Too Connected to Fail: The Risk Spillover from the Real Estate Industry to Real Sector

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Abstract

Under the background of downward of the real estate industry, the systemic risk caused by the real estate has begun to receive high attention from the government and investors. The paper uses the EGARCH-SGT-dynamic CoVaR model to comprehensively measure and compare the extreme risk spillover effects of China's real estate industry to 25 real industries from the industry-wide analytical perspective, and analyzes the evolution characteristics of risk spillover level under various factors from 2005 to 2023. The final conclusions are follows: firstly, the risk spillover effect of the real estate industry to the real industries is comprehensive and systematic. Existing researches only focus on the risk spillover effect of the real estate industry to some upstream and downstream real industries leads to a serious underestimation of the real estate real industry risk; Secondly, during the stages of expansion of the real estate industry respectively, leading to an increase and decrease in risk spillovers to the real industries; Thirdly, the risk spillover level of the real estate industry to building materials, national defense and military industry, coal, textile and clothing, machinery, commerce and retail, electronics, computer, light industry manufacturing, steel, media and basic chemical industry is generally higher than other industries, belong to the "system vulnerability real industries". This study can not only provioide theoretical basis for the financial regulatory authorities to grasp the key points of real estate systemic risk prevention, but also provides reference for investors of the real industry shocks to make decisions.

Keywords: The real estate-real industry risk, systemic risk, CoVaR

1 Introduction

The global financial crisis of 2008, followed by the European sovereign debt crisis, reignited concerns about systemic risk (Gomez-Gonzalez et al., 2018). Traditionally, systemic risk refers to the risk of a disruption to the well-functioning of financial services that is caused by an impairment of all or parts of the financial system and has the potyential to have serious negative consequences on the real economy Martínez-Jaramillo et al. (2010); Silva et al. (2018). Thus, mitigating systemic risk is of utmost importance for financial supervisors and policy makers.

Previous studies have primarily focused on risk spillovers within the financial sector (Billio et al., 2012; Chen et al., 2022; Ke et al., 2024), between financial and real estate sectors (Huang et al., 2022; Ouyang and Zhou, 2023; Aharon et al., 2024), between financial and real sectors (Silva et al., 2018; Brunnermeier et al., 2020; Xiang and Borjigin, 2023), as well as within different housing markets (Gomez-Gonzalez et al., 2018; Cohen and Zabel, 2020; Zhu and Lizieri, 2021). Notwithstanding fruitful results have been yielded in existing studies, they all keep silent on the spillover effects of real estate market risks on the broader real economy. As Iacoviello and Neri (2010) suggests, the dynamics of the housing market are not just a passive reflection of macroeconomic conditions but can also significantly drive business cycles. For instance, the 2008 subprime mortgage crisis, triggered by a sharp decline in U.S. real estate prices, caused a severe global financial meltdown. Similarly, the bursting of the Japanese real estate bubble in the late 20th century led to a prolonged economic downturn in Japan. These cases highlight the critical need to understand and measure the spillover risks from the real estate sector to other industries in order to prevent and mitigate systemic risks (Iacoviello and Neri, 2010; Iacoviello, 2010).

Following the abolition of welfare housing in 1998 and the subsequent housing market reforms, real estate became a primary driver of China's economic development. The sector contributes approximately 10% to China's GDP and supports over 15% of urban employment (Rogoff and Yang, 2021). Real estate-related income accounts for 50% of local government revenues, and real estate assets constitute 60% of urban household wealth (Ouyang and Zhou, 2023). By the end of 2020, the liabilities of China's publicly traded real estate companies had reached RMB 10.47 trillion, with 31.2% arising from contract liabilities and 17.65% from long-term bank loans (Altman et al., 2022).

On the other hand, this rapid growth has also introduced substantial financial systemic risks. As highlighted by Zhou Xiaochuan, former governor of the People's Bank of China, and Guo Shuqing, chairman of the China Banking and Insurance Regulatory Commission, the real estate sector is the "biggest gray rhino" in the Chinese economy, with the potential for a Minsky moment should a crisis occur.[1] Especially under the circumstance of industrial transformation and upgrading in China, cross-industry risk contagion has become a significant hidden danger affecting financial stability. Specifically, The interconnectedness of the real estate sector with industries such as construction, finance, retail, and manufacturing suggests that fluctuations in the real estate market can trigger cascading effects across the economy. As housing prices rise, real estate developers often expand borrowing to fuel construction, potentially inflating a housing bubble. When prices fall, developers face liquidity risks and solvency problems, which not only disrupt their own operations but also reverberate throughout the industrial chain. These effects can lead to massive losses in related sectors through channels such as asset-liability linkages and input-output relationships. As a pillar industry of the national economy, the real estate industry has a large financing scale and a long industrial chain and forms extensive and close industrial associations with other real economic industries through supply-demand relationships. The real estate industry's vast scale and deep integration with the broader economy underscore its status as "too big to fail" and, moreover, "too connected to fail."

However, the sector's rapid development has also exposed significant vulnerabilities, such as high leverage, overcapacity, and excessive financialization (Ouyang and Zhou, 2023). The sharp decline in China's real estate market since mid-2021 has exposed the sector's sys-

[1] See http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/3410388/index.html.

temic risks, with Evergrande Group serving as a prominent example of the "too connected to fail" phenomenon. As the second-largest property developer in China and a member of the Fortune Global 500, Evergrande's debt crisis exemplifies the vulnerabilities inherent in the sector. Since 2021, more than 50 Chinese property firms have defaulted on their debt. Xiao Yuanqi, deputy director of China's National Financial Regulatory Administration, noted that China's financial institutions bear "an inescapable responsibility to provide strong support" to the property sector.[2] This raises critical questions: is there a contagion effect between the real estate industry and the broader real sector? To what extent do real estate market fluctuations affect other sectors? Which industries exhibit resilience, and which show vulnerability? What mechanisms underlie the cross-industry transmission of real estate risks?

Against this backdrop, this paper comprehensively measures the extreme risk spillover from China's real estate industry to 25 real industries from 2005 to 2023, using CITIC primary industry index data. We analyze the dynamic evolution of these spillovers under financial crisis, stringent macro-control regulatory policies, COVID-19 pandemic, and property crisis. We regard our contributions as threefold. First, to the best of our knowledge, this study provides the most comprehensive investigation of the dynamic extreme risk spillover from China's real estate industry to real sector. Specifically, unlike previous studies which only considered very limited industries, this study incorporates 25 industries, thereby providing an in-depth picture of the risk transmission among industries. Second, this study is the first to provide a time-varying perspective to investigate the evolution of risk spillover levels from 2005 to 2023, considering impacts from some critical events in Chinese housing market such as the financial crisis, frequent regulatory policies, and real estate market conditions. We reveal the dynamic transmission mechanism of real estate industry to specific industries, providing a more targeted policy suggestions. This in-depth examination of the dynamic transmission mechanism of financial crises has great practical importance for both

[2] See https://edition.cnn.com/2024/01/31/business/evergrande-explainer-what-next-intl-hnk/index.html.

investors, to take preventive measures against the spread of crises, and for policymakers, to regulate the financial markets and manage market expectations.

Our findings can be summarized as follows. First, the risk spillover from the real estate industry to the real sector is profound and systematic. Studies confined to upstream and downstream industries will lead to a significant underestimation of real estate-related risks. Thus, the real estate industry is too connected to fail. Second, during periods of financial crisis and real estate expansion, the risk spillover from the real estate industry to the real sector increases substantially. And we found that tight policies can inhibit expansion, thus influencing the intensity of risk spillover. Third, the risk spillover is generally higher for industries such as building materials, national defense, coal, textiles, machinery, commerce, electronics, computers, light manufacturing, steel, media, and basic chemicals, which are part of the "systemically fragile real economy". This study not only offers a theoretical foundation for regulatory authorities to prioritize real estate risk prevention but also provides valuable insights for stock investors in the real economy to make informed decisions.

The rest of this paper is organized as follows. Section 2 introduces the methodology. Section 3 presents the data description. Section 4 reports the empirical results. Section 5 concludes.

2 Methodology

2.1 VaR and CoVaR measures

Ever since the early 1990s, the leading tool for measuring market risk has been the Value at Risk (VaR). Downside VaR summarizes the worst loss of asset j that will not be exceeded at a confidence level of $1-\alpha$, such that $Pr(R_{j,t} \leq VaR^{j}_{\alpha,t}) = \alpha$.

VaR alone, however, is insufficient for capturing the risk spillover that may occur among various assets in a portfolio. To address this limitation, Tobias and Brunnermeier (2016) propose the conditional Value at Risk measure (CoVaR), which is further generalized by Girardi and Ergün (2013). In particular, the downside CoVaR of sector j, denoted as $CoVaR^{j|i}_{\beta,t}$, could measure the maximum potential loss of sector j when sector i (i.e., real estate sector in this study) is experiencing distress. Let $R_{j,t}$ be the returns for the sector index j. The CoVaR under confidence level $1-\beta$ can be formally defined as the β-quantile of the conditional distribution of $R_{j,t}$ as:

$$\Pr(R_{_{j,t}} \leq CoVaR^{j|i}_{\beta,t} \mid R_{_{i,t}} \leq VaR^{i}_{_{\alpha,t}}) = \beta, \quad \alpha, \beta \in (0,1), \tag{1}$$

where $VaR^{i}_{_{\alpha,t}}$ is the VaR for sector i, measuring the maximum loss that sector i may experience for a confidence level $1-\alpha$ and a specific time horizon, that is, the α-quantile of the sector i return distribution: $Pr(R_{_{i,t}} \leq VaR^{i}_{_{\alpha,t}}) = \alpha$. We could express Eq. (1) as:

$$\frac{\Pr\left(R_{j,t} \leq CoVaR^{j|i}_{\beta,t}, R_{i,t} \leq VaR^{i}_{\alpha,t}\right)}{\Pr\left(R_{i,t} \leq VaR^{i}_{\alpha,t}\right)} = \beta. \tag{2}$$

Given that $\Pr\left(R_{i,t} \leq VaR^{i}_{\alpha,t}\right) = \alpha$, the CoVaR in Eq. (2) can be expressed as:

$$\Pr\left(R_{j,t} \leq CoVaR^{j|i}_{\beta,t}, R_{i,t} \leq VaR^{i}_{\alpha,t}\right) = \alpha\beta. \tag{3}$$

2.2 Estimating CoVaR with ARMA-EGARCH-SGT-dynamic copula

As recommended by Reboredo and Ugolini (2015), we compute the CoVaR through ARMA-EGARCH-SGT-dynamic copula approach. Quantile regression poses challenges in identifying suitable state variables for price fluctuations in our sector indices Tobias and Brunnermeier (2016). On the other hand, copula's flexibility in specifying the marginal distributions of individual asset returns and their dependence structure separately is well-documented (Reboredo et al., 2016). This methodological decision aligns well with our study's requirements, as it involves jointly modeling returns for real estate industry and other real industries. Importantly, we employ a dynamic copula approach to capture the nonlinear, tail, time-varying, and asymmetric correlations - characterize the structure of interdependence between paired variables. In particular, let $R_{i,t}$ and $R_{j,t}$ denote the returns of real estate industry and other real industries, respectively. Note that Eq. (3) can be expressed in terms of the joint distribution function of $R_{j,t}$ and $R_{i,t}$, $F_{R_{j,t},R_{i,t}}$, as:

$$F_{R_{j,t},R_{i,t}}(CoVaR^{j|i}_{\beta,t}, VaR^{i}_{\alpha,t}) = \alpha\beta, \tag{4}$$

and that, according to the Sklar (1959)'s theorem, the joint distribution function of two continuous variables can be expressed in terms of a copula function. Hence Eq. (4) can be written as:

$$C(u,v) = \alpha\beta, \tag{5}$$

where $C(\cdot,\cdot)$ is a copula function, $u = F_{R_{j,t}}(CoVaR^{j|i}_{\beta,t})$ and $v = F_{R_{i,t}}(VaR^{i}_{\alpha,t})$.

The copula functions commonly-used in the empirical analysis include the Gaussian copula with tail independence; the Student-t copula with symmetric tail dependence; the Gumbel copula with upper tail dependence and lower tail independence; the rotated Gumbel copula with lower tail dependence and upper tail independence; and the Symmetrized Joe-Clayton (SJC) copula with differing upper and lower tail dependence (Reboredo et al., 2016). However, the Gaussian copula fails to capture tail dependence, and the Student-t copula describes only symmetric and full range of dependence structure (Sun et al., 2020). Moreover, the superiority of mixed copula model in capturing the dependence structure among different data series has been well-documented (Chang, 2012; Chen et al., 2014; Sun et al., 2020). As the mixed copula model is a linear combination of several single copula models, it inherits the basic properties of all sub copula models. Driven by their flexibility of characterizing the tail dependence patterns, we primarily focus on the MixGrG copula (i.e., Mixture Gumbel/ 180-degree rotated Gumbel copula) and SJC copula in this study.

The MixGrG is a common static Archimedean mixed copula model. This model has three parameters, which are δ_G of Gumbel copula, δ_{rG} of rotated Gumbel copula, and ω_G, the weight of Gumbel copula. The Gumbel copula is asymmetric and displays upper tail dependence and lower tail independence, while the 180-degree rotated Gumbel copula displays upper tail independence and lower tail dependence. Thus, their linear combination can describe the upper and lower tail dependence simultaneously. Besides, this model can also simultaneously describe the symmetric and asymmetric dependence structure. Therefore, this model enjoys very high flexibility, which can be expressed as:

$$C_{MixGrG}(R_i, R_j; \delta_G, \delta_{rG}, w_G) = w_G C_{Gumbel}(R_i, R_j; \delta_G) + (1 - w_G) C_{rotated\ Gumbel}(R_i, R_j; \delta_{rG}),$$

where

$$C_{Gumbel}(R_i, R_j; \delta_G) = \exp(-[(-\ln R_i)^{\delta_G} + (-\ln R_j)^{\delta_G}]^{\frac{1}{\delta_G}}),\ 1 \leq \delta_G < \infty$$

$$C_{rotated\ Gumbel}(R_i, R_j; \delta_{rG}) = R_i + R_j - 1 + C_{Gumbel}(1 - R_i, 1 - R_j; \delta_{rG}),\ 1 \leq \delta_{rG} < \infty.$$

And the SJC copula can be written as:

$$C(R_i, R_j; \delta_S, \theta_S) = 1 - \Big(1 - \left[(1 - (1 - R_i)^{\theta_S})^{-\delta_S} + (1 - (1 - R_j)^{\theta_S})^{-\delta_S} - 1\right]^{-1/\delta_S}\Big)^{1/\theta_S}, \theta_S \geq 1, \delta_S > 0.$$

To account for time-varying dependence, we allowed the parameters of some copula specifications to change over time. The three parameters of dynamic MixGrG copula are assumed to follow the ARMA(1, q) process given by:

$$\delta_{G,t} = \omega_G + \beta_G \delta_{G,t-1} + \alpha_G \times \frac{1}{q} \sum_{k=1}^{q} \left| R_{i,t-k} - R_{j,t-k} \right|, \tag{6}$$

$$\delta_{rG,t} = \omega_{rG} + \beta_{rG} \delta_{rG,t-1} + \alpha_{rG} \times \frac{1}{q} \sum_{k=1}^{q} \left| (1 - R_{i,t-k}) - (1 - R_{j,t-k}) \right|, \tag{7}$$

$$w_{G,t} = \Lambda\left(\omega_w + \beta_w w_{G,t-1} + \alpha_w \times \frac{1}{q}\sum_{k=1}^{q}|R_{i,t-k} - R_{j,t-k}|\right), \tag{8}$$

where we set $q = 10$, $\Lambda \equiv (1 - e^{-x})(1 + e^{-x})^{-1}$ is the modified logistic transformation that keeps the value of $\omega_{G,t}$ in $(0, 1)$ (See Patton, 2006). And the two time-varying parameters of dynamic SJC copula model can be defined as follows:

$$\theta_{S,t} = \omega_S + \beta_S \theta_{S,t-1} + \alpha_S \frac{1}{q}\sum_{k=1}^{q}|R_{i,t-k} - R_{j,t-k}|,$$

$$\delta_{S,t} = \bar{\omega}_S + \bar{\beta}_S \delta_{S,t-1} + \bar{\alpha}_S \frac{1}{q}\sum_{k=1}^{q}|R_{i,t-k} - R_{j,t-k}|.$$

To derive the joint distribution of the two return series, we first model the marginal distributions of each series separately and then fit the copula model $C(\cdot)$ with the filtered returns z_{it}. Following Reboredo et al. (2016), the marginal densities of the sector returns $(R_{n,t})$ were characterized by an ARMA(p, q) model:

$$R_{n,t} = \mu_{n,t} + \varepsilon_{n,t} = \sum_{i=1}^{p}\varphi_{n,i}R_{n,t-i} + \sum_{j=1}^{q}\phi_{n,j}\varepsilon_{n,t-j} + \varepsilon_{n,t}, \tag{9}$$

where p and q are non-negative integers and where $\varphi_{n,i}$ and $\phi_{n,j}$ are the autoregressive (AR) and moving average (MA) parameters. $\varepsilon_{n,t} = \sigma_{n,t}z_{n,t}$, where $\sigma^2_{n,t}$ is the conditional variance that has dynamics as given by an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model in this study:

$$\ln(\sigma^2_{n,t}) = \omega_n + \sum_{k=1}^{r}\alpha_{n,k}\left(\frac{|\varepsilon_{n,t-k}|}{\sigma_{n,t-k}} - E\left[\frac{|\varepsilon_{n,t-k}|}{\sigma_{n,t-k}}\right]\right) + \sum_{h=1}^{m}\beta_{n,h}\ln(\sigma^2_{n,t-h}) + \sum_{k=1}^{r}\gamma_{n,k}\frac{\varepsilon_{n,t-k}}{\sigma_{n,t-k}} \tag{10}$$

where γ_n is the coefficient of the leverage term. We choose this model for its ability to characterize the leverage effect which is a well-established empirical fact in Chinese equity market (Long et al., 2014). This coefficient is usually a negative number, which implies that the previous negative news tend to exert a larger influence on the variance of the current returns than that of positive ones. $z_{n,t}$ is an $i.i.d.$ random variable with zero mean and unit variance.

Considering the non-normal characteristics of sector indices returns, the conventional ARMA-EGARCH-normal model fails to capture the patterns. SGT distribution, advanced by Theodossiou (1998), is displaced for well-describing the distribution of asset returns exhibiting skewness and leptokurtosis. The probability density function for the SGT distribution can be represented as follows:

$$f\left(z_{n,t} \mid \kappa_n, \lambda_n, \eta_n\right) = C_n \cdot \left(1 + \frac{\left|z_{n,t} + \delta_n\right|^{\kappa_n}}{\left(\left(\eta_n + 1\right)/\kappa_n\right)\left(1 + sign\left(z_{n,t} + \delta_n\right)\lambda_n\right)^{\kappa_n} \theta_n^{\kappa_n}}\right)^{-\frac{\eta_n+1}{\kappa_n}} \tag{11}$$

where

$$C_n = 0.5\kappa_n \left(\frac{\eta_n + 1}{\kappa_n}\right)^{-\frac{1}{\kappa_n}} B\left(\frac{\eta_n}{\kappa_n}, \frac{1}{\kappa_n}\right)^{-1} \theta_n^{-1}, \quad \theta_n = \frac{1}{\sqrt{g_n - \rho_n^2}}$$

$$g_n = \left(1 + 3\lambda_n^2\right) B\left(\frac{\eta_n}{\kappa_n}, \frac{1}{\kappa_n}\right)^{-1} \left(\frac{\eta_n + 1}{\kappa_n}\right)^{\frac{2}{\kappa_n}} B\left(\frac{\eta_n - 2}{\kappa_n}, \frac{3}{\kappa_n}\right)$$

$$\rho_n = 2\lambda_n B\left(\frac{\eta_n}{\kappa_n}, \frac{1}{\kappa_n}\right)^{-1} \left(\frac{\eta_n + 1}{\kappa_n}\right)^{\frac{1}{\kappa_n}} B\left(\frac{\eta_n - 1}{\kappa_n}, \frac{2}{\kappa_n}\right), \delta_n = \rho_n \theta_n,$$

where λ_n is a skewness parameter, "$sign(\cdot)$" is the sign function, $B(\cdot)$ is the beta function, and δ_n is the Pearson's skewness and mode of $f(z_{n,t})$. The scaling parameters η_n, κ_n, and λ_n obey the following constraints: $\eta_n > 2$, $\kappa_n > 0$, and $-1 < \lambda_n < 1$. The skew parameter λ_n controls the rate of descent of the density around the mode of z. In the case of positive skewness ($\lambda_n > 0$), the density function is skewed to the right. In contrary, the density function is skewed to the left with the negative skewness ($\lambda_n < 0$). The parameters η_n and κ_n control the tail and the height of the density. Smaller values of κ_n and η_n result in larger values for the kurtosis (i.e., more leptokurtosis p.d.f.s) and vice versa. The SGT distribution nests several well-known distributions, as reported in Table A.1.

Given the marginal distributions and the time-varying mixed copula model specified, we can use the procedure proposed by Reboredo et al. (2016) to represent $CoVaR$ in Eq. (1)

and $\Delta CoVaR$ in Eq. (16). With the specific form of the copula function (5), we can solve Eq. (4) in order to obtain the value of $F_{R_{j,t}}(CoVaR_{\beta,t}^{j|i})$ first (i.e., $C^{-1}(\alpha\beta;\alpha)$). Then, we can obtain the $CoVaR$ value as the quantile of the function of $R_{j,t}$:

$$CoVaR_{\beta,t}^{j|i} = F_{R_{j,t}}^{-1}(C^{-1}(\alpha\beta;\alpha)). \tag{12}$$

2.3 Hypothesis tests for contagion effects

In this section, we test for the contagion effects from the real estate industry to the real sector. Specifically, we test for the significance of systemic risk by comparing the cumulative distribution for $CoVaR_{\beta,t}^{j|i}$ and the $VaR_{\beta,t}^{j}$ of the real sector using the KS bootstrapping test as proposed by Abadie (2002) and applied by Bernal et al. (2014) to compare $CoVaR$ values. The KS test measures the difference between two cumulative quantile functions relying on the empirical distribution function but without considering any underlying distribution function. It is defined as:

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_x |F_m(x) - G_n(x)|, \tag{13}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative $CoVaR$ and VaR distribution functions, respectively, and n and m are the size of the two samples. With the statistic we tested the hypothesis of no systemic impact from real estate industry to the real sector as:

$$H_0 : CoVaR_{\beta,t}^{j|i} = VaR_{\beta,t}^{j}, \tag{14}$$

against the alternative hypothesis that the real estate industry show significant contagion effects on real sector,

$$H_0 : CoVaR_{\beta,t}^{j|i} < VaR_{\beta,t}^{j}. \tag{15}$$

2.4 Tail-risk spillover measures and their influencing factors

The KS test statistic, as expressed in Eq. (13), is a valuable tool for testing the contagion effects from real estate industry to real sector. Therefore, we use the downside-to-downside $\Delta CoVaR$ proposed by Tobias and Brunnermeier (2016) and Girardi and Ergün (2013) to quantify the risk spillover from real estate industry (denoted as i for simplicity here) to other real industry j, which is the difference in the $CoVaR$ of real industry j when real estate industry i is under distress ($i = VaR^i_\alpha$) and the median state ($i = VaR^i_{0.5}$). $\Delta CoVaR$ can be signified as:

$$\Delta CoVaR^{j|i}_{\beta,t} = CoVaR^{j|i \leq VaR^i_{\alpha,t}}_{\beta,t} - CoVaR^{j|i=VaR^i_{0.5,t}}_{\beta,t}. \tag{16}$$

$\Delta CoVaR^{j|i}_{\beta,t}$ captures the change in extreme losses of real industry i when the real estate industry i shift from normal to extreme market conditions. We use this as a measure of contagion intensity in the real sector when discussing tail-risk spillovers from the real estate industry. The larger the $\Delta CoVaR^{j|i}_{\beta,t}$ is, the higher the risk spillover level of the asset j when it confronted with extreme losses, and vice versa.

3 Data

We empirically assess the spillover effects between the real estate industry and a range of upstream and downstream industries using daily data from the 26 level-1 industry indices of China International Trust Investment Corporation (CITIC). These industry indices, sourced from the WIND database, cover the period from January 4, 2005, to May 31, 2023. Given the comprehensive nature of CITIC's level-1 industry indices and the substantial heterogeneity among industries, we selected them as our sample to ensure a thorough analysis. Specifically, our research focuses on the real estate industry alongside 25 other industries, encompassing a diverse set of economic activities. The 26 industries included in our analysis are Real Estate, Petrochemical, Coal, Nonferrous, Electricity & Utilities, Steel, Basic Chemicals, Construction, Building Materials, Light Industry, Machinery, Power Equipment, National Defense, Automobile, Retail Trade, Catering & Travel, Home Appliances, Textiles & Garments, Pharmaceuticals, Food & Beverages, Agriculture, Forestry, Animal Husbandry & Fishery, Banks, Non-banking, Transportation, Electronic Components, Communications, Computers, Media, comprehensive, and comprehensive finance. We sourced the data from WIND database. All industry index data were sourced from the WIND database and converted into logarithmic return sequences for analysis, as defined in Eq. (17):

$$R_{n,t} = 100 \cdot ln(p_{n,t}/p_{n,t-1}), \tag{17}$$

where $p_{n,t}$ represents the closing prices of industry n at day t and $R_{n,t}$ is the corresponding return rate.

Figure A.1 illustrates the temporal dynamics of returns for each industry index. A preliminary examination of the data reveals that the intensity of co-movement between the real estate industry and the real economy fluctuated over time and across industries. Return volatility in both the real estate and real industries also varied throughout the sample period, particularly during the global financial crisis, the 2015 stock market crash, and the COVID-19 pandemic. However, the extent of volatility differed significantly across industries. For example, industries such as Building Materials, Coal Mining, Diversified Metals, Defense, Electricals, and Computers experienced intense volatility, while sectors like Petrochemicals, Power & Utilities, and Construction Engineering exhibited relatively lower variability.

Table 1 presents the descriptive statistics for the returns of all the industry indices considered. Average returns ranged from 0.010 for the Steel industry to 0.073 for the Food & Beverage industry, while standard deviations vary from 1.729 of Power & Utilities industry to 2.400 for the Computer industry. An initial inspection of Table 1 reveals that Food & Beverages, Household Appliances, Pharmaceuticals, and Electrical Equipment & New Energy exhibit higher mean returns, whereas Computer, Diversified Metals, Coal Mining, and Defense are high-risk industries are the most volatile industries based on standard deviation.

This indicates significant variation in return behavior across industries. Similarly, the large gaps between maximum and minimum industry returns suggest greater price fluctuations in Coal Mining, Electrical Equipment & New Energy, Defense, Computer, and Media industries. All industries exhibit negative skewness values, implying that asset returns are skewed to the left. The skewness is particularly pronounced in the Light Manufacturing and Textiles & Apparel industries, suggesting a higher likelihood of large declines. Regarding kurtosis, all industries display high values, indicating distributions with thicker tails than a normal distribution. Consequently, the Jarque-Bera test strongly rejects the normality assumption for all series. The results of the ADF non-stationary tests confirm that all industry return series are stationary. Moreover, the Ljung-Box Q(5) statistics suggests the presence of serial correlation in all of the industries, while the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic indicates significant ARCH effects in all return series.

Table 1: Descriptive statistics of industry index returns

Industry	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	J-B	ADF	Q(5)	ARCH
Real Estate	0.034	2.105	9.448	-9.975	-0.446	6.023	1850.1*	-16.288*	22.51*	152.89*
Petrochemical	0.022	1.753	9.369	-10.448	-0.510	7.140	3387.1*	-15.611*	20.02*	144.41*
Coal Mining	0.024	2.359	9.519	-10.524	-0.210	5.432	1135.3*	-15.549*	8.53*	167.04*
Diversified Metals	0.041	2.372	9.538	-10.216	-0.374	5.229	1030.1***	-15.488***	19.49***	265.19***
Power & Utilities	0.022	1.729	9.496	-10.429	-0.797	8.853	6856.9*	-15.289*	21.22*	552.52*
Steel	0.010	2.067	9.508	-10.326	-0.483	6.668	2681.4*	-15.031*	18.41*	311.96*
Basic Chemical Engineering	0.039	1.935	9.238	-10.225	-0.706	6.510	2667.0*	-15.666*	45.52*	341.25*
Construction Engineering	0.029	1.919	9.555	-10.474	-0.544	7.402	3830.8*	-15.306*	13.51*	315.15*
Building Materials	0.042	2.069	9.413	-10.102	-0.570	6.068	1996.3*	-15.353*	35.96*	306.79*
Light Manufacturing	0.027	1.974	9.375	-10.000	-0.879	7.219	3893.8*	-15.284*	40.65*	352.16*
Machinery	0.041	1.970	9.474	-10.375	-0.674	6.814	3049.2*	-14.957*	35.36*	273.61*
Electrical Equipment & New Energy	0.051	2.083	9.538	-10.526	-0.535	6.101	2006.1*	-15.302*	26.84*	351.58*
Defense	0.048	2.355	9.533	-10.528	-0.466	5.827	1651.7*	-16.077*	38.38*	403.73*
Automobile	0.047	1.999	9.319	-10.375	-0.592	6.185	2152.6*	-14.906*	28.05*	259.82*

Continued

Industry	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	J-B	ADF	Q(5)	ARCH
Commerce & Trade Retail Business	0.029	1.895	9.430	-10.441	-0.769	7.734	4617.1*	-15.476*	37.25*	466.54*
Consumer Service	0.049	2.139	9.537	-10.401	-0.521	5.966	1841.7*	-15.911*	30.28*	369.77*
Household Appliances	0.056	1.928	9.528	-10.480	-0.414	6.080	1895.8*	-14.991*	19.26*	257.38*
Textiles & Apparel	0.023	1.958	9.527	-10.412	-0.838	7.598	4464.4*	-15.206*	48.29*	442.55*
Pharmaceuticals	0.055	1.865	9.499	-10.334	-0.567	6.425	2425.2*	-15.549*	36.18*	342.91*
Food & Beverage	0.073	1.811	9.239	-10.053	-0.289	5.643	1364.5*	-15.192*	15.38*	15.381*
Agriculture, Forestry, Fishery & Animal Husbandry	0.037	2.084	9.449	-10.475	-0.561	6.368	2348.1*	-16.154*	51.76*	440.38*
Transportation	0.014	1.819	9.528	-10.273	-0.668	7.961	4920.0*	-15.425*	22.21*	286.73*
Electricals	0.043	2.257	9.360	-10.597	-0.643	5.815	1785.1*	-16.421*	17.14*	196.24*
Telecommunications	0.034	2.075	9.557	-10.308	-0.491	6.177	2060.3*	-16.185*	10.20*	306.06*
Computer	0.041	2.400	9.532	-10.533	-0.512	5.380	1251.5*	-15.493*	27.58*	350.40*
Media	0.024	2.257	9.528	-10.529	-0.528	5.674	1541.0*	-15.733*	12.26*	295.72*

* Daily data cover the period January 4, 2005 to May 31, 2023. Std. Dev. denote the standard deviation for series. The skewness and kurtosis of normal distribution are 0 and 3, respectively. J-B denote the Jarque-Bera statistics for normality. $Q(5)$ is the Ljung-Box statistics for serial correlation in returns computed with 5 lags and ARCH denotes Engle's LM test for heteroskedasticity computed using 1 lag. An asterisk (*) indicates rejection of the null hypothesis at 5%.

4 Empirical results

4.1 Marginal model results

The marginal models in Eqs. (9)-(11) were estimated for returns for the different industries. The values of the p and q parameters were chosen-considering lag values ranging from zero to a maximum of two-so as to minimize the AIC values following Reboredo et al. (2016). Table A.2 reports results for real estate and real industry returns. Consistent with the descriptive evidence on non-normality amnd fat tails reported in Table A.2, the estimated values for the degrees of freedom (i.e., κ), the skewness (i.e., λ) and their statistical significance confirm that the error terms are nor normal and in most cases are asymmetric and fat-tailed.

We also checked the goodness-of-fit of our marginal models. The last rows of Table A.2 indicate that neither autocorrelation nor ARCH effects remain in the residuals of the marginal models. Furthermore, we test the adequacy of the SGT distribution model by testing the null hypothesis that standardized model residuals were uniform $(0, 1)$, comparing the empirical and theoretical distribution function using the Kolmogorov-Smirnov (KS), Cramér-von Mises (CvM), and Anderson-Darling tests. The p-values for these tests, reported in last rows of Table A.2, indicate that, for most of the marginal models, the null of the correct specification of the distribution function could be rejected at the 5% significance level. Overall, our goodness-of-fit tests indicate that the marginal distribution models are not mis-specified, so the copula model was able to correctly capture dependence between real estate and real industries.

4.2 Copula model results

We estimated the time-varying versions of the bi-variate MixGrG and SJC copula models for industry returns. We used as observations the probability integral transformation of the standardized residuals from the marginal models reported in Table A.2, selecting the best copula model as the one that yielded the best AIC value corrected for small-sample bias.

Tables A.3 and A.4 present estimates for the real estate industry returns and their dependence on returns from various real industries. The empirical results indicate a positive and significant dependence between the real estate sector and most real industries. Comparing the two copula specifications, the AIC values favor the time-varying MixGrG copula as the optimal model for all industry pairs. Figure A.2 illustrates the dynamics of dependence over the sample period, showing significant fluctuations in industries such as Transportation, Commerce & Trade Retail, Consumer Services, Telecommunications, and Electricals. These fluctuations underscore the importance of employing a time-varying copula model. In contrast, the dependence parameters for industries such as Petrochemicals, Machinery, Electrical Equipment & New Energy, Defense, and Media show relatively stable trajectories, suggesting a more consistent relationship. Notably, the dependence between the real estate industry and nearly all real sectors exhibited a pronounced increase during the 2015 stock market crash. Similarly, the real estate sector's relationship with several industries remained highly correlated during the 2008 subprime crisis and the COVID-19 pandemic, highlighting the impact of extreme events on dependence relationships.

4.3 The risk spillover from real estate industry to real sector

Using the best-fitting copula and following the two-step procedure described above, we obtained the CoVaR values for the real sector returns at the 95% confidence level ($\beta = 0.05$), conditional on the VaR values for exchange rate returns at the 95% and 50% confidence levels.

Table presents the results of the KS bootstrapping test for the role of real industries when the real estate industry is in distress.

Figure 1 illustrates the evolution of CoVaR for real sectors under both normal and stress conditions in the real estate industry, along with the corresponding -ΔCoVaR for ease of interpretation. These are represented by red, blue, and yellow lines, respectively. These figures illustrate the spillover of systemic risk from the real estate industry to real sector.

Periods of extreme events are highlighted in gray, while dashed vertical lines indicate the issuance dates of key policies in the Chinese housing market.[3] It could be observed that all real industries exhibit similar trends in spillover risk from the real estate industry.

Figure 1 demonstrates that both CoVaR and ΔCoVaR measures clearly capture the impact of major financial crises, including the "subprime mortgage crisis", the "2015 stock market disaster", the escalation of Sino-US trade conflict, and the "COVID-19 pandemic". Each of these events corresponds to a significant reduction in CoVaR and ΔCoVaR values (or, equivalently, a sharp increase in $-\Delta$CoVaR value), indicating a substantial amplification of risk spillovers from the real estate industry to real sector. Notably, the spike in $-\Delta$CoVaR during the 2015 stock market disaster is sharper than that observed during the subprime mortgage crisis, suggesting a more abrupt systemic risk transmission. The trajectories of $-\Delta$CoVaR indicate that the spillover effect from the real estate industry began rising in late 2006 and returned to normal levels by early 2010, lasting approximately three and a half years. During the 2015 stock market crash, ΔCoVaR began increasing in mid-2014 and normalized by late 2016, lasting around one and a half years. For the COVID-19 pandemic, ΔCoVaR started rising in late 2019 and stabilized by early 2023, lasting approximately three years. In terms of systemic risk magnitude, -ΔCoVaR during the 2015 stock market crash was significantly higher than during the subprime mortgage crisis and COVID-19 pandemic. As shown in Fig. 1, -ΔCoVaR values for many real industries peaked at 14 during the 2015 stock market disaster, frequently exceeding 9.00 on most days. In contrast, during the subprime mortgage crisis, -ΔCoVaR values ranged from 4.00 to 6.00, whereas from 3.00 to 5.00 during the Sino-US trade conflict and the COVID-19 pandemic. These findings suggest that the impact of the subprime mortgage crisis and COVID-19 pandemic is more prolonged, while the stock market crash had a relatively short-lived effect.

We offer several potential explanations here. First, in the first half of 2007, amid an overheated real estate market, the accelerated expansion of the real estate sector led to a

[3]See Table A.5 for a detailed summary of major policies and events in the Chinese housing market.

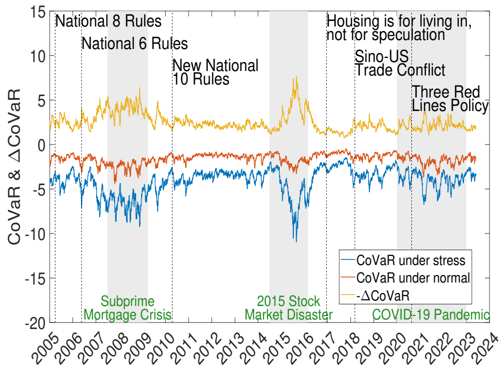
sharp increase in demand for the real economy, deepening industrial linkages, increasing capital flows, and widening channels for risk transmission. As a result, financial distress in the real estate sector was more easily transmitted to other industries through multiple interconnected pathways. Second, during the U.S. subprime mortgage crisis, the Sino-US trade conflict, and the COVID-19 pandemic, financial market turmoil further strengthened the information transmission channels between the real estate and real economy sectors. In particular, persistent stock market declines fueled investor panic, exacerbating the herd effect, where extreme losses in the real estate sector prompted irrational sell-offs of real economy assets. This intensified systemic risk spillovers, significantly increasing risk transmission beyond normal levels. Third, the 2015–2016 stock market crash was primarily driven by the combined effects of real estate overheating and equity market turbulence. On one hand, from mid-2015 to late 2016, China's real estate sector remained highly active, leading to further expansion of both direct and indirect linkages with the real economy and widening risk transmission channels. On the other hand, the stock market collapse amplified the intensity of risk spillovers through the information transmission mechanism. The interplay of direct financial linkages, indirect economic dependencies, and heightened information flows pushed systemic risk spillovers from the real estate sector to unprecedented levels. Finally, it is noteworthy that the CoVaR values under both normal and stress conditions were relatively smaller during the COVID-19 pandemic, leading to a lower measured risk spillover effect compared to previous crises. This, however, does not necessarily indicate lower systemic risk. Instead, it reflects a structural difference in market conditions. During the COVID-19 period, the real economy experienced substantial losses due to lockdowns, disruptions in commercial activities, and real economic contraction. Consequently, real sector firms already faced heightened risk even when the real estate industry was in a normal state, which mechanically reduced the measured spillover effect. Overall, risk spillovers from the real estate sector to the real economy intensify during periods of real estate expansion and stock market crises. This highlights the need for enhanced regulatory oversight and early warning mechanisms for real estate-related financial risks. Stock market regulators should strengthen risk monitoring during these phases, while investors in real economy sectors must remain vigilant about government macroeconomic policies and real estate market developments. Proactive risk management is crucial to mitigating potential investment losses from extreme shocks in the real estate industry.

Moreover, policy interventions appear to have influenced systemic risk spillovers. After the introduction of the "National 8 Rules" in 2005 and "National 6 Rules" in 2006, which aimed to stabilize the housing market, risk spillovers from the real estate industry declined (i.e., ΔCoVaR is larger), although the effect was short-lived. Following the introduction of the "New National 10 Rules" in 2010, spillovers exhibited a long-lasting mild downward trend, except for a temporary increase in the second half of 2011, suggesting a limited but observable policy effect. After the adoption of the principle that "housing is for living in, not for speculation" and the issuance of the "three red lines policy", risk spillovers from the real estate industry remained relatively low, though the effect of the "three red lines policy" is not very pronounced.

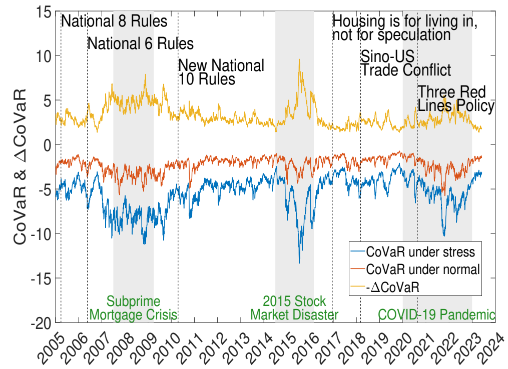
Several factors have contributed to periodic reductions in the systemic risk spillover from the real estate sector to the broader economy. First, following the introduction of the aforementioned rules, the Chinese government implemented a series of tight real estate and monetary policies aimed at cooling down an overheated real estate market. These policies effectively curbed excessive real estate development investment and restrained rapid housing price appreciation. As real estate expansion slowed, the industrial correlation between the real estate sector and the real economy weakened, leading to a decline in systemic risk spillovers. Second, a series of macroeconomic control measures centered around the principles of "housing for living, not for speculation" and "not using real estate as a means of short-term economic stimulus" played a crucial role in stabilizing the real estate market. The implementation of a long-term real estate regulatory framework successfully curbed the excessive expansion of the sector, further reducing the risk spillover effect. Although tight macroeconomic policies and stock market rebounds have successfully reduced systemic risk spillovers in various periods, their effectiveness has often been short-lived. Notably, we observe that shortly after the implementation of those policies, risk spillover levels from the real estate sector rebounded. This suggests that while these policies temporarily curbed excessive expansion, they failed to ensure long-term stability in the real estate market. In conclusion, tight macroeconomic controls and stock market recoveries have played key roles in reducing systemic risk spillovers from the real estate sector. However, without long-term structural reforms, risk spillovers remain susceptible to policy reversals and cyclical fluctuations in financial markets.

Table 2 presents a descriptive analysis for the ΔCoVaR measure across real industries, ranking the full-time average risk spillover from the real estate industry to 25 real industries in descending order. The analysis reveals that the risk spillover from the real estate industry to upstream and downstream industries is not significantly higher than that to non-upstream and downstream industries. For instance, industries such as Defense, Coal Mining, Electronics, Computers, Media, Automobiles, Agriculture, Forestry, Fishery, & Animal Husbandry, Telecommunications, Petrochemical, Pharmaceuticals, and Food & Beverages, though not directly connected to real estate in terms of industrial chain positioning, exhibit ΔCoVaR values that exceed those of many upstream and downstream industries. Notably, Defense, Coal Mining, Electronics, Computers, and Media rank 2nd, 3rd, 7th, 8th, and 12th in terms of the magnitude of risk spillover, respectively, indicating strong spillover effects from the real estate industry. This observation suggests that the magnitude of risk spillover from real estate does not depend directly on the position of industries within the industrial chain.

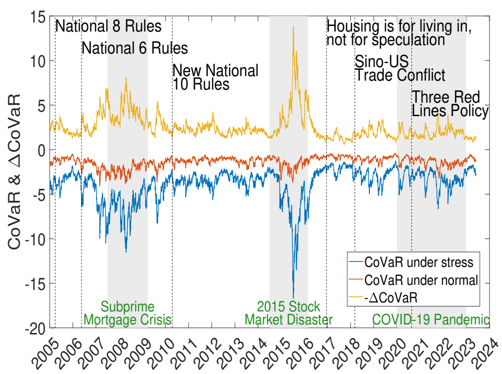
The primary reason for these spillover effects is the multi-channel nature of risk transmission. In addition to the direct industrial chain linkages, spillover risks also propagate through investment associations, credit linkages, indirect connections, and information flows. Therefore, the spillover risk from the real estate industry to other sectors is comprehensive and systemic. To manage real estate risks, it is essential not only to focus on upstream and



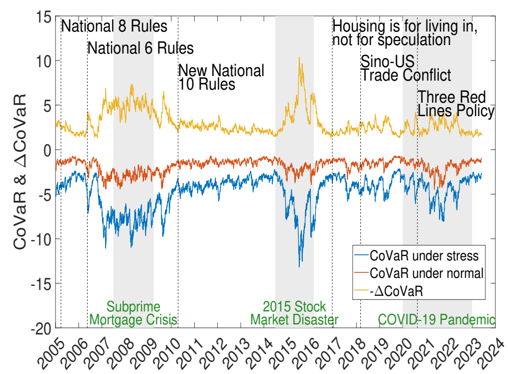
(a) Petrochemical



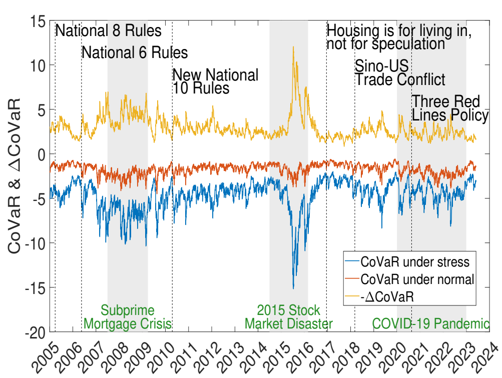
(b) Coal Mining



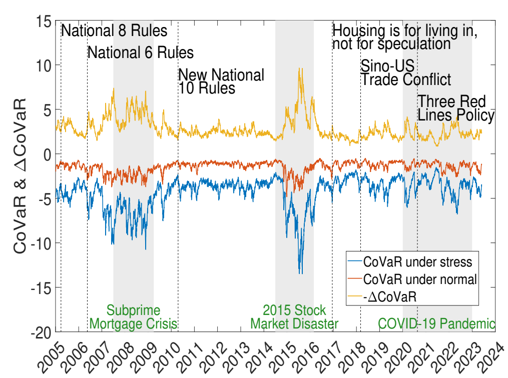
(c) Diversified Metals



(d) Power & Utilities



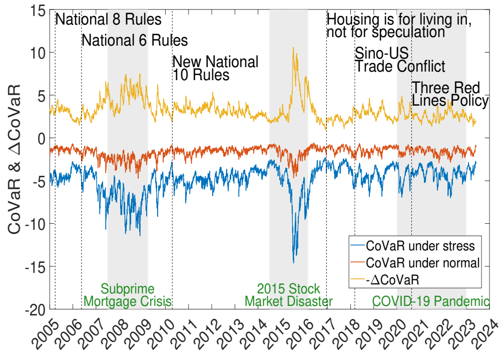
(e) Steel



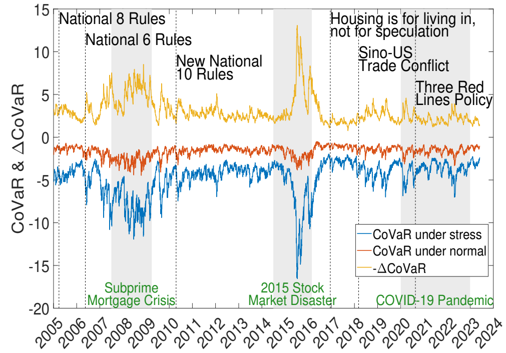
(f) Basic Chemical Engineering

Figure 1: CoVaR and ΔCoVaR estimates for real sector

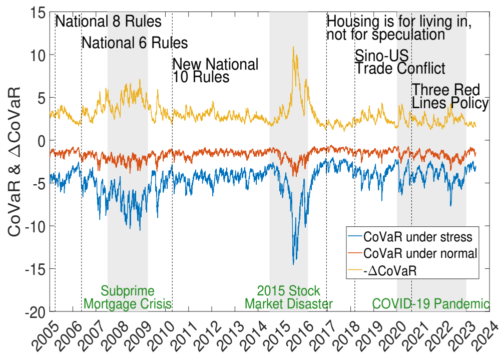
Note: This figure depicts CoVaR of real sector when real estate industry are under both stress and normal states, along with the ΔCoVaR, from 2005 to 2023 which are used to quantify the risk spillover effects from January 4, 2005 to May 31, 2023. Periods of extreme events are highlighted in gray, while dashed vertical lines indicate the issuance dates of key policies in the Chinese housing market. Note that we depict the -ΔCoVaR for the view convenience.



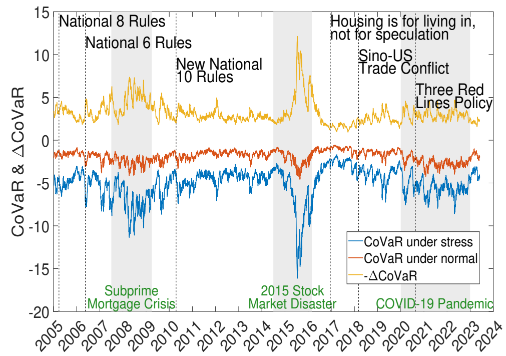
(g) Construction Engineering



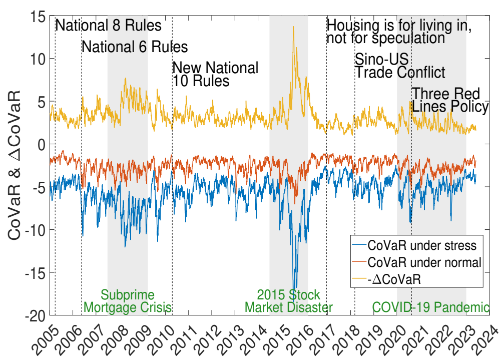
(h) Building Materials



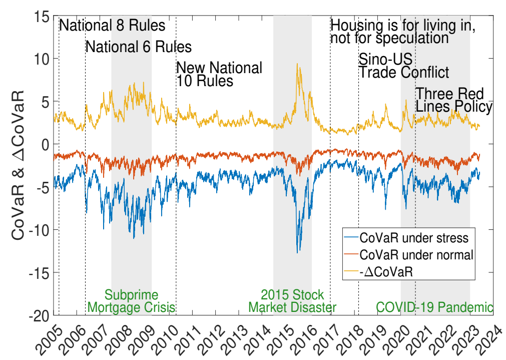
(i) Light Manufacturing



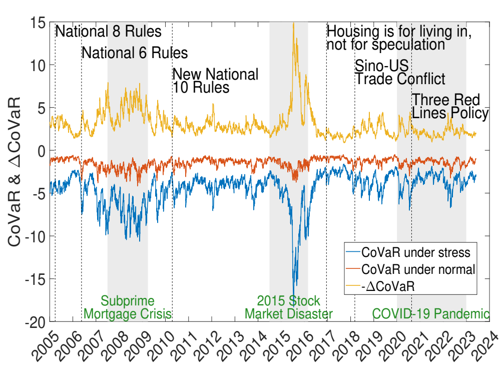
(j) Machinery



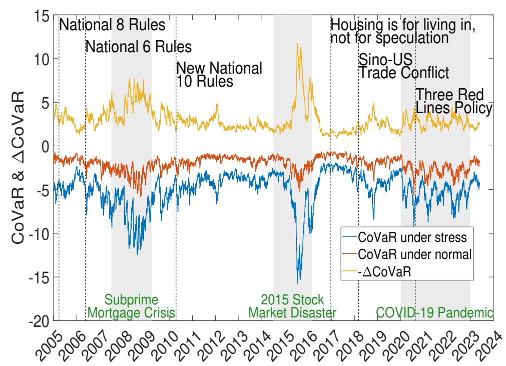
(k) Electrical Equipment & New Energy



(l) Defense

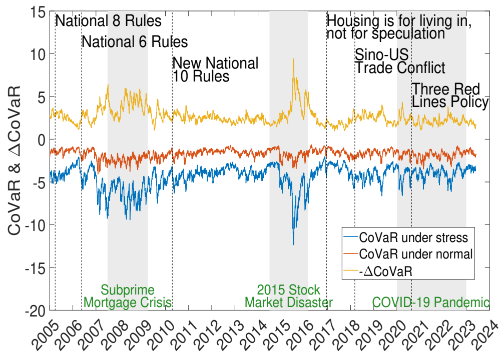


(m) Automobile

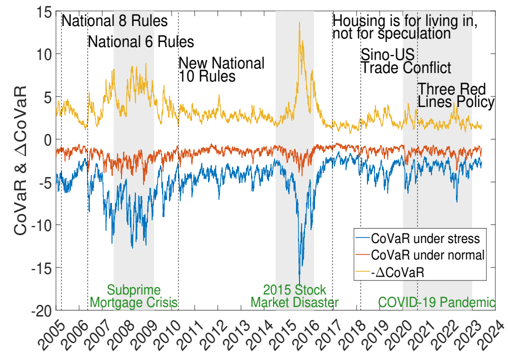


(n) Commerce & Trade Retail Business

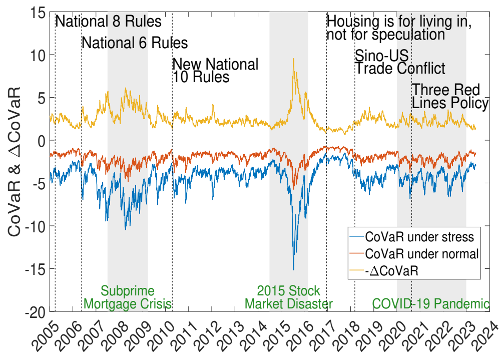
Figure 1: (Continued)



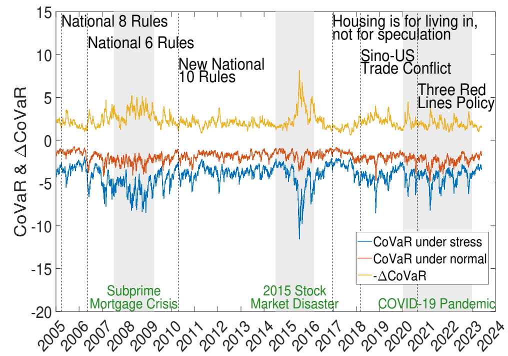
(o) Consumer Service



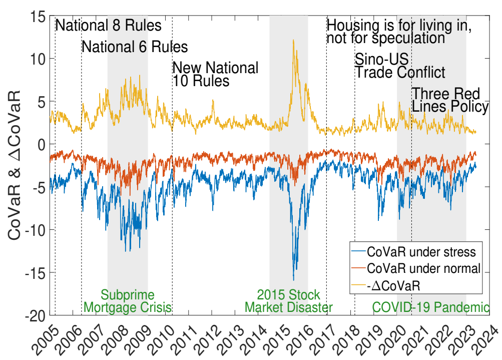
(p) Household Appliances



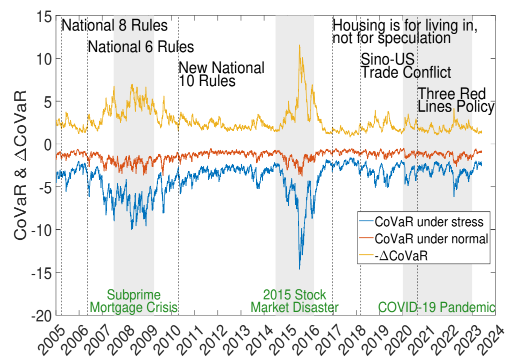
(q) Textiles & Apparel



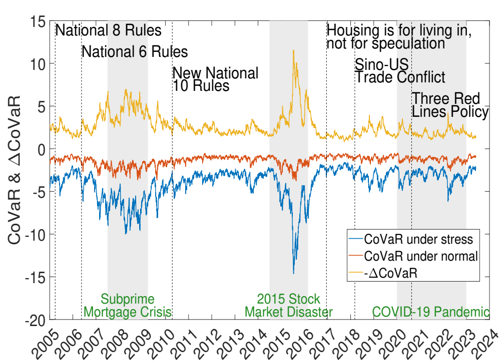
(r) Pharmaceuticals



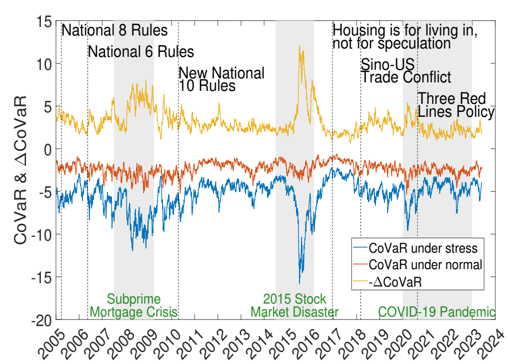
(s) Food & Beverage



(t) Agriculture, Forestry, Fishery & Animal Husbandry

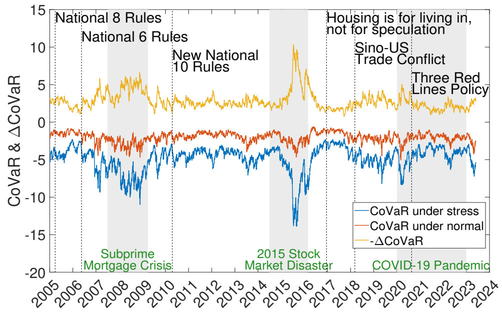


(u) Transportation

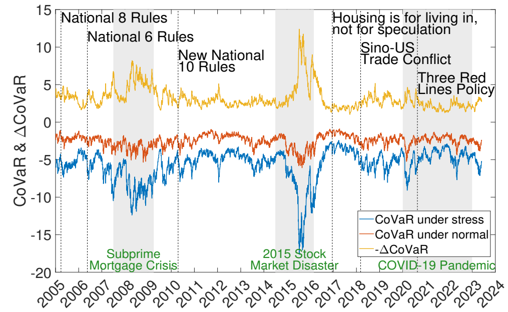


(v) Electricals

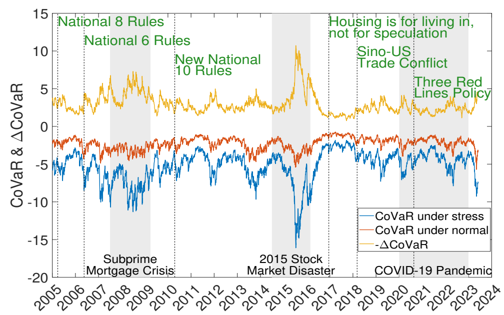
Figure 1: (Continued)



(w) Telecommunications



(x) Computer



(y) Media

Figure 1: (Continued)

downstream industries but also to pay equal attention to non-connected industries. Existing research has typically concentrated on the risk spillover to upstream and downstream industries, leading to a potential underestimation of risks posed by the real estate sector.

Table 2 also shows that, from the perspective of the ΔCoVaR of the entire sample, the twelve industries with the highest risk spillover from the real estate industry — Building Materials, Coal Mining, Defense, Computers, Electrical Equipment & New Energy, Diversified Metal, Electricals, Textiles & Apparels, Light Manufacturing, Machinery, Commerce & Trade Retail Business, and automobile—represent industries that would experience greater losses during periods of extreme losses in the real estate market than sectors outside this group. These industries can be classified as "systemically vulnerable real industries." Given the elevated risk spillover, government regulators should prioritize monitoring and mitigating risks in these sectors during overheated real estate markets and stock market crises. Investors should also exercise extra caution when considering investments in real estate and in industries with high ΔCoVaR values. Among these industries, the $\Delta CoVaR$ of Building Materials, Coal Mining, Defense, Computers, Electrical Equipment & New Energy, and Diversified Metal is at the forefront as a whole, so it is the top priority of supervision. In contrast, industries such as Power & Utilities, Petrochemicals, Pharmaceuticals, and Food & Beverages exhibit relatively low ΔCoVaR values, indicating that they face lower risk spillover from extreme losses in the real estate sector.

Industry	Position in the industrial chain	Mean	Std. Dev.	Max	Min	Industry	Position in the industrial chain	Mean	Std. Dev.	Max	Min
Building Material	Upstream Downstream	3.20	1.25	10.60	0.93	Consumer Service	Downstream	2.97	1.44	11.71	0.85
Coal Mining		3.20	1.20	9.60	1.38	Media		2.96	1.36	10.72	0.75
Defense		3.18	1.40	13.72	1.01	Basic Chemical Engineering	Upstream	2.96	1.30	12.60	0.83
Computer		3.17	1.49	12.40	1.01	Agriculture, Forestry, Fishery & Animal Husbandry		2.88	1.44	12.18	0.88
Electrical Equipment & New Energy	Upstream	3.14	1.33	12.13	0.93	Telecommunications		2.84	1.24	10.33	0.74
Diversified Metal	Upstream	3.13	1.30	11.58	1.10	Construction Engineering	Upstream Downstream	2.81	1.22	9.65	0.84
Electricals		3.11	1.53	12.05	0.70	Household Appliances	Downstream	2.67	0.99	9.42	0.97
Textiles & Apparels	Downstream	3.07	1.70	13.72	0.66	Transportation	Upstream	2.64	1.40	11.57	-0.80
Light Manufacturing	Downstream	3.04	1.55	13.09	0.76	Power & Utilities	Upstream Downstream	2.52	1.44	13.87	0.56
Machinery	Upstream	3.02	1.27	10.93	1.01	Petrochemical		2.51	1.00	7.68	0.69
Commerce & Trade Retail Business	Downstream	3.02	1.64	14.91	0.88	Pharmaceuticals		2.47	1.06	9.54	0.63
Automobile		2.99	1.19	9.41	1.03	Food & Beverage		2.20	0.84	8.17	0.60
Steel	Upstream	2.98	1.34	10.37	1.32						

* The table reports the descriptive $-\Delta$CoVaR statistics (percentages) at the 95% confidence level for the real sector from January 4, 2005 to May 31, 2023 using the best copula fit and the multivariate EGARCH model with SGT distribution.

5 Conclusion

In the current context of a downturn in the real estate industry and the frequent collapse of real estate companies, it is both urgent and necessary to comprehensively assess the risks associated with real estate entities. This paper employs the EGARCH-SGT-dynamic ΔCoVaR model and stock market industry index data from 2005 to 2023 to measure and compare the extreme dynamic risk spillover effects of China's real estate industry on 25 real industries. The study finds the following. First, the risk spillover from the real estate industry to the real sector is both comprehensive and systematic. Existing studies have focused mainly on a limited number of upstream and downstream industries, which severely underestimates the true risk spillover impact. Second, during periods of financial crises and real estate expansion, the risk spillover from the real estate industry to other sectors increases significantly. Third, government macroeconomic policies significantly influence the short-term risk spillover. Loose real estate and monetary policies can foster industry expansion, thereby increasing spillover risks, while tight policies inhibit development, reducing spillover risks accordingly. Fourth, the overall risk spillover is higher for industries such as building materials, national defense, coal, textiles, machinery, trade and retail, electronics, computers, light manufacturing, steel, media, and basic chemicals, marking these sectors as "systemically vulnerable real industries".

Implications for Regulatory Authorities and Investors are proposed as follows: First, to mitigate risks from real estate entities, regulatory authorities should expand their focus beyond upstream and downstream industries and assess risk spillover across the entire industrial sector. Second, during financial crises or periods of rapid real estate expansion, early warning systems and enhanced supervision are crucial to managing real estate risks. Third, regulatory authorities should develop differentiated strategies based on the systemic vulnerability of different industries, with special focus on "systemically vulnerable real industries." Fourth, establishing a comprehensive emergency response mechanism for real estate risks is essential. Authorities must act promptly to block risk transmission paths and mitigate spillover effects to the broader economy. Fifth, encouraging real industries to diversify operations, expand their industrial chains, and innovate is key to reducing their dependence on the real estate sector. Finally, investors should be particularly cautious when considering real estate and "systemically fragile real industries" stocks, especially during stock market turmoil or overheated real estate markets, to mitigate potential risks.

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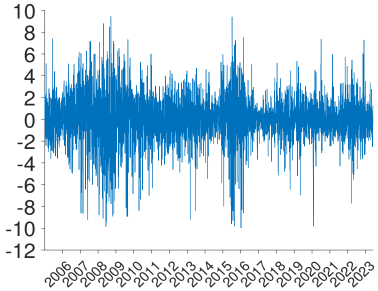
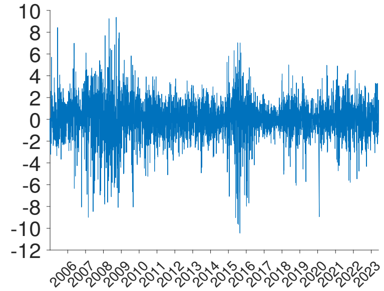
Appendix

Table A.1: The special case of SGT distribution

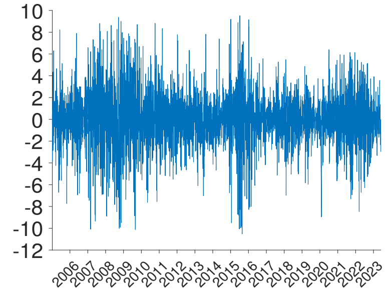
	λ_n	κ_n	η_n	Notes
Skew generalized t (SGT)	Free	Free	Free	$\lambda > 0$ skew to the right
Skew t (ST)	Free	2	Free	$\lambda < 0$ skew to the left
Skew GED (SGED)	Free	Free	∞	
Skew normal	Free	2	∞	$\kappa_n > 2$ thinner tail than normal
Skew Laplace	Free	1	∞	$\kappa_n < 2$ thicker tail than normal
General t (GT)	0	Free	Free	
Student t	0	2	Free	
GED	0	Free	∞	
Normal	0	2	∞	
Cauchy	0	2	1	
Laplace	0	1	∞	
Uniform	0	∞	∞	



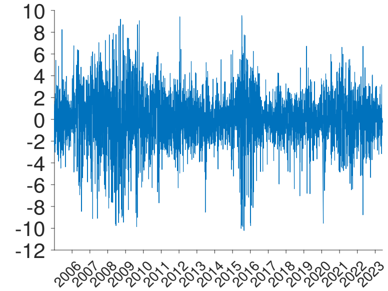
(a) Real Estate



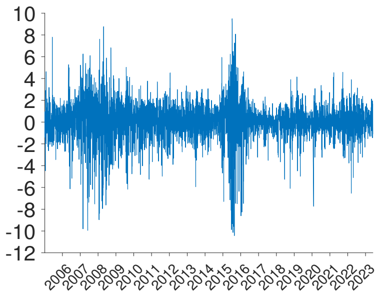
(b) Petrochemical



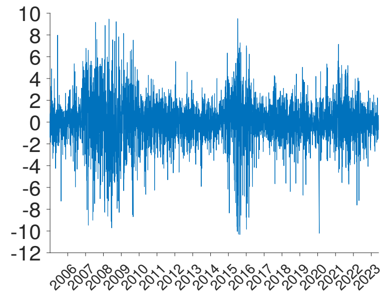
(c) Coal Mining



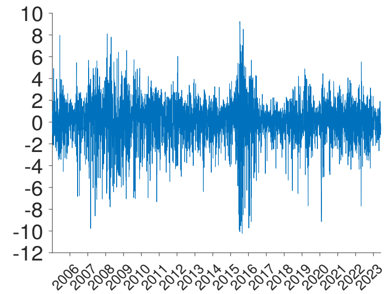
(d) Diversified Metals



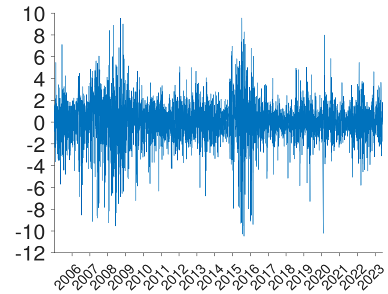
(e) Power & Utilities



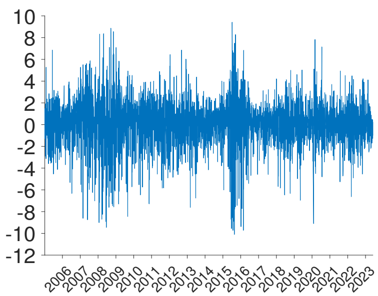
(f) Steel



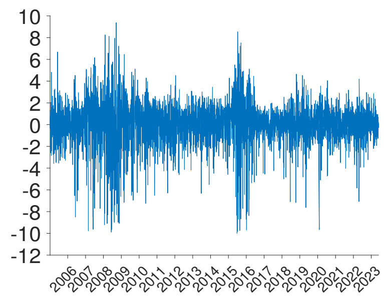
(g) Basic Chemical Engineering



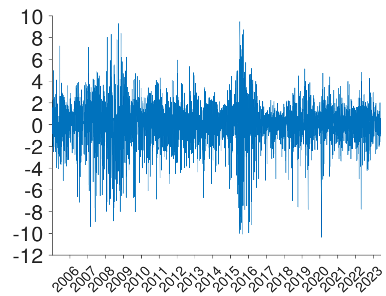
(h) Construction Engineering



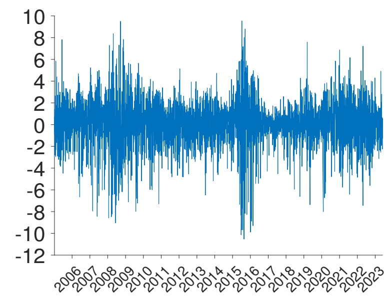
(i) Building Materials



(j) Light Manufacturing

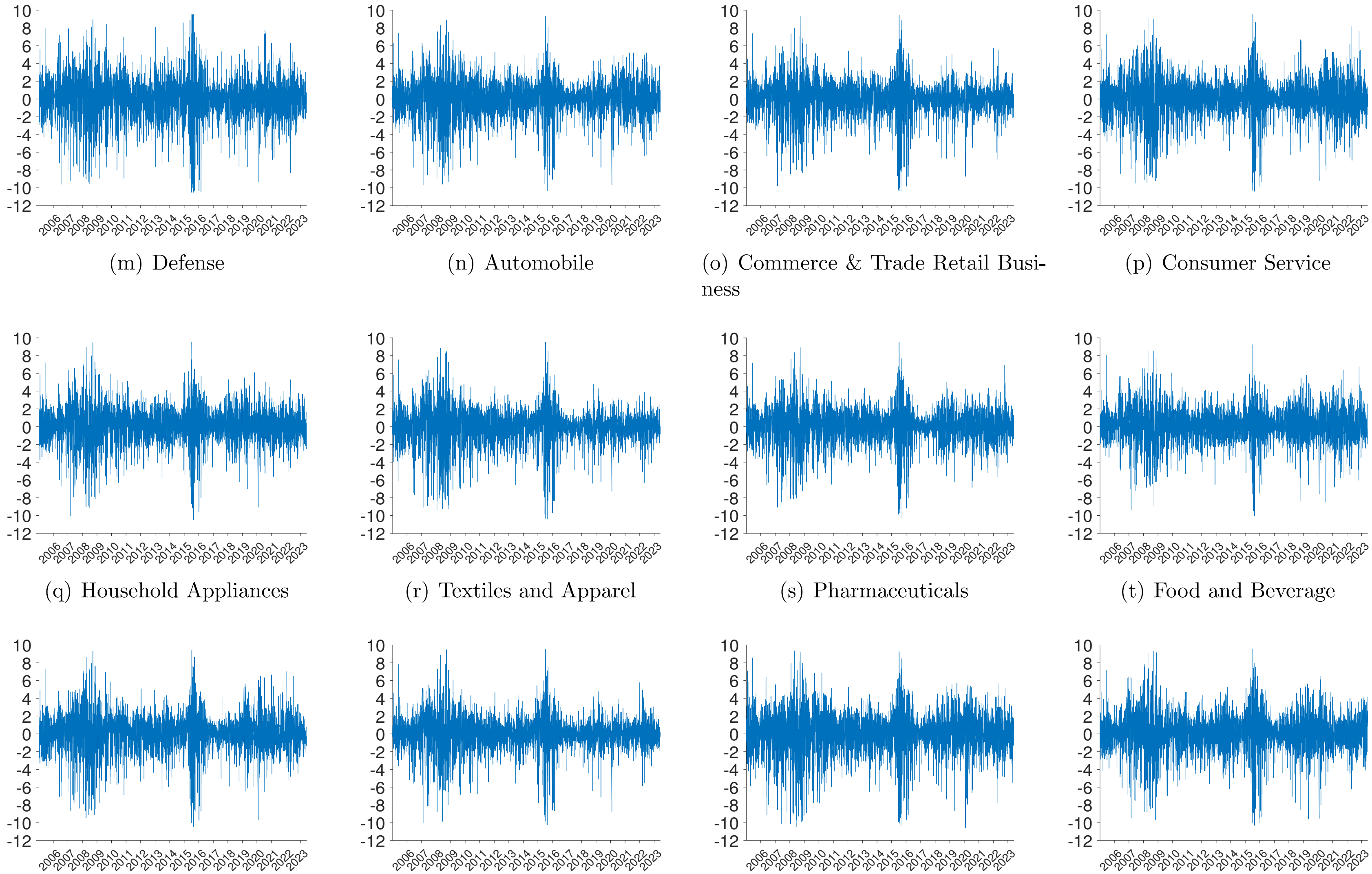


(k) Machinery



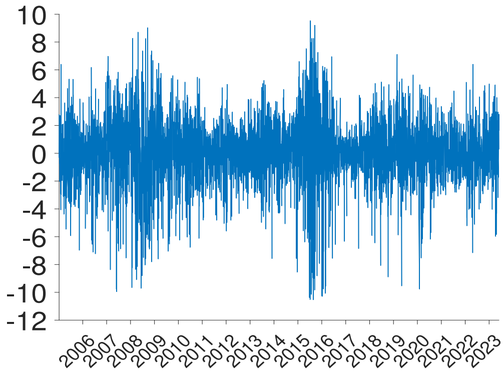
(l) Electrical Equipment & New Energy

Figure A.1: Time series plot of daily sector index returns

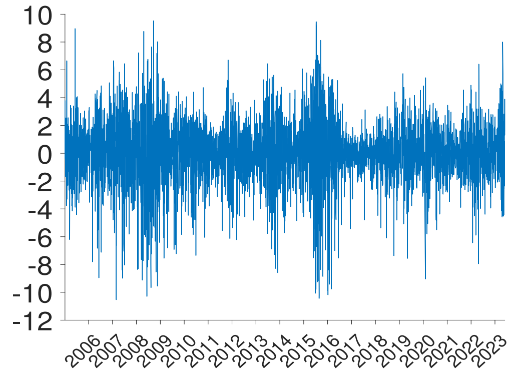


(m) Defense
(n) Automobile
(o) Commerce & Trade Retail Business
(p) Consumer Service
(q) Household Appliances
(r) Textiles and Apparel
(s) Pharmaceuticals
(t) Food and Beverage
(u) Agriculture, Forestry, Fishery & Animal Husbandry
(v) Transportation
(w) Electricals
(x) Telecommunications

Figure A.1: Time series plot of daily sector index returns



(y) Computer



(z) Media

Figure A.1: Time series plot of daily sector index returns

Table A.2: Parameter estimates for marginal models of sector index returns

Industry	φ_1	φ_2	ϕ_1	ϕ_2	ω	α	β	γ	κ	λ	η	LL	AIC	$Q(5)$	ARCH	KS	CvM	AD
(1)	-0.889*	0	0.902*	0	0.017*	0.142*	0.992*	-0.003	-0.030*	1.867*	6.578*	-8971.12	17960.2	5.138	0.108	[0.508]	[0.385]	[0.381]
	(-9.42)		(10.16)		(4.19)	(9.33)	(386.61)	(0.00)	(-2.00)	(13.06)	(4.92)			[0.400]	[0.743]			
(2)	-0.173*	-0.876*	0.165*	0.850*	0.016*	0.138*	0.991*	0.012	-0.094*	1.591*	8.935*	-8144.72	16311.4	8.785	0.490	[0.542]	[0.257]	[0.239]
	(-2.38)	(-7.03)	(2.13)	(6.13)	(4.06)	(8.19)	(327.14)	(1.49)	(-5.44)	(13.91)	(3.72)			[0.118]	[0.484]			
(3)	0	0	0	0	0.018*	0.124*	0.992*	0.021*	-0.032	1.547*	11.361*	-9594.50	19203.1	7.199	2.917	[0.696]	[0.644]	[0.750]
					(3.80)	(7.99)	(365.13)	(2.71)	(-1.81)	(12.57)	(2.50)			[0.206]	[0.088]			
(4)	0.575*	0.416*	-0.548*	0.434*	-0.028*	0.164*	0.986*	0.003*	-0.096*	1.577*	20.889	-9610.05	19242.1	12.780	5.123	[0.837]	[0.583]	[0.454]
	(13.95)	(9.92)	(-12.40)	(-9.71)	(4.38)	(9.38)	(261.70)	(0.31)	(-5.33)	(10.98)	(1.19)			[0.026]	[0.024]			
(5)	-0.789*	0	0.808*	0	0.016*	0.183*	0.989*	-0.001	-0.153*	1.814*	7.224*	-7698.32	15414.6	6.375	0.975	[0.594]	[0.479]	[0.455]
	(-7.37)		(7.92)		(4.63)	(10.60)	(3.47)	(0.00)	(-8.24)	(13.34)	(4.76)			[0.272]	[0.324]			
(6)	0.799*	0	0.824*	0	0.015*	0.134*	0.993*	0.025*	-0.103*	1.620*	8.999*	-8764.15	17546.3	4.405	1.214	[0.950]	[0.936]	[0.978]
	(-9.09)		(9,94)		(4.12)	(8.63)	(408.63)	(3.28)	(-5.97)	(13.66)	(3.58)			[0.493]	[0.271]			
(7)	-0.698*	0	0.741*	0	0.026*	0.184*	0.983*	-0.019*	-0.245*	1.745*	10.382*	-8545.26	17108.5	20.920	6.290	[0.361]	[0.422]	[0.395]
	(-6.61)		(7.51)		(4.73)	(10.42)	(236.71)	(-2.19)	(13.02)	(13.40)	(3.16)			[0.001]	[0.012]			
(8)	-0.792*	0	0.816*	0	0.020*	0.162*	0.989*	0.008	-0.097*	1.768*	7.535	-8431.47	16880.9	7.250	2.432	[0.153]	[0.267]	[0.255]
	(-5.64)		(6.12)		(4.67)	(9.91)	(324.16)	(0.73)	(-5.28)	(13.05)	(4.42)			[0.203]	[0.119]			
(9)	0.559*	0.434*	-0.504*	-0.478*	0.023*	0.144*	0.986*	-0.028*	-0.154*	1.629*	11.239*	-8932.01	17886.0	9.291	0.657	[0.312]	[0.253]	[0.270]
	(2.79)	(2.18)	(-2.58)	(-2.48)	(4.51)	(9.22)	(273.31)	(-3.19)	(-8.50)	(12.60)	(2.66)			[0.098]	[0.418]			
(10)	0.276*	0.714*	-0.229	-0.748	0.020*	0.164*	0.988*	-0.024*	-0.252*	1.956*	6.938*	-8459.34	16940.7	8.852	4.365	[0.252]	[0.270]	[0.255]
	(2.85)	(7.47)	(-2.53)	(-8.43)	(4.74)	(10.60)	(322.58)	(-2.61)	(-12.37)	(12.87)	(4.81)			[0.115]	[0.037]			
(11)	-0.771*	0	0.811*	0	0.020*	0.149*	0.989*	-0.017*	-0.210*	1.897*	7.046*	-8610.18	17238.4	13.526	5.329	[0.028]	[0.086]	[0.084]
	(-9.64)		(11.03)		(4.48)	(9.51)	(316.58)	(-2.22)	(-10.33)	(13.33)	(4.86)			[0.019]	[0.021]			
(12)	-0.768*	0	0.806*	0	0.019*	0.151*	0.990*	-0.008*	-0.183*	1.765*	9.717*	-8945.62	17909.2	7.356	1.393	[0.304]	[0.215]	[0.189]
	(-9.99)		(11.34)		(4.20)	(9.46)	(331.93)	(-0.83)	(-9.71)	(12.77)	(3.22)			[0.196]	[0.238]			
(13)	0.336	0	0.365	0	0.039*	0.186*	0.980*	0.006	-0.126*	1.644*	10.731*	-9578.22	19173.5	5.704	3.078	[0.489]	[0.367]	[0.418]
	(-1.01)		(1.11)		(4.55)	(9.39)	(192.48)	(0.53)	(-7.14)	(12.54)	(2.76)			[0.336]	[0.079]			
(14)	-0.747*	0	0.783*	0	0.019*	0.147*	0.990*	-0.015	-0.150*	1.759*	9.624*	-8747.19	17512.4	7.259	3.931	[0.143]	[0.143]	[0.127]
	(-5.72)		(6.41)		(4.46)	(9.47)	(342.21)	(-1.88)	(-7.60)	(12.82)	(3.19)			[0.202]	[0.047]			
(15)	0.202*	0.783*	-0.160*	-0.804*	-0.023*	0.185*	0.986*	-0.022*	-0.207*	1.788*	6.951*	-8240.80	16503.6	19.424	8.292	[0.740]	[0.731]	[0.716]
	(2.67)	(10.55)	(-2.26)	(-11.80)	(4.92)	(10.72)	(279.12)	(-2.18)	(-11.31)	(13.43)	(4.91)			[0.002]	[0.004]			
(16)	0	0	0.322*	-0.061*	0.017*	0.147*	0.991*	-0.007	-0.163*	1.861*	8.788*	-9000.7	18019.4	5.716	0.002	[0.227]	[0.159]	[0.156]
			(2.16)	(-4.10)	(4.18)	(9.45)	(381.07)	(-1.06)	(-8.08)	(12.76)	(3.62)			[0.335]	[0.966]			

Continued

Industry	φ_1	φ_2	ϕ_1	ϕ_2	ω	α	β	γ	κ	λ	η	LL	AIC	$Q(5)$	ARCH	KS	CvM	AD
(17)	0	0	0.014	-0.051	0.024*	0.140*	0.985*	-0.009	-0.068*	1.569*	16.137	-8765.79.70	17549.6	3.199	0.632	[0.051]	[0.019]	[0.012]
			(1.00)	(-3.39)	(3.94)	(8.04)	(217.10)	(-1.06)	(-3.77)	(12.30)	(1.73)			[0.669]	[0.427]			
(18)	0.247*	0.750*	-0.206	-0.778*	0.019*	0.180*	0.989*	-0.017	-0.235*	1.645*	8.985*	-8231.31	16484.7	27.894	8.818	[0.726]	[0.632]	[0.646]
	(1.98)	(6.01)	(-1.75)	(-6.67)	(4.83)	(10.84)	(347.19)	(-1.94)	(-13.89)	(13.37)	(3.55)			[0.00]	[0.003]			
(19)	-0.620*	0	0.678*	0	0.016*	0.151*	0.990*	-0.008	-0.164*	1.874*	9.556*	-8443.39	16903.8	21.807	1.393	[0.011]	[0.031]	[0.025]
	(-5.96)		(6.93)		(4.37)	(10.01)	(348.51)	(-1.03)	(-8.00)	(13.23)	(3.53)			[0.001]	[0.238]			
(20)	-0.740*	0	0.771*	0	0.027*	0.159*	0.980*	-0.013	-0.039*	1.698*	12.674*	-8577.51	17173.2	2.802	0.634	[0.018]	[0.002]	[0.001]
	(-6.80)		(7.48)		(4.31)	(9.01)	(190.57)	(-1.44)	(-2.05)	(12.84)	(2.38)			[0.287]	[0.426]			
(21)	0	0	0.059*	-0.052*	0.021*	0.174*	0.988*	-0.001	-0.155*	1.754*	9.907*	-8820.08	17658.2	7.614	1.823	[0.346]	[0.323]	[0.345]
			(4.16)	(-3.55)	(4.38)	(9.56)	(304.84)	(0.00)	(-8.03)	(13.54)	(3.44)			[0.179]	[0.177]			
(22)	-0.632*	0	0.666*	0	0.014*	0.146*	0.992*	-0.001	-0.106*	1.800*	7.254*	-8047.26	16112.5	2.802	1.696	[0.255]	[0.343]	[0.315]
	(-3.87)		(4.20)		(4.41)	(9.66)	(420.37)	(-0.22)	(-5.49)	(13.45)	(4.79)			[0.731]	[0.193]			
(23)	0	0	0.019	-0.034*	0.020*	0.136*	0.990*	-0.009*	-0.188*	1.883*	8.750*	-9382.24	18782.5	3.601	0.534	[0.082]	[0.036]	[0.031]
			(1.35)	(-2.25)	(4.21)	(9.21)	(341.42)	(-1.23)	(-9.02)	(12.54)	(3.58)			[0.608]	[0.465]			
(24)	-0.836	0	0.864*	0	0.019*	0.138*	0.989*	-0.006	-0.137*	1.713*	11.050*	-8973.82	17965.7	4.110	0.167	[0.363]	[0.395]	[0.413]
	(-12.12)		(13.66)		(4.00)	(8.50)	(307.16)	(-0.67)	(-7.13)	(12.86)	(2.70)			[0.534]	[0.683]			
(25)	0.220*	0.775*	-0.186*	-0.800*	0.021*	0.137*	0.989*	-0.015	-0.141*	1.843*	9.679*	-9646.43	19314.9	3.632	0.849	[0.640]	[0.491]	[0.524]
	(2.90)	(10.25)	(-2.80)	(-12.01)	(4.21)	(9.38)	(333.28)	(-1.79)	(-7.05)	(13.32)	(3.42)			[0.604]	[0.357]			
(26)	0	0	0.012	-0.038*	0.017*	0.147*	0.992*	0.002	-0.144*	1.820*	9.483*	-9290.85	18599.7	7.142	0.151	[0.950]	[0.904]	[0.941]
			(0.81)	(-2.56)	(4.18)	(10.02)	(404.07)	(0.35)	(-7.39)	(12.38)	(3.34)			[0.210]	[0.698]			

* The table presents parameter estimates and t statistics (in parentheses) for the marginal model described in Eqs. (9)-(11). For view convenience, we exhibit the 26 industries in numbers ranging from (1) to (26), which represent Real Estate, Petrochemical, Coal, Nonferrous, Electricity & Utilities, Steel, Basic Chemicals, Construction, Building Materials, Light Industry, Machinery, Power Equipment, National Defense, Automobile, Retail Trade, Catering & Travel, Home Appliances, Textiles & Garments, Pharmaceuticals, Food & Beverages, Agriculture, Forestry, Animal Husbandry & Fishery, Banks, Non-banking, Transportation, Electronic Components, Communications, Computers, Media, respectively. LL is the log-likelihood value; $Q(5)$ is the Ljung-Box statistics for serial correlation in the residual model calculated with 5 lags; ARCH denotes Engle's LM test for ARCH effect with 1 lag. KS, CvM, and AD denote the Kolmogorov–Smirnov, Cramér-von Mises and Anderson-Darling tests for adequacy of the SGT distribution model. P values (in square brackets) below 0.05 indicate rejection of the null hypothesis. An asterisk (*) indicates significance at 5%.

Table A.3: Time-varying MixGrG copula model estimates for real estate sector index and other sector index returns

Sector	ω_G	β_G	α_G	ω_{rG}	β_{rG}	α_{rG}	ω_w	β_w	α_w	AIC
Petrochemical	0.067*	0.008*	0.461*	0.130*	0.046*	0.268*	0.321*	1.034	1.391*	-2914.7
	(0.07)	(0.01)	(0.46)	(0.13)	(0.05)	(0.27)	(0.32)	(1.03)	(1.39)	
Coal Mining	3.184*	-0.349*	-7.316*	0.441*	0.343*	11.275*	0.730	-4.001	-9.192	-2715.6
	(0.41)	(0.05)	(3.10)	(0.06)	(0.02)	(0.19)	(3.00)	(2.21)	(19.44)	
Diversified Metals	0.832	0.165	-0.430	0.499*	0.326*	-1.401*	-1.499	-0.011	-0.157	-2631.8
	(1.71)	(0.69)	(1.95)	(0.04)	(0.01)	(0.06)	(0.97)	(1.37)	(0.80)	
Power & Utilities	2.980*	-0.077	-7.581*	0.461*	0.327*	-1.145*	-1.849*	4.323*	-3.837*	-3610.5
	(0.86)	(0.12)	(3.46)	(0.06)	(0.02)	(0.19)	(0.21)	(0.27)	(1.87)	
Steel	0.700*	0.180*	1.109	0.498*	0.327*	-1.416*	-0.358	-1.872	-6.407	-3111.0
	(0.13)	(0.06)	(0.90)	(0.01)	(0.00)	(0.07)	(1.29)	(5.21)	(3.77)	
Basic Chemical	3.738*	-0.256	-10.390*	0.643	0.290	-1.764	-1.830	4.432	-5.425	-3457.8
Engineering	(0.70)	(0.14)	(2.98)	(1.54)	(0.32)	(4.90)	(2.98)	(5.29)	(10.51)	
Construction	1.178*	0.080	-0.299	0.655*	0.285*	-1.658	-1.398*	-0.003	-0.083	-4408.3
Engineering	(0.46)	(0.20)	(1.00)	(0.06)	(0.00)	(1.04)	(0.41)	(0.98)	(0.99)	
Building Materials	0.949*	0.230*	-2.241*	0.481*	0.318*	-0.933*	-1.710*	4.595*	-5.570*	-4254.7
	(0.05)	(0.01)	(0.37)	(0.04)	(0.02)	(0.06)	(0.03)	(0.14)	(0.88)	
Light Manufacturing	0.882*	0.240*	-1.979*	0.626*	0.290*	-1.587*	1.913*	-4.964*	-19.415*	-3609.8
	(0.15)	(0.02)	(0.82)	(0.06)	(0.01)	(0.19)	(0.76)	(0.64)	(6.28)	

Continued

Sector	ω_G	β_G	α_G	ω_{rG}	β_{rG}	α_{rG}	ω_w	β_w	α_w	AIC
Machinery	1.111	-0.004	-0.362	0.714	0.276	-1.795	-1.512	-0.024	-0.037	-3580.7
	(39.12)	(13.75)	(7.68)	(25.18)	(4.63)	(20.28)	(3.18)	(1.71)	(21.35)	
Electrical Equipment	0.916	0.190	-0.315	0.506*	0.318*	-1.347*	-1.241*	0.030	-0.157	-2914.2
& New Energy	(0.84)	(0.16)	(1.00)	(0.03)	(0.00)	(0.48)	(0.62)	(0.98)	(1.00)	
Defense	0.618*	0.279*	-0.307	0.571*	0.311*	-1.889*	-2.025*	0.00	-1.71	-2035.4
	(0.09)	(0.01)	(0.36)	(0.05)	(0.01)	(0.19)	(0.24)	(0.93)	(0.91)	
Automobile	1.345	0.107	-0.050	0.443	0.332	-1.007	-1.437	-0.009	-0.246	-3524.3
	(0.83)	(1.28)	(0.98)	(3591.3)	(12721)	(153.29)	(0.86)	(0.99)	(1.09)	
Commerce & Trade	3.032*	-0.091	-10.643*	0.535*	0.307*	-1.172*	-1.764*	4.120*	-3.745*	-4073.4
Retail Business	(0.41)	(0.07)	(2.57)	(0.07)	(0.02)	(0.23)	(0.08)	(0.14)	(0.81)	
Consumer Service	3.225*	-0.279*	-6.844*	0.489*	0.331*	-1.434*	-1.898*	4.762*	-4.876*	-2883.7
	(0.16)	(0.04)	(0.70)	(0.03)	(0.01)	(0.10)	(0.01)	(0.08)	(0.49)	
Household	0.561*	0.293*	-0.451	0.559*	0.301*	-1.416*	2.249	-0.224	-25.857	-3342.6
Appliances	(0.00)	(0.00)	(0.30)	(0.07)	(0.03)	(0.19)	(2.25)	(2.92)	(17.02)	
Textiles & Apparel	1.013*	-0.043	-0.223	0.602	0.293	-1.133	-1.391	0.000	-0.077	-3590.1
	(0.94)	(0.36)	(0.97)	(0.25)	(0.04)	(0.50)	(0.96)	(1.00)	(0.95)	
Pharmaceuticals	0.684	0.267	-0.568	0.575	0.190	-1.198	-1.175	0.045	-0.314	-2396.4
	(0.59)	(0.11)	(0.92)	(1.25)	(1.01)	(1.47)	(0.64)	(0.99)	(1.02)	

Continued

Sector	ω_G	β_G	α_G	ω_{rG}	β_{rG}	α_{rG}	ω_w	β_w	α_w	AIC
Food & Beverage	0.638	0.285*	-0.991	0.685	0.230	-1.772	4.219	-2.470*	-32.136	-2125.2
	(0.44)	(0.12)	(0.53)	(0.58)	(0.16)	(1.64)	(3.63)	(0.69)	(24.34)	
Agriculture, Forestry, Fishery	0.452	0.334	-1.067	0.749	0.271	-2.623	-1.059	0.067	-0.385	-2674.4
& Animal Husbandry	(81.69)	(268.44)	(5.74)	(6.14)	(6.82)	(4.19)	(2.42)	(1.10)	(1.01)	
Transportation	-1.638	1.173*	-3.350	0.994*	0.200*	-2.486*	-2.781	0.104	0.692	-3916.1
	(0.87)	(0.50)	(2.97)	(0.26)	(0.02)	(0.69)	(1.50)	(1.05)	(2.03)	
Electricals	1.243*	0.194	-3.172*	0.555*	0.313*	-1.734*	-1.753	4.125*	-3.517	-2555.7
	(0.62)	(0.20)	(0.25)	(0.06)	(0.01)	(0.27)	(1.10)	(0.37)	(2.32)	
Telecommunications	0.758*	0.231	-0.673	0.662*	0.286*	-1.991*	-1.617*	-0.047	-0.330	-2558.0
	(0.38)	(0.17)	(0.91)	(0.09)	(0.02)	(0.46)	(0.53)	(0.98)	(0.73)	
Computer	2.100*	-0.057	-4.411*	0.332*	0.378*	-1.165*	-0.110	2.403*	-12.302*	-2332.4
	(0.22)	(0.04)	(0.61)	(0.04)	(0.01)	(0.11)	(0.22)	(0.49)	(0.84)	
Media	0.149	0.449	-1.333	1.382	-0.048	-1.886	-1.125	0.015	-0.451	-2411.4
	(0.22)	(0.09)	(0.31)	(0.18)	(0.11)	(0.23)	(0.38)	(0.96)	(1.03)	

* This table reports estimates and standard errors (in brackets) for the different copula models for different industries. AIC values are provided for comparison. For time-varying parameter (TVP) copulas, q was set to 10. An asterisk (*) indicates significance of the parameter at 5%.

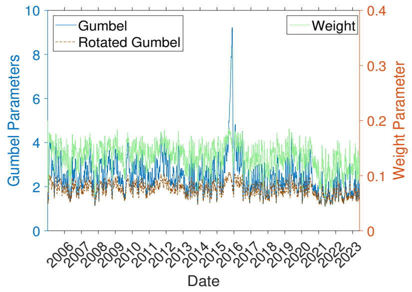
Table A.4: Time-varying SJC copula model estimates for real estate sector index and other sector index returns

Sector	ω_{sG}	β_{sG}	α_{sG}	$\bar{\omega}_{sG}$	$\bar{\beta}_{sG}$	$\bar{\alpha}_{sG}$	AIC
Petrochemical	-1.755*	3.984*	-1.829*	1.305*	0.121*	-5.930*	-2905.3
	(0.02)	(0.02)	(0.12)	(0.01)	(0.00)	(0.04)	
Coal Mining	0.991	0.494	-11.181*	0.613*	1.075	-5.542	-2633.8
	(1.66)	(4.54)	(1.66)	(0.02)	(4.36)	(11.91)	
Diversified Metals	0.308*	2.034*	-11.815*	0.557*	1.204*	-5.332*	-2637.1
	(0.09)	(0.13)	(0.48)	(0.07)	(0.08)	(0.42)	
Power & Utilities	0.231*	1.936*	-9.917*	1.326*	0.336*	-6.239*	-3487.3
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.01)	
Steel	-1.081*	3.267*	-4.458*	1.662*	-0.544*	-5.626*	-3042.6
	(0.18)	(0.10)	(1.25)	(0.06)	(0.08)	(0.44)	
Basic Chemical Engineering	1.988*	-0.337	-15.929*	0.192	1.813*	-4.973*	-3351.1
	(0.63)	(0.21)	(1.62)	(0.78)	(0.24)	(0.14)	
Construction Engineering	0.352	1.248	-7.063*	1.760*	-0.329	-5.835*	-4245.2
	(1.19)	(1.86)	(1.07)	(0.07)	(0.24)	(0.83)	
Building Materials	-1.741	4.073	-2.270	0.686	0.989	-4.393	-4150.8
	(17.76)	(34.33)	(18.46)	(18.20)	(0.63)	(6.01)	
Light Manufacturing	-1.675*	3.889	-2.117	-1.028	3.061	-2.280	-3535.3
	(0.32)	(2.14)	(3.94)	(5.59)	(3.78)	(10.62)	
Machinery	-0.196	2.317*	-7.594	0.619	1.336	-5.857*	-3550.8
	(1.36)	(0.18)	(4.35)	(1.39)	(1.65)	(2.25)	
Electrical Equipment	0.834*	1.407*	-13.108*	-1.386*	3.513*	-1.781*	-2959.2
& New Energy	(0.24)	(0.15)	(0.82)	(0.06)	(0.06)	(0.10)	
Defense	-1.372*	3.967*	-5.411*	-0.949*	2.955*	-2.644*	-2015.8
	(0.07)	(0.24)	(0.13)	(0.30)	(0.37)	(0.58)	
Automobile	-0.046	2.440*	-9.655*	1.096*	0.881*	-6.753*	-3620.3

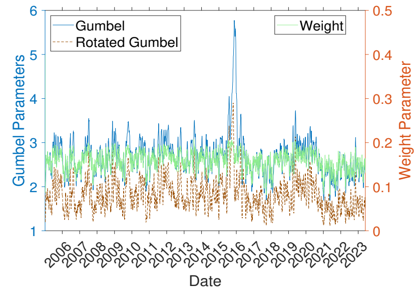
Continued

Sector	ω_{sG}	β_{sG}	α_{sG}	$\bar{\omega}_{sG}$	$\bar{\beta}_{sG}$	$\bar{\alpha}_{sG}$	AIC
	(0.05)	(0.03)	(0.39)	(0.03)	(0.02)	(0.66)	
Commerce & Trade	0.650*	2.752*	-5.703*	0.801*	0.932*	-5.167*	-3935.4
Retail Business	(0.09)	(0.16)	(0.44)	(0.24)	(0.24)	(0.33)	
Consumer Service	3.003*	-0.697*	-21.739*	-1.540*	3.605*	-1.260*	-2816.8
	(0.04)	(0.02)	(0.21)	(0.01)	(0.02)	(0.01)	
Household Appliances	1.723*	0.462*	-15.889*	-1.672*	3.726*	-0.869*	-3245.4
	(0.00)	(0.01)	(0.09)	(0.00)	(0.02)	(0.00)	
Textiles & Apparel	1.297*	0.770*	-12.976*	0.404*	1.460*	-5.085*	-3588.5
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.01)	
Pharmaceuticals	1.691*	0.812*	-18.149*	1.978*	-0.256*	-9.180*	-2579.6
	(0.07)	(0.06)	(0.33)	(0.02)	(0.01)	(0.14)	
Food & Beverage	3.394*	-1.509*	-22.654*	-1.598*	3.630*	-1.158*	-2069.2
	(0.06)	(0.02)	(0.55)	(0.01)	(0.03)	(0.01)	
Agriculture, Forestry,	-0.104	2.340*	-8.737*	0.948	0.714	-6.257*	-2667.4
Fishery & Animal Husbandry	(0.25)	(0.54)	(2.11)	(2.45)	(3.54)	(0.3)	
Transportation	-0.619*	2.885	-6.801*	0.868*	0.846	-5.020	-3884.4
	(0.06)	(1.76)	(3.22)	(0.28)	(0.44)	(8.36)	
Electricals	1.936*	0.692*	-18.564*	-1.607*	3.706*	-1.257*	-2519.6
	(0.03)	(0.03)	(0.33)	(0.02)	(0.03)	(0.02)	
Telecommunications	-0.968	3.360	-5.967	-1.471	3.521	-1.420	-2546.9
	(0.81)	(7.24)	(17.03)	(1.33)	(3.97)	(16.00)	
Computer	-1.511*	4.091*	-4.524*	-1.737*	3.790*	-0.784*	-2298.7
	(0.17)	(0.02)	(0.09)	(0.06)	(0.10)	(0.01)	
Media	4.346	-2.106*	-28.463*	-1.556*	3.561*	-1.071*	-2477.1
	(4.95)	(1.01)	(13.62)	(0.12)	(1.54)	(0.21)	

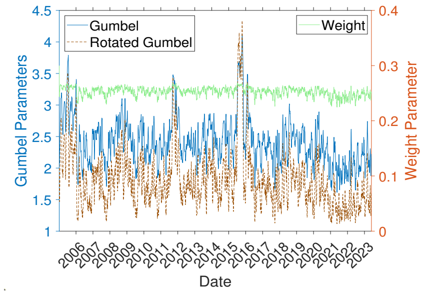
* See notes in Table A.3



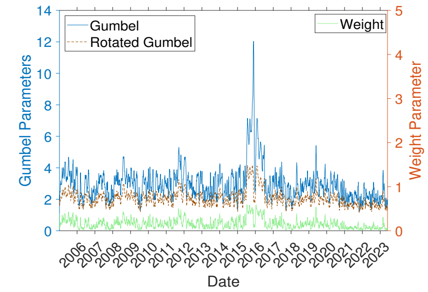
(a) Petrochemical



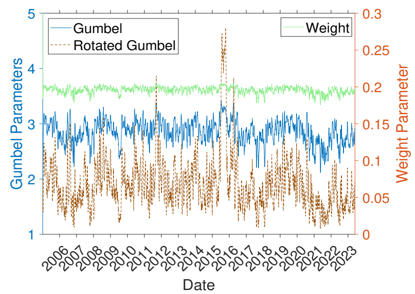
(b) Coal Mining



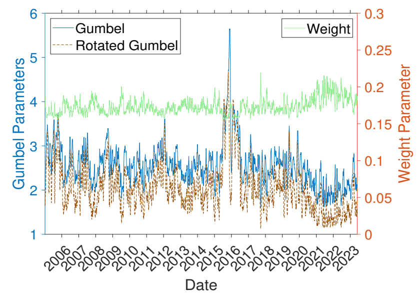
(c) Diversified Metals



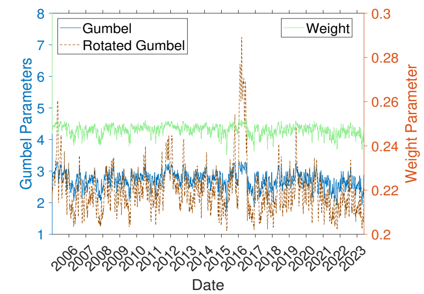
(d) Power & Utilities



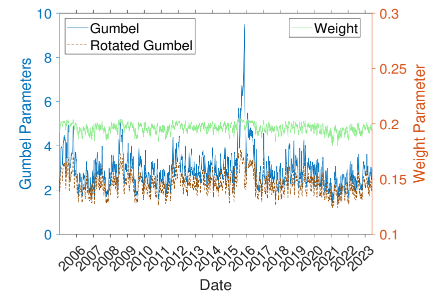
(e) Steel



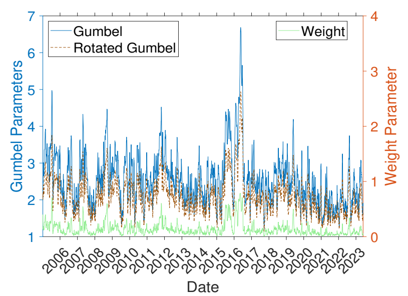
(f) Basic Chemical Engineering



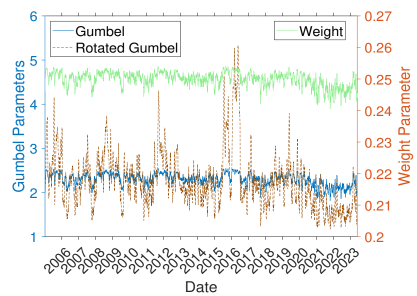
(g) Construction Engineering



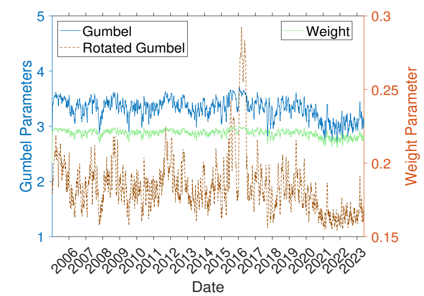
(h) Building Materials



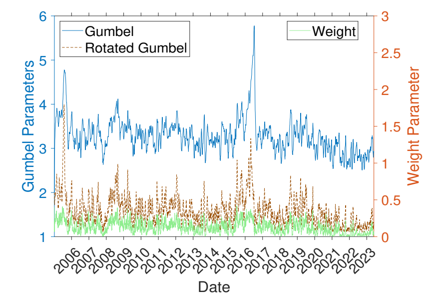
(i) Light Manufacturing



(j) Machinery

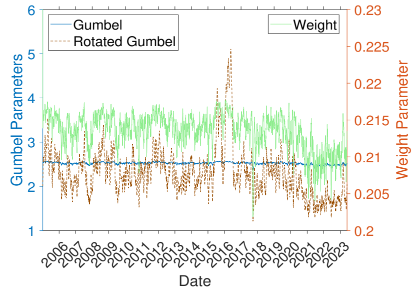


(k) Electrical Equipment & New Energy

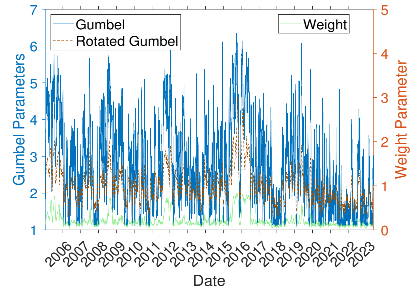


(l) Defense

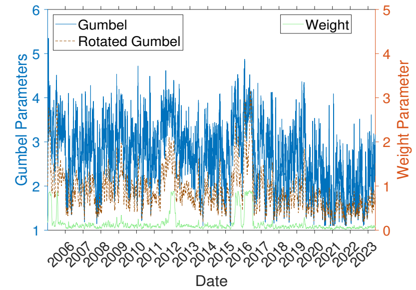
Figure A.2: Time series plot of daily sector index returns



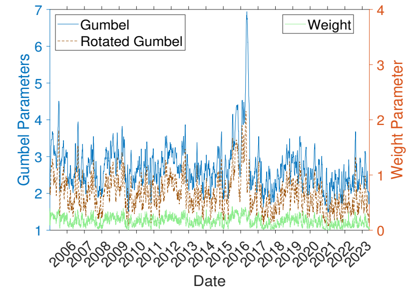
(m) Automobile



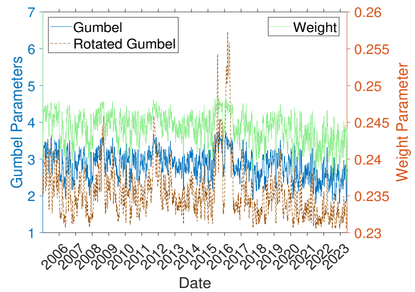
(n) Commerce & Trade Retail Business



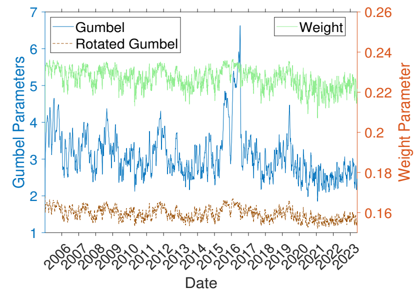
(o) Consumer Service



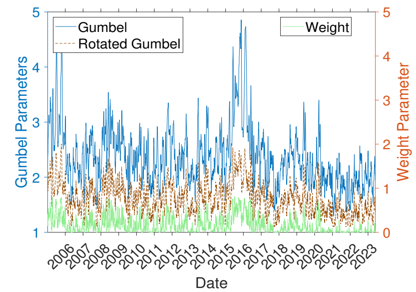
(p) Household Appliances



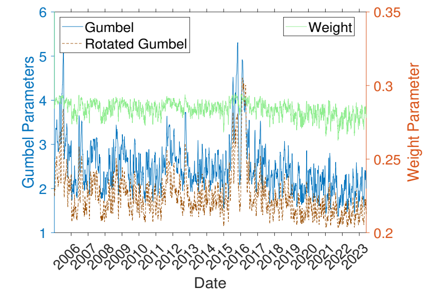
(q) Textiles and Apparel



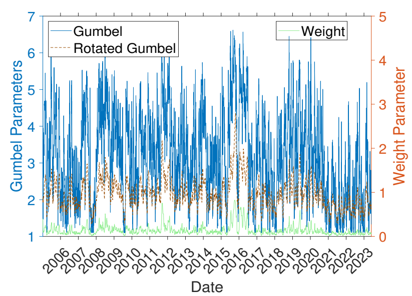
(r) Pharmaceuticals



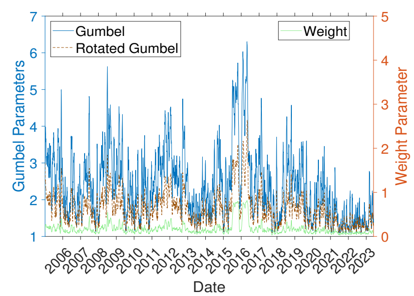
(s) Food and Beverage



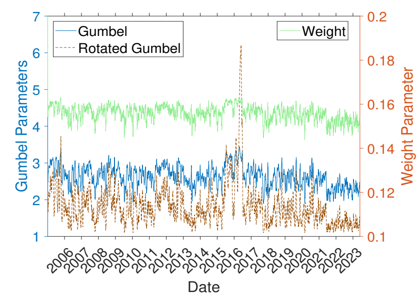
(t) Agriculture, Forestry, Fishery & Animal Husbandry



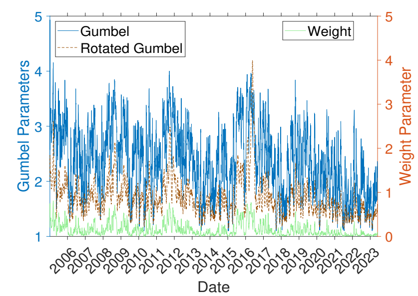
(u) Transportation



(v) Electricals

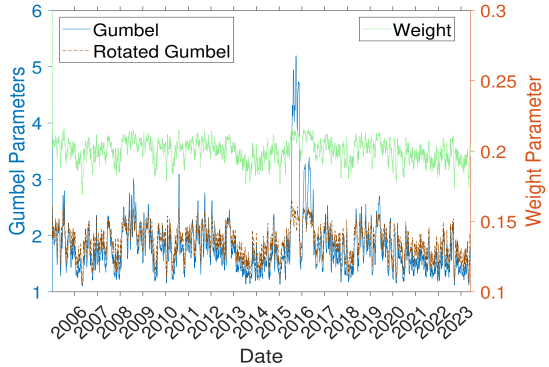


(w) Telecommunications



(x) Computer

Figure A.2: Time series plot of daily sector index returns



(y) Media

Figure A.2: Time series plot of daily sector index returns

	$CoVaR_{normal}$	$CoVaR_{stress}$	H_0: $CoVaR_{normal} = CoVaR_{stress}$ H_1: $CoVaR_{normal} > CoVaR_{stress}$		$CoVaR_{stress}$	$CoVaR_{stress}$
Petrochemical				Commerce & Trade		
Coal Mining				Retail Business		
Diversified Metals				Consumer Service		
Power & Utilities				Household Appliances		
Steel				Textiles & Apparel		
Basic Chemical Engineering				Pharmaceuticals		
Construction Engineering				Food & Beverage		
Building Materials				Agriculture, Forestry, Fishery, & Animal Husbandry		
Light Manufacturing				Transportation		
Machinery				Telecommunications		
Electrical Equipment & New Energy				Computer		
Defense				Media		
Automobile						

Table A.5: Housing policy and financial crisis history from 2005 to 2023

Date	Main event	Name
2005.3.26	Notice of the State Council on Resolutely Curbing the Soaring of Housing Prices in Some Cities	Old National 8 Rules
2005.4.27	The State Council proposed eight measures to regulate the real estate market	National 8 Rules
2006.5.24	General Office of the State Council issued the "Notice of the General and other departments on adjusting the housing supply structure and stabilizing housing prices"	National 6 rules
2007.5.30	Stamp duty was increased from 0.1% to 0.3%, causing the stock market to fall sharply in the short term.	530 Stock Market Disaster
2007.8 -2009.3	The US subprime mortgage crisis began to spread around the world. Stock prices began to fall sharply.	U.S. Subprime Mortgage Crisis

Continued

Date	Main event	Name
2009.11	In November, the Greek Finance Minister announced that Greece's fiscal deficit and public debt far exceeded expectations. On December 8, the world's three major rating agencies downgraded Greece's sovereign rating. Since 2010, other European countries have also begun to fall into crisis.	European Debt Crisis
2010.4.17	General Office of the State Council issued the "Notice of the State Council on Resolutely Curbing the Soaring of Housing Prices in Some Cities"	New National 10 Rules
Late 2015 - Early 2016	The stock prices suddenly plummeted for consecutive days, and a situation of "thousands of stocks hitting the limit down" appeared.	2015 stock market disaster
2015.11.10	At the 11th meeting of the Central Financial Leading Group, President Xi Jinping proposed "supply-side structural reform". "Real estate destocking" became one of the primary tasks.	Supply-side reform
2016.3.5	Premier Li Keqiang firstly mentioned in the government's work report to adopt different policies in different cities as appropriate to their local conditions, in order to cut housing inventory.	Adopting Different Policies in Different Cities
2016.9.30	Beijing introduced new property market policies to comprehensively increase down payment ratios. Subsequently, many cities across the country followed suit.	930 New Policy
2016.12.11	The meeting of the Political Bureau of the Central Committee pointed out that "we should accelerate the research and establishment of a long-effect mechanism for the stable and healthy development of the real estate industry that conforms to national conditions and adapts to market laws."	Real estate long-effect mechanism
2016.12.16	"housing is for living in, not for speculation" was firstly proposed at Central Economic Work Conference	housing is for living in, not for speculation
2017.3.17	Beijing introduces the strictest purchase and loan restrictions	317 New Policy
2018.3.8	U.S. President Donald Trump began setting tariffs and other trade barriers on China	Sino-US trade conflicts
2019.3.18	Vice Premier Han Zheng proposed the "one city, one policy" and "pilot program for long-effect mechanism" during his inspection at the Ministry of Housing and Urban-Rural Development.	One City, One Policy
2019.7.31	The Political Bureau of the Central Committee clearly stated that "real estate will not be used as a means to stimulate the economy in the short term."	Real estate will not be used as a means to stimulate the economy in the short term
2019.12	The outbreak of COVID-19 pandemic	The COVID-19 Pandemic

Continued

Date	Main event	Name
2020.8.20	The Ministry of Housing and Urban-Rural Development and the People's Bank of China have proposed three red lines for the financial conditions of real estate companies.	Three Red Lines Policy
2020.12.28	The Central Economic Work Conference pointed out that "we must persist in promoting both renting and purchasing, accelerate the development of the long-term rental housing market, promote the construction of affordable housing, support the commercial housing market to better meet the reasonable housing needs of buyers, and adopt policies based on the specific conditions of each city to promote a virtuous cycle and healthy development of the housing industry."	Real estate industry begin a virtuous cycle
2022	The central government has repeatedly released stability maintenance signals and made "delivery of buildings" one of the key tasks in the second half of the year. As the central government's stability maintenance signals were released intensively, local cities followed suit and relaxed regulation to stimulate the recovery of the real estate market. However, the long-term effect is not obvious, and market demand is still weak.	Real estate market stabilization