	0.061	0.094	1.387

Table 7: **Cross-sectional asset pricing results: Second-stage Fama–MacBeth regressions**

This table reports results of the second-stage Fama & MacBeth (1973) regressions. The linear factor models include seven risk factors: cross-sectoral crash risk (CSC) beta, basis (Basis), momentum (MOM), basis-momentum (BMom), relative basis (RB), hedging pressure (HP), and skewness (Skew). We consider 35 portfolios as test assets: 5 basis, 5 momentum, 5 basis-momentum, 5 CSC beta, 5 relative basis, 5 hedging pressure, and 5 skewness portfolios and report the estimated risk premium, root mean square error (RMSE), and cross-sectional R^2. The t-statistics are based on both Newey & West (1986) in parentheses and Shanken (1992) correction in square brackets. The sample period is from January 1995 to May 2022.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
γ_0	-0.003	-0.002	-0.002	-0.003	-0.002	-0.002	-0.003	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.002
	(-1.01)	(-0.67)	(-0.96)	(-1.10)	(-0.97)	(-0.93)	(-1.10)	(-0.96)	(-0.87)	(-0.72)	(-1.15)	(-1.03)	(-1.10)	(-0.89)
	[-1.40]	[-0.92]	[-1.04]	[-1.20]	[-1.32]	[-1.00]	[-1.19]	[-1.03]	[-0.91]	[-0.75]	[-1.19]	[-1.06]	[-1.15]	[-0.93]
$\lambda_{CSC\text{-}\beta}$	0.013		0.013		0.013	0.013		0.012		0.012		0.011		0.011
	(3.54)		(3.52)		(3.55)	(3.52)		(3.34)		(3.31)		(3.11)		(3.18)
	[3.42]		[3.72]		[3.41]	[3.72]		[3.51]		[3.48]		[3.28]		[3.35]
λ_{AVG}			0.001	0.001		0.001	0.001	0.001	0.000	0.000	0.001	0.001	0.001	0.000
			(0.44)	(0.74)		(0.40)	(0.74)	(0.46)	(0.31)	(0.03)	(0.71)	(0.49)	(0.63)	(0.27)
			[0.20]	[0.33]		[0.18]	[0.33]	[0.21]	[0.14]	[0.01]	[0.32]	[0.22]	[0.29]	[0.13]
λ_{Basis}							0.005	0.005	0.004	0.004	0.005	0.005	0.005	0.005
							(1.66)	(1.64)	(1.43)	(1.40)	(1.82)	(1.72)	(1.82)	(1.61)
							[1.70]	[1.67]	[1.46]	[1.43]	[1.89]	[1.79]	[1.89]	[1.67]
λ_{MOM}							0.011	0.010	0.010	0.009	0.009	0.009	0.009	0.008
							(2.59)	(2.46)	(2.36)	(2.23)	(2.39)	(2.23)	(2.36)	(2.12)
							[2.64]	[2.51]	[2.42]	[2.28]	[2.35]	[2.18]	[2.34]	[2.11]
λ_{BMom}		0.008		0.008	0.008	0.008					0.004	0.005	0.004	0.005
		(2.11)		(2.11)	(2.09)	(2.09)					(1.19)	(1.44)	(1.18)	(1.43)
		[2.26]		[2.27]	[2.24]	[2.23]					[1.25]	[1.52]	[1.25]	[1.52]
λ_{RB}											0.006	0.005	0.006	0.005
											(2.38)	(2.17)	(2.34)	(2.05)
											[2.12]	[1.92]	[2.12]	[1.84]
λ_{HP}									0.015	0.015			0.006	0.009
									(2.74)	(2.77)			(0.96)	(2.75)
									[2.34]	[2.34]			[0.86]	[2.57]
λ_{Skew}											0.010	0.009	0.010	0.009
											(3.08)	(2.84)	(3.04)	(2.75)
											[2.90]	[2.63]	[2.88]	[2.57]
RMSE	0.12	0.15	0.12	0.15	0.09	0.09	0.12	0.08	0.11	0.07	0.08	0.05	0.08	0.05
R^2	0.29	0.13	0.27	0.12	0.45	0.43	0.24	0.47	0.31	0.55	0.47	0.62	0.46	0.62

Table 8: **Cross-sectional asset pricing results: GMM estimation**

This table reports GMM estimation results. The linear factor models include seven risk factors: cross-sectoral crash risk (CSC) beta, basis (Basis), momentum (MOM), basis-momentum (BMom), relative basis (RB), hedging pressure (HP), and skewness (Skew) factors. We consider 35 portfolios as test assets: 5 basis, 5 momentum, 5 basis-momentum, 5 CSC beta, 5 relative basis, 5 hedging pressure, and 5 skewness portfolios and report factor loading b, estimated risk premium λ, and GMM-based heteroskedasticity and autocorrelation-consistent (HAC) standard errors in parentheses. We also summarize the HJ distance of Hansen & Jagannathan (1997) and the corresponding p-value for the null hypothesis H_0 : HJ distance = 0. The λ estimates are multiplied by 100 for ease of readability. The sample period is from January 1995 to May 2022.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$b_{CSC\text{-}\beta}$	3.525***		3.567***		3.651***	3.685***		3.096***		3.124***		2.550**		2.711**
	(1.11)		(1.05)		(1.13)	(1.05)		(1.06)		(1.12)		(1.07)		(1.06)
$\lambda_{CSC\text{-}\beta}$	1.248***		1.259***		1.252***	1.260***		1.179***		1.168***		1.091***		1.109***
	(0.37)		(0.34)		(0.37)	(0.34)		(0.34)		(0.34)		(0.33)		(0.33)
b_{AVG}			-0.166	0.766		-0.133	0.520	-0.226	-1.028	-1.814	0.184	-0.305	-0.007	-0.986
			(2.19)	(2.18)		(2.24)	(2.28)	(2.30)	(2.34)	(2.42)	(2.42)	(2.39)	(2.48)	(2.48)
λ_{AVG}			0.059	0.098		0.054	0.102	0.064	0.043	0.003	0.098	0.069	0.090	0.041
			(0.32)	(0.31)		(0.32)	(0.31)	(0.32)	(0.31)	(0.32)	(0.32)	(0.32)	(0.31)	(0.32)
b_{Basis}							2.311*	2.079*	1.246	0.988	3.314**	2.848**	3.124**	2.171
							(1.24)	(1.24)	(1.32)	(1.32)	(1.41)	(1.41)	(1.47)	(1.43)
λ_{Basis}							0.487*	0.477*	0.411	0.399	0.536*	0.505*	0.523*	0.459*
							(0.28)	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)
b_{MOM}							2.268***	1.968**	1.385	1.063	1.678*	1.255	1.575	0.875
							(0.85)	(0.84)	(0.92)	(0.91)	(0.94)	(0.94)	(1.00)	(0.99)
λ_{MOM}							1.096***	1.042**	1.001**	0.944**	0.952**	0.883**	0.943**	0.849**
							(0.41)	(0.42)	(0.41)	(0.42)	(0.40)	(0.40)	(0.40)	(0.40)
b_{BMom}		2.316**		2.333**	2.474**	2.473**					-0.084	0.577	-0.054	0.72
		(1.07)		(1.06)	(1.05)	(1.05)					(1.07)	(1.08)	(1.09)	(1.09)
λ_{BMom}		0.818**		0.820**	0.814**	0.813**					0.423	0.514	0.421	0.512
		(0.36)		(0.36)	(0.36)	(0.36)					(0.34)	(0.34)	(0.34)	(0.34)
b_{RB}											3.204**	2.682*	3.063**	2.166
											(1.42)	(1.42)	(1.46)	(1.42)
λ_{RB}											0.595**	0.543**	0.588**	0.518*
											(0.27)	(0.27)	(0.27)	(0.27)
b_{HP}									5.043**	5.154**			0.661	2.254
									(2.34)	(2.41)			(2.56)	(2.56)
λ_{HP}									1.468**	1.477**			0.582	0.880
									(0.59)	(0.61)			(0.63)	(0.62)
b_{Skew}											2.259**	1.698	2.170*	1.357
											(1.07)	(1.08)	(1.13)	(1.13)
λ_{Skew}											0.977***	0.884***	0.971***	0.857**
											(0.34)	(0.34)	(0.34)	(0.34)
R^2	0.30	0.15	0.30	0.17	0.48	0.48	0.31	0.53	0.40	0.62	0.57	0.69	0.57	0.71
HJ distance	0.43	0.45	0.43	0.45	0.42	0.42	0.43	0.40	0.40	0.36	0.37	0.34	0.35	0.32
p-value	0.05	0.02	0.05	0.02	0.06	0.06	0.03	0.07	0.11	0.22	0.13	0.23	0.18	0.33

Table 9: **Cross-sectional asset pricing results: Alternative disaster and downside risk factors**

This table reports results of the second-stage Fama & MacBeth (1973) regresisons. We consider nine control variables, one at a time, in addition to the CSC beta factor, average (AVG), basis, and momentum (MOM) factors: the change in tail risk index (ΔTR) of Kelly & Jiang (2014), change in global tail risk concern (ΔGRIX) of Gao et al. (2019), left jump variation (LJV) of Bollerslev et al. (2015), change in the VIX (ΔVIX), change in news-implied rare disaster index (ΔNVIX) of Manela & Moreira (2017), downside risk factor of Lettau et al. (2014), equity return volatility (RVol) of Ang, Hodrick, et al. (2006), equity return skewness (RSkew) of Bali et al. (2016), and coskewness (CoSkew) of Harvey & Siddique (2000). We consider 35 portfolios as test assets: 5 basis, 5 momentum, 5 basis-momentum, 5 CSC beta, 5 relative basis, 5 hedging pressure, and 5 skewness portfolios and report estimated risk premium, root mean square error (RMSE), and cross-sectional R^2. The t-statistics are based on both Newey & West (1986) in parentheses and Shanken (1992) correction in square brackets.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
γ_0	-0.005	-0.003	-0.004	-0.003	-0.005	-0.002	-0.003	-0.002	-0.002
	(-1.76)	(-1.03)	(-1.36)	(-1.32)	(-1.86)	(-0.96)	(-0.99)	(-0.97)	(-0.97)
	[-1.69]	[-1.08]	[-1.39]	[-1.33]	[-1.88]	[-1.03]	[-1.05]	[-1.03]	[-1.05]
λ_{CSC}	0.010	0.012	0.011	0.011	0.011	0.012	0.012	0.012	0.012
	(2.74)	(2.53)	(2.97)	(3.24)	(2.79)	(3.35)	(3.47)	(3.39)	(3.34)
	[2.87]	[2.90]	[3.13]	[3.37]	[2.98]	[3.52]	[3.65]	[3.54]	[3.52]
$\lambda_{\Delta TR}$	0.021								
	(2.77)								
	[2.47]								
$\lambda_{\Delta GRIX}$		-0.066							
		(-0.92)							
		[-0.85]							
λ_{LJV}			0.001						
			(1.41)						
			[1.53]						
$\lambda_{\Delta VIX}$				-0.104					
				(-2.46)					
				[-2.05]					
$\lambda_{\Delta NVIX}$					-1.599				
					(-1.99)				
					[-1.59]				
λ_{DR}						0.002			
						(0.28)			
						[0.29]			
λ_{RVol}							0.007		
							(0.57)		
							[0.53]		
λ_{RSkew}								0.000	
								(-0.11)	
								[-0.11]	
λ_{CoSkew}									0.001
									(0.14)
									[0.13]
Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
RMSE	0.12	0.15	0.09	0.07	0.10	0.08	0.08	0.08	0.08
R^2	0.29	0.43	0.51	0.54	0.50	0.45	0.46	0.45	0.45

Table 10: **Robustness checks**

In Panel A, we report the turnover of long-short CSC beta portfolios and take into account of transaction cost (TC) by subtracting 8.6 bps from the gross return. We also calculate the break-even proportional transaction cost (in bps) which leads to zero net returns. Panel B summarizes commodity futures portfolio returns with an alternative pricing model, i.e., Eq.(20), to obtain the CSC beta. In Panel C, we report portfolio returns based on a longer estimation window for obtaining the CSC beta. In Panel C, we construct the CSC index with 30 US equity sectors and examine portfolio returns based on this alternative CSC index. We report the monthly mean excess returns (Ret-Rf), annualized standard deviations (S.D.) and Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt). Newey & West (1986) adjusted t-statistics are reported in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1995 to May 2022.

Panel A: Transaction costs						
	Turnover	Gross return		Net return		Break-even TC (bps)
		Mean (%)	SR	Mean (%)	SR	
CSC beta	0.299	1.039***	0.604	1.013***	0.589	508
		(3.27)		(3.06)		

Panel B: Alternative model specification						
	P1	P2	P3	P4	P5	P1-P5
Ret-Rf	0.517	0.409	-0.228	-0.060	-0.582	1.099***
	(1.37)	(1.17)	(-0.83)	(-0.21)	(-1.62)	(2.86)
S.D.	0.212	0.170	0.164	0.155	0.183	0.220
SR	0.293	0.289	-0.167	-0.047	-0.381	0.598
Skew	-0.814	-0.407	-0.026	0.076	-0.782	0.125
Kurt	8.302	5.016	3.780	3.349	6.503	4.203

Panel C: Longer estimation window						
	P1	P2	P3	P4	P5	P1-P5
Ret-Rf	0.412	0.088	-0.328	-0.091	-0.384	0.796**
	(1.11)	(0.22)	(-0.90)	(-0.29)	(-1.30)	(2.55)
S.D.	0.188	0.198	0.181	0.162	0.183	0.208
SR	0.264	0.053	-0.218	-0.068	-0.252	0.459
Skew	-0.093	-1.388	-0.656	-0.190	0.096	-0.084
Kurt	5.257	9.476	6.027	3.998	3.480	3.687

Panel D: Alternative measure of the CSC index						
	P1	P2	P3	P4	P5	P1-P5
Ret-Rf	0.266	0.151	0.208	-0.114	-0.447	0.713**
	(0.74)	(0.44)	(0.61)	(-0.43)	(-1.46)	(2.14)
S.D.	0.188	0.174	0.164	0.160	0.174	0.198
SR	0.169	0.104	0.152	-0.086	-0.309	0.431
Skew	-0.390	-0.752	-0.243	-0.472	-0.538	-0.192
Kurt	3.972	6.114	4.630	4.937	4.767	3.104

Appendix A US sectors

We use 17 US equity sectors, including food (FD), banks, insurance companies, & other financials (FN), mining & minerals (MM), oil & petroleum products (OL), chemicals (CM), consumer durables (CD), drugs, soap, perfumes, & tobacco (CN), construction & construction materials (CM), steel works (SW), fabricated products (FP), machinery & business equipment (ME), automobiles (AT), utilities (UT), textiles, apparel & footwear (TX), transportation (TP), retail stores (RS), and other (OT). The summary statistics for these sectors are reported in Table A.1.

Appendix B Commodity risk factors and other characteristics

We use portfolio sorting and systematic long-short strategies to construct a set of commodity risk factors and characteristics. 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 rebalanced monthly with updated pricing characteristics.

Average (AVG): Bakshi et al. (2019) find that a model without featuring an average factor fails to explain the time-series variation in commodity futures returns. We therefore calculate the average (AVG) factor 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) and Yang (2013), we apply the roll-yield to measure the slope of the futures curve of commodity k at time t as follows:

$$\text{Basis}_{k,t} = \log(P_{k,t}^{(1)}) - \log(P_{k,t}^{(2)}), \tag{B.1}$$

where $P_{k,t}^{(1)}$ and $P_{k,t}^{(2)}$ represent the first-nearest and second-nearest contracts price of commodity k at time t, respectively. The term structure (basis) strategy buys (sells) contracts with the highest (lowest) roll-yield sorted quintile portfolios.

Momentum (MOM): 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 momentum factor as follows:

$$\mathrm{MOM}_{k,t} = (\frac{1}{12})\sum_{j=0}^{11} r_{k,t-j}, \tag{B.2}$$

where $r_{k,t-j}$ represents the first-nearest contract returns of commodity k in month $t-j$. Based on this $MOM_{k,t}$ signal, we first sort commodities into quintile portfolios at the end of month t. Next, 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:

$$\mathrm{MOM}_{k,t}^{Cum} = \prod_{j=0}^{11}(1 + r_{k,t-j}) - 1. \tag{B.3}$$

Empirical results from using alternative momentum formation procedures are qualitatively similar.

Basis-Momentum (BMom): 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 first- and second-nearby futures contracts:

$$\mathrm{BMom}_{k,t} = \prod_{j=0}^{11}(1 + r_{k,t-j}^{(1)}) - \prod_{j=0}^{11}(1 + r_{k,t-j}^{(2)}), \tag{B.4}$$

where $r_{k,t-j}^{(1)}$ and $r_{k,t-j}^{(2)}$ represent the first- and second-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.

Relative basis (RB): Gu et al. (2023) propose a better measure of convenience yield implied by the Theory of Storage, the relative basis (RB). They find that the RB dominates the traditional basis in predicting future commodity returns and better reflects temporary fluctuations in commodity inventories. Moreover, the RB is a priced characteristic in commodity futures markets. The RB is calculated as the difference between a traditional short-term basis and a similarly defined long-term basis:

$$\mathrm{RB}_{k,t} = \frac{\log(P_{k,t}^{(1)}) - \log(P_{k,t}^{(2)})}{T_2 - T_1} - \frac{\log(P_{k,t}^{(2)}) - \log(P_{k,t}^{(3)})}{T_3 - T_2}, \tag{B.5}$$

where $P_{k,t}^{(1)}$, $P_{k,t}^{(2)}$ and $P_{k,t}^{(3)}$ are futures prices for the first-, second- and third-nearest futures contract of commodity k with expiration dates T_1, T_2, and T_3, respectively, at the end of month t. The RB factor is constructed by taking a long (short) position in commodities with high (low) relative basis characteristics.

Hedging pressure (HP): Following Kang et al. (2020), we construct the hedging pressure (HP) variable to characterize the trading behaviour of market participants in commodity futures markets. In particular, we compute $HP_{k,w}$ for commodity k in week w as follows:

$$\mathrm{HP}_{k,w} = \frac{CS_{k,w} - CL_{k,w}}{OI}, \tag{B.6}$$

where $CS_{k,w}$ and $CL_{k,w}$ are the number of contracts that commercial traders take short positions and the number of contracts that they take long positions, respectively, OI is the commodity's most recent open interest, that is, the total number of contracts outstanding for commodity k in week w. Since the COT report provided by the CFTC is available at the weekly frequency, we use the HP calculated for the week at the end of each month as the monthly HP measure. We form the HP factor by taking a long (short) position in commodities with high (low) hedging pressure.

Liquidity: Following Szymanowska et al. (2014) which apply the Amivest measure for liquidity of Amihud et al. (1997), we construct the liquidity sorting variable as follows:

$$\text{Amivest}_{k,t} = \frac{1}{D}\sum_{d=1}^{D}\frac{VOL_{k,d}}{|r_{k,d}|}, \tag{B.7}$$

where $r_{k,d}$ and $VOL_{k,d}$ denote the first-nearest contracts' daily return and daily dollar volume of commodity k at time d, respectively. D represents the number of days in the prior two-month. A lower value of this measure indicates low liquidity and is associated with higher expected returns as investors require compensation for holding assets with poor liquidity. Therefore, the liquidity variable is constructed as the return difference between the commodity futures portfolios that consist of commodities with the lowest and highest liquidity proxied by the Amivest measure.

Volatility: Following Szymanowska et al. (2014), we use the coefficient of variation (CV) to measure the volatility as follows:

$$\text{CV}_{k,t} = \frac{\sigma^2_{k,t}}{|\mu_{k,t}|}, \tag{B.8}$$

where $\sigma^2_{k,t}$ represents the variance of the first-nearest contract's daily return series of commodity k at time t during the previous 36 months, and $\mu_{k,t}$ denotes the absolute value of corresponding past 36-month mean daily return of commodity k at month t. Based on the CV forecasting variable, we take long (short) positions in sorted quintile portfolios containing commodities with the highest (lowest) volatilities.

Skewness: Following Fernandez-Perez et al. (2018), we construct the skewness sorting variable as follows:

$$\text{Skew}_{k,t} = \frac{\frac{1}{D}\sum_{d=1}^{D}(r_{k,d}-\mu_{k,t})^3}{\sigma^3_{k,t}}, \tag{B.9}$$

where $r_{k,d}$ represents the daily return of commodity k at time d, $\mu_{i,t}$ and $\sigma_{k,t}$ denote the previous 12-month average daily return and the standard deviation of these past 12-month daily returns of commodity k at month t, respectively. D stands for the number of days in the prior 12 months. The skewness strategy is conducted by buying (selling) quintile portfolios consisting of the most negatively (positively) skewed commodities.

Value: Following Asness et al. (2013) and Fernandez-Perez et al. (2017), we measure the value effect as follow:

$$\text{Value}_{k,t} = \log \frac{\frac{1}{D}\sum_{d=1}^{D} F_{k,d,1}}{F_{k,t,1}}, \tag{B.10}$$

where $F_{k,t,1}$ denotes the price of first-nearest futures contract of commodity k at time t. We set D as the number of days between 4.5 (54) and 5.5 (66) years (months) ago. The numerator is the average daily futures price of commodity k from 54 to 66 months ago. Therefore, a higher value of this signal means that the long-term value of this asset is higher than the contemporaneous price, indicating an upward trend of returns in the subsequent period. The performance of this value strategy is computed by the return gap between the quintile portfolios consisting of commodities with the highest (lowest) $\text{Value}_{k,t}$.

Open interest: Motivated by Hong & Yogo (2012) and Szymanowska et al. (2014), we construct the open interest (OI) factor by sorting commodities into quintile portfolios based on the aggregate open interest along the entire term structure and then conducting the long-short portfolio strategy. We define the open interest signal as:

$$\Delta\text{OI}_{k,t} = OI_{k,t} - OI_{k,t-1}, \tag{B.11}$$

where $OI_{k,t}$ denotes the aggregate open interests of all available contracts for commodity k at the end of month t. This signal therefore measures the monthly changes of OI over the futures curve of all available commodities. We implement the open interest strategy by buying (selling) quintile portfolios consisting of the highest (lowest) changes of OI commodities.

Appendix C Predicting stock market returns

To examine the predictability of cross-sectoral crash risk for future stock market returns, we run the following predictive regression:

$$R_{t\to t+h} = \alpha + \beta \cdot \text{CSC}_t + \epsilon_{t\to t+h}, \tag{C.1}$$

where $R_{t \to t+h}$ is the average market excess returns for the period from t to $t+h$, $h = 1, 3, 6, 9, 12, 24$ months. We calculate the in-sample R^2 and bootstrapped p values for the Hodrick (1992) t-statistics for slope estimates β.

To evaluate the out-of-sample (OOS) predictive ability, we compute the OOS R^2 of Campbell & Thompson (2008) and the mean squared forecasting error (MSFE)-adjusted statistic of Clark & West (2007):

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T} \left(R_t - \widehat{R}_t\right)^2}{\sum_{t=1}^{T} \left(R_t - \bar{R}_t\right)^2}, \tag{C.2}$$

where $\sum_{t=1}^{T} \left(R_t - \widehat{R}_t\right)^2$ is the MSFE of the forecasting model (C.1) and $\sum_{t=1}^{T} \left(R_t - \bar{R}_t\right)^2$ is the MSFE of the benchmark model. Consistent with Campbell & Thompson (2008) and Welch & Goyal (2008), we start with an initialization period of 20 years to generate the first OOS return forecast. We implement a 20-year rolling window and repeat this forecasting exercise until the end of the sample period to estimate $\bar{R}_t$ (Faias & Zambrano, 2022; Welch & Goyal, 2008). A positive value of R^2_{OOS} indicates that Model (C.1) forecasts stock market returns with greater accuracy than the benchmark model does in terms of the MSFE, and vice versa. We collect monthly US value-weighted total market return index and three-month Treasury bill rates from the Bloomberg.

Table C.1 summarizes in-sample estimation and out-of-sample forecasting results. In Panel A, we observe that estimates for slope coefficients are all positive and significant from 1- to 24-month ahead horizons. The economic magnitude of the slope coefficients is sizable ranging from 0.28% to 0.45%. More specifically, since the CSC measure is standardized to have zero mean and unit variance, one standard deviation increase in the CSC risk is associated with a 0.45% increase in one-month ahead US stock market returns. The in-sample regression R^2s are also economically significant ranging from 1.10% to 7.92%. In Panel B, the CSC risk significantly predicts stock market returns out of sample, in line with the evidence in Panel A. In particular, the out-of-sample R^2 based on the MSFE-adjusted statistics is economically large at 2.06%

and statistically significant at the 5% level. Our results show that the CSC risk possesses a strong ability in predicting average stock market returns and this is consistent with theoretical predictions of rare disaster models (Faias & Zambrano, 2022).

Table A.1: **US equity sector**

This table reports the summary statistics of 17 US equity sectors. These include food (FD), banks, insurance companies, & other financials (FN), mining & minerals (MM), oil & petroleum products (OL), chemicals (CM), consumer durables (CD), drugs, soap, perfumes, & tobacco (CN), construction & construction materials (CM), steel works (SW), fabricated products (FP), machinery & business equipment (ME), automobiles (AT), utilities (UT), textiles, apparel & footwear (TX), transportation (TP), retail stores (RS), and other (OT). We report annualized mean returns (Mean) and standard deviations (SD), skewness (Skew), kurtosis (Kurt), maximum (Max), minimum (Min), first-order autocorrelation coefficient ($\rho(1)$). The sample period starts from 1989 to 2022.

Sector	Mean	SD	Skew	Kurt	Max	Min	$\rho(1)$
FD	0.12	0.16	-0.09	11.99	0.10	-0.10	-0.05
FN	0.12	0.30	-0.06	10.50	0.18	-0.16	0.00
MM	0.13	0.26	-0.10	16.46	0.19	-0.20	-0.05
OL	0.12	0.23	-0.11	10.35	0.14	-0.14	0.02
CM	0.08	0.21	-0.34	9.77	0.11	-0.14	0.02
CD	0.12	0.23	-0.28	10.82	0.14	-0.12	-0.02
CN	0.13	0.17	-0.07	9.79	0.11	-0.08	-0.02
CM	0.14	0.23	-0.33	14.16	0.14	-0.19	0.01
SW	0.11	0.31	-0.12	10.50	0.20	-0.16	0.01
FP	0.12	0.20	-0.20	10.64	0.13	-0.12	-0.01
ME	0.14	0.26	0.20	9.62	0.16	-0.13	-0.02
AT	0.13	0.26	-0.11	9.09	0.15	-0.14	0.00
UT	0.12	0.20	-0.39	12.55	0.12	-0.13	0.00
TX	0.11	0.17	0.10	21.20	0.14	-0.12	-0.05
TP	0.13	0.19	-0.06	8.45	0.11	-0.09	-0.01
RS	0.13	0.24	0.07	17.68	0.15	-0.15	-0.06
OT	0.11	0.19	-0.18	10.36	0.10	-0.12	-0.04

Table C.1: **Stock market return predictability of CSC risk**

This table summarizes the in- (Panel A) and out-of-sample (Panel B) stock market return predictability results for the CSC risk. Panel A reports the in-sample R^2 and bootstrapped p values for the Hodrick (1992) t-statistics for slope estimates β in percentage for the predictive regression: $R_{t\to t+h} = \alpha + \beta \cdot \text{CSC}_t + \epsilon_{t\to t+h}$, where $R_{t\to t+h}$ is the average market excess returns from mont t to $t+h$, $h = 1, 3, 6, 9, 12, 24$ months and CSC_t is the standardized CSC risk measure for month t with zero mean and unit variance. Panel B reports the OOS R^2 of Campbell & Thompson (2008) and the mean squared forecasting error (MSFE)-adjusted statistic of Clark & West (2007). We also report Clark & West (2007)'s MSFE-adjusted statistics for the null hypothesis that the stock return forecasts based on the benchmark model encompass the forecasts based on the competing model. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1990 to May 2022.

Panel A: In-sample estimation			
h (months)	β(%)	p-value	R^2(%)
1	0.445**	0.033	1.097
3	0.425**	0.033	2.968
6	0.392**	0.046	4.760
9	0.354*	0.054	5.610
12	0.343*	0.084	6.736
24	0.282*	0.089	7.924
Panel B: Out-of-sample forecasting			
	R^2_{OOS}(%)	MSFE-adjusted	CW p-value
CSC	2.063**	1.738	0.041