Financial Contagion in China, Real Estate Markets, and Regulatory Intervention

Shiyun Cao[1], Jennifer T. Lai[2], Paul McNelis[3]

[1]Institute for Economic and Social Research, Jinan University, China
[2]School of Finance, Guangdong University of Foreign Studies, Guangzhou, China
[3]Department of Economics, Boston College, Chestnut Hill, Massachusetts, U.S.A.

November 26, 2024

Abstract

This paper assesses the network connectedness of risks in China's stock market, focusing on how shocks in the real estate sector impact financial institutions. We analyze the effect of financial instability in real estate firms on the stability of the broader financial system. To measure the transmission of these risks, we use two key methods: generalized forecast error variance decomposition and the ΔCoVaR approach.Our findings reveal that banks often serve as net receivers of risk, while non-bank financial institutions amplify the transmission of real estate-related risks. This highlights the critical role of non-banks in propagating risk throughout the financial system and underscores the importance of robust systemic risk monitoring across financial networks.

1 Introduction

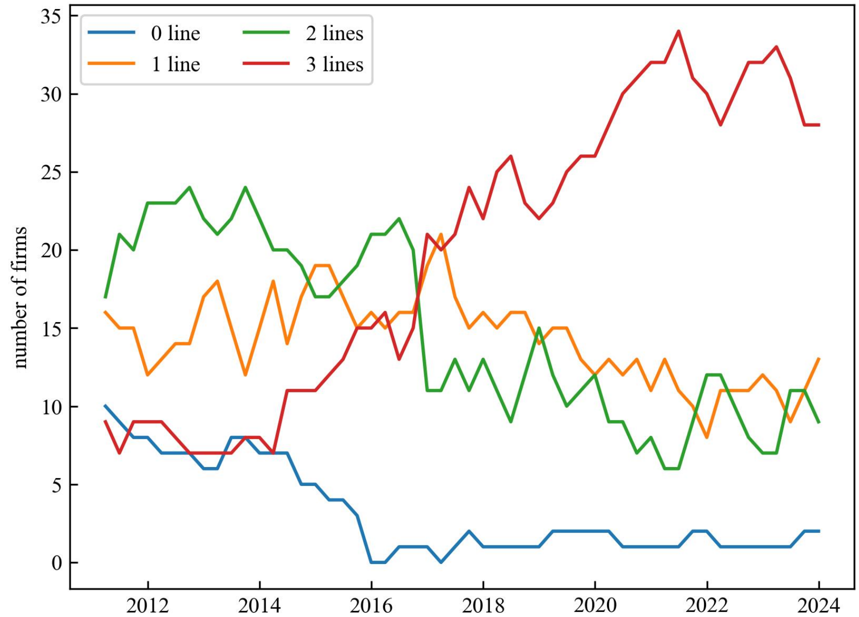
Over the past 20 years, driven by urbanization and structural transformation, China's housing market has experienced rapid growth, with housing prices rising at nearly twice the pace of national income (Chen and Wen, 2017, Garriga *et al.*, 2023). However, this growth has been accompanied by aggressive expansion relying on high-leverage financing, exposing banks to significant risks, as developers borrow without repaying their debt. As Chu *et al.* (2023) highlight, excessive leverage in real estate firms is a effective predictor of future stock price crashes, underscoring the broader financial market implications of the sector's instability.

Recognizing real estate as a notable risk to bank returns (Carmichael and Coën, 2018, Duca and Ling, 2020), policymakers introduced stricter regulations to control housing markets since 2017 to mitigate financial risks and curb unbridled borrowing. In 2020, the "Three Red Lines" policy was introduced to take a more structured approach to deleveraging and controlling their outstanding debt. Fig 1 illustrates the distribution of real estate firms across different risk categories. Notably, there is an upward trend in the number of firms that crossed 3 redlines, highlighting the possibility of the real estate sector falling into a liquidity crisis.

While the policy set limits on future borrowing, it has exacerbated liquidity pressures on heavily indebted firms, many of which are unable to refinance or repay existing loans. As Chu *et al.* (2023) highlight, excessive leverage in real estate firms is a effective predictor of future stock price crashes, underscoring the broader financial market implications of the sector's instability. This instability can trigger contagion effects, as real estate developers' defaults could spill over to the banking sector, potentially impacting overall financial stability.

Against this background, we assess how uncertainty originating in the real estate sector shocks the banking sector through financial network, and exam the role of financial institutions play in amplifying or mitigating these risks. What's more, we explore how these measures of contagion interact with regulatory policy interventions in both stable and volatile market conditions, and how they influence the transmission of risks across the financial system.

Figure 1: Real Estate Classifications under the Red Line Policies

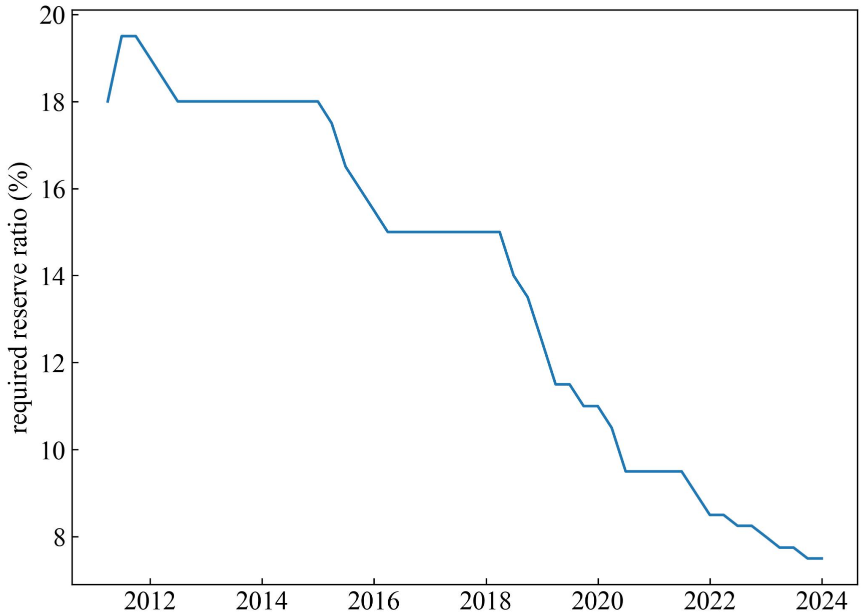


Notes: The "Three Red Lines" policy imposed varying lending restrictions on real estate firms based on three key financial ratios: asset-liability ratio, short-term debt ratio, and net gearing ratio. Firms that overstep these lines are considered more leveraged and will face tighter borrowing limits.
Data source: authors' calculation. The classification of real estate firms is based on firms' financial reports.

The financial industry has demonstrated a pronounced vulnerability to shocks, where disruptions initially affecting a few institutions can quickly spread across the entire industry through the financial network. Even shocks that originate outside the industry have led to significant losses within it, exacerbating instability in financial markets. The interconnected nature of risks within the financial industry means that banks cannot be evaluated in isolation. The spread of risk through network contagion, especially during periods of stress, is a critical factor in a financial firm's exposure (Demirer *et al.*, 2018, Hautsch *et al.*, 2014). The network's density naturally influences how extensively shocks propagate, thereby increasing the financial system's vulnerability (Acemoglu *et al.*, 2015, Atalay, 2017). This interdependence underscores the importance of assessing banking sector risks alongside those in other parts of the financial market.

To infer such information, we collected the stock prices of banks, security companies, insurance companies, and real estate firms from 2011 to 2023. We proposed two methods to measure the directed connectedness among them, with a primary focus on risk transmission related to the banking sector, providing a comprehensive view of how these sectors interact with and influence each other in terms of risk contagion. To measure the risk contagion effect, we employ Generalized Forecast Error Decomposition (GFEVD), due to (Diebold and Yılmaz, 2014), which is broadly used

Figure 2: Quarterly time series of the required reserve ratio



in assessing the directed uncertainty contagion effect (Baruník *et al.*, 2022, Demirer *et al.*, 2018, Yang *et al.*, 2018). Additionally, we employed ΔCovar(Adrian and Brunnermeier, 2016), which captures the tail dependency structures among different sectors and measures how firms perform when experiencing systemic distress(Breugem *et al.*, 2024, Duan *et al.*, 2021), to assess the change in the value at risk(VaR) of each bank conditional on distress in the real estate and the non-banks sectors, relative to their median returns, as well as the banks' systemic risk.

To further evaluate the interaction between real estate regulatory intervention and financial market volatility, we utilize the directed connectedness derived from GFEVD and ΔCovar estimation to construct contagion indices both within- and between-sector. These indices help to analyze how shocks spread throughout the financial market. In addition, we incorporate two key regulatory instruments, the Three Red Lines metric, which ranks real estate firms based on their financial health, and the Required Reserve Ratio(RRR), a monetary instrument the People's Bank of China (PBoC) used to influences credit availability and, in turn impacts economic activities. This structural monetary policy is often adjusted to redirect credit resources and ease financial instability(Chen *et al.*, 2018, Wei and Han, 2020). [1] By incorporating the dispersion of redline rankings and weighted RRR into VAR model, along with the contagion indices, we examine the effects of regulatory interventions on risk spillover across financial sectors.

Our analysis reveals distinct patterns of risk transmission within the financial system. First, banks consistently exhibit negative net connectedness in GFEVD estimation, indicating their roles as net risk receivers in the financial system. Meanwhile, non-bank financial firms show more varied results, with some acting as modest risk transmitters. Second, non-banks are significantly affected by the real estate sector's tail risk, with these spillover effects becoming more pronounced after 2020. As risk transmission from real estate firms to non-banks increases, cross-sector risk amplifies, leading to greater diversification in real estate classifications, and further heightening risks within the banking sector. This highlights the critical role of non-banks in transmitting real estate risks,

[1] Since 2018, the People's Bank of China has cut the reserve requirement ratio 18 times, providing approximately 14.4 trillion yuan in long-term funding. http://www.pbc.gov.cn/rmyh/4027845/index.html

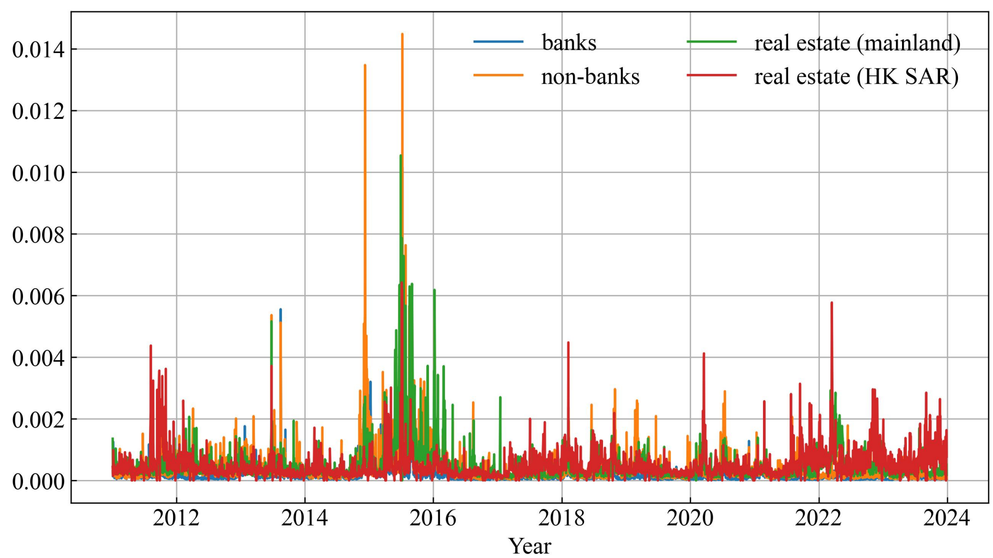
reinforcing the importance of monitoring their systemic risk contributions.

The rest of the paper is organized as follows. Section 2 describes the data used in our research. In section 3 we describe the two methods applied to estimate the directed connectedness. Section 4 presents the results for the contagion network of the financial market. Section 5 further examines the relationship between- and within-sector contagion indices and policy intervention based on weighted directed graphs and Impulse Response paths with bootstrapped confidence intervals. Section 6 concludes.

2 Data

We use A-share stock trading data to compute daily individual stock volatility measures from 4 January 2011 to 29 December 2023. As we focus mainly on real estate risk, we include some real estate giants listed in Hong Kong as well. Our sample consists of 82 stocks: 16 banks, 4 insurance companies, 10 financial institutions, and 52 property firms. We normalize the price indices by dividing the starting values and taking the logarithmic values. Therefore, the mean and medium values represent the percentage of net expected gains or losses relative to the starting day of the sample. Table 1 presents the summary statistics of financial institutions in our research, one can notice that most institutions' returns are positive. Figure 3 illustrates the normalized median volatility, measured by stock prices. We observed a high median value between 2015 and 2016, a period influenced by the stock market crash that elevated overall market volatility.

Figure 3: Normalized Garman-Klass Range Volatility-Median Value



Notes: This figure shows the median range volatility series for the banking sector, non-bank sector(which includes insurance companies and financial institutions), and real estate sector listed in two markets covering the period from 4 January 2011 to 29 December 2023 with a daily frequency.

To capture the contagion dynamic, we control for macroeconomic factors using 7 variables. We include VIX [2] to account for overall market uncertainty, and the Hang Seng China Enterprises Index(HSCEI) stock index to adjust for common factors affecting Chinese mainland companies.

[2]The VIX is the implied volatility from the options on the Standard and Poor 500 stock index. It shares similar trends with the China market's VIX and offers a longer data history. Therefore, we use the US VIX in our analysis. The trend comparison between the two indices is provided in the Appendix.

To capture short-term liquidity conditions and interest rate impact in China, we make use of the 1-week Shanghai Interbank Offered Rate (SHIBOR) and 3-month Chinese Treasury bond rate. Additionally, we control global factors, such as the World Uncertainty Index(Ahir *et al.*, 2022), Chinese trade policy uncertainty(Davis *et al.*, 2019), and CNY/USD exchange rate, which reflect macroeconomic and geopolitical conditions. Table 2 provides summary statistics of the control variables. All control variables are normalized using the formula $x^* = (x - x_{min})/(x_{max} - x_{min})$.

Table 1: Descriptive Statistics of returns, 2011-2023

Variable	Name	Mean	Std. Dev.	Min	Max
PinganB	Ping An Bank	0.000	0.001	0.000	0.013
NBCB	Bank of Ningbo	0.000	0.001	0.000	0.016
SPDB	Shanghai Pudong Development Bank	0.000	0.000	0.000	0.006
HXB	Huaxia Bank Co.	0.000	0.001	0.000	0.012
CMBC	China Minsheng Bank Co.	0.000	0.001	0.000	0.010
CMB	China Merchants Bank	0.000	0.001	0.000	0.012
NJCB	Bank of Nanjing	0.000	0.001	0.000	0.014
CIB	Industrial Bank of China	0.000	0.000	0.000	0.007
BOB	Bank of Beijing	0.000	0.000	0.000	0.009
ABC	Agricultural Bank of China	0.000	0.000	0.000	0.006
COMM	Bank of Communication	0.000	0.001	0.000	0.010
ICBC	Industrial and Commercial Bank of China	0.000	0.000	0.000	0.010
CEB	China Everbright Bank	0.000	0.001	0.000	0.017
CCB	China Construction Bank	0.000	0.000	0.000	0.012
BOC	Bank of China	0.000	0.001	0.000	0.013
CITICB	China Citic Bank	0.000	0.001	0.000	0.013
NESC	Northeast Securities	0.001	0.001	0.000	0.016
GYZQ	Sealand Securities	0.001	0.001	0.000	0.016
GHZQ	Guohai Securities	0.001	0.001	0.000	0.017
GF	GF Securities	0.001	0.001	0.000	0.019
CJS	Changjiang Securities	0.001	0.001	0.000	0.019
Yuexiu Fin	Yuexiu Capital	0.001	0.001	0.000	0.019
ECITIC	CITIC Securities	0.000	0.001	0.000	0.016
HTSEC	Haitong Securities	0.000	0.001	0.000	0.012
CMS	China Merchants Securities	0.001	0.001	0.000	0.018
Pingan	Ping An Insurance	0.000	0.001	0.000	0.013
Newchinalife	Newchinalife Insurance	0.000	0.001	0.000	0.018
XYZQ	Industrial Securities	0.001	0.001	0.000	0.019
CPIC	China Pacific Insurance (Group)	0.000	0.001	0.000	0.009
Chinalife	China Life Insurance	0.000	0.001	0.000	0.011
Vanke	Vanke	0.000	0.001	0.000	0.011
ZY	Shenzhen Zhenye	0.001	0.001	0.000	0.016
Shahe	Shahe	0.001	0.001	0.000	0.014
ZZ	Zhongzhou	0.001	0.001	0.000	0.017
China-ia	Shenzhen Wongtee	0.001	0.001	0.000	0.016
OCT	Overseas Chinese Town	0.001	0.001	0.000	0.016

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Table 1 – continued from previous page

Variable	Name	Mean	Std. Dev.	Min	Max
JRJ	Financial Street Holdings	0.000	0.001	0.000	0.015
UKF	Chongqing Yukaifa Co.	0.001	0.001	0.000	0.014
Rongan	Rongan	0.001	0.001	0.000	0.015
SFHY	Shunfa Hengye Corporation	0.001	0.001	0.000	0.020
Jinke	Jinke Property Group	0.001	0.001	0.000	0.014
suning	Suning Universal	0.001	0.001	0.000	0.017
Cccg	CCCG Real Estate	0.001	0.001	0.000	0.017
Wuyi	China Wuyi	0.001	0.001	0.000	0.017
cqcasin	CASIN Real Estate Development Group	0.001	0.001	0.000	0.017
JBDC	Tianjin Jinbin Development	0.001	0.001	0.000	0.014
Shirong	Shirong	0.001	0.001	0.000	0.019
cosmosgroup	Cosmos Group	0.001	0.001	0.000	0.016
risesun	Risesun Real Estate Development	0.001	0.001	0.000	0.015
HFCT	Hefei Urban Construction Development	0.001	0.001	0.000	0.016
Bingjiang	Binjiang Group	0.001	0.001	0.000	0.016
Worldunion	World Union Properties Consultancy	0.001	0.001	0.000	0.018
langold	Langold Real Estate	0.001	0.001	0.000	0.020
Polycn	Poly Developments and Holdings Group	0.001	0.001	0.000	0.014
Greattown	Greattown Holdings	0.001	0.001	0.000	0.019
DLDC	Beijing Dalong Weiye Real Estate	0.001	0.001	0.000	0.017
Greedc	Gree Real Estate	0.001	0.001	0.000	0.015
BUCID	Urban Construction Development	0.001	0.001	0.000	0.013
TFFZ	Jinto City Development	0.001	0.001	0.000	0.013
Gemdale	Gemdale Corporation	0.001	0.001	0.000	0.017
BA	Beijing Airport High-Tech Park	0.001	0.001	0.000	0.015
Greenland	Greenland Holdings	0.001	0.001	0.000	0.011
EBJB	Everbright Jiabao	0.001	0.001	0.000	0.018
NHP	Shanghai New Huangpu Real Estate	0.001	0.001	0.000	0.014
Cinda	Cinda Real Estate	0.001	0.001	0.000	0.020
LJZ	Lujiazui Finance & Trade Zone Development	0.000	0.001	0.000	0.017
Metro Land	Metro Land Corporation	0.001	0.001	0.000	0.014
Bright	Bright Real Estate Group	0.001	0.001	0.000	0.016
Huayuan	Huayuan Property	0.001	0.001	0.000	0.019
Tibet UD	Tibet Urban Development and Investment	0.001	0.001	0.000	0.018
ZJpark	Zhangjiang Hi-Tech Park Development	0.001	0.001	0.000	0.012
Yuexiu	Yuexiu Property	0.000	0.001	0.000	0.009
Poly	Poly Property Group	0.001	0.001	0.000	0.015
AsiaStandard	Asia Standard International	0.000	0.001	0.000	0.022
Wanda	Wanda Hotel Development	0.002	0.009	-0.007	0.386
CRLand	China Resources Land Limited	0.001	0.001	0.000	0.014
CountryGarden	Country Garden Holdings	0.001	0.002	0.000	0.057
RF	Guangzhou R&F Properties	0.001	0.002	0.000	0.056
Agile	Agile Group Holdings	0.001	0.001	0.000	0.039
Aoyuan	China Aoyuan Group Limited	0.001	0.002	0.000	0.053
Greentown	Greentown China Holdings	0.001	0.001	0.000	0.015

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Table 1 – continued from previous page

Variable	Name	Mean	Std. Dev.	Min	Max
Evergrande	China Evergrande Group	0.001	0.004	0.000	0.110

Table 2: Normalized control variable

	Mean	Std. Dev.	Min	Max
VIX	0.275	0.143	0	1
CNYUSD	0.488	0.229	0	0.873
HSCEI	0.617	0.179	0	1
SHIBOR: 1W	0.428	0.108	0.177	1
World Uncertainty Index	0.5	0.193	0	1
Trade Policy Uncertainty	0.583	0.207	0.008	1
Tbond: 3M	0.591	0.142	0.023	1

We compile the Redline classification of real estate firms from their quarterly and annual financial reports, based on the Three Red Line policy indicators. These indicators, referred to as "redlines", includingwhether the short-term debt ratio falls below 1, whether the asset-liability ratio (excluding advanced) exceeded 70%, and whether the net gearing ratio exceeded 100%. Developers who overstepped all three redlines will prohibited from taking new debts in the following year. If one or two lines are breached, debt growth is capped at 10% and 5%, respectively. We make use of the rank dispersion to observe compliance trends and evaluate if policy ranking can serve as a warning signal for potential risks in the real estate sector. By using rank dispersion, we can observe trends in compliance and evaluate if the policy ranking can act as a warning signal for potential risk in the real estate sector.

3 Method

This section briefly introduces the two methods we used to analyze interconnectedness across financial sectors. The first measures come from time-varying generalized variance decomposition matrices, which quantify the risk spread from one to another. The second approach is ΔCoVaR, which we use to capture the directional systemic risk when a specific sector is under distress.

3.1 GFEVD method

Volatility reflects investor sentiment, particularly during periods of heightened uncertainty. If volatility tracks fear, then volatility connectedness captures how that fear spillovers to others(Demirer *et al.*, 2018). This makes volatility connectedness a valuable tool for monitoring real-time risk in a crisis.

To measure volatility, we construct a stock price range volatility measure from daily open (o), close (c), high(h), and low (l) prices following the work of Garman and Klass (1980).

$$\hat{\sigma}_t^2 \equiv 0.511(h-l)^2 - 0.019\left[(c-o)(h-l-2o) - 2(h-o)(l-o)\right] - 0.383(c-o)^2$$

We base our connectedness measurement of risk contagion on the Forecast Error Variance Decomposition matrix composed through VARX estimation (Diebold and Yılmaz, 2014). Specifically, we use a lag length of 5 days to construct the 20-day-ahead forecast error variance; 7 control variables are included in this regression. The connectedness measure then relies on the variance decomposition, which quantifies the contribution of volatility to the system.

Consider a stationary volatility measure $\hat{\sigma}_t^2$ with orthogonal shocks, the H-step generalized forecast error variance of the ith variable due to shocks in the jth variable can be defined as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=1}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}$$

where σ_{jj}^{-1} is the standard deviation of the error term for the jth equation, Σ is the variance matrix of the error vector, and e_i is a selection vector of one in the ith element and zero otherwise.

To evaluate the connectedness of the overall network, we compute the TOTAL connectedness through the equation:

$$C^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)$$

where $\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}$. Once we measure the aggregate connectedness, we further assess the role of each variable in the network to identify which variables act as risk transmitters or receivers. We define the TO connectedness as:

$$C_{i \to \cdot}^H = \sum_{\substack{j=1, \\ j \neq i}}^{N} \tilde{\theta}_{ji}^g(H)$$

which characterizes the total volatility transmitted by ith variable to other variables. Conversely, FROM connectedness measures the total volatility received by variable i from all other variables:

$$C_{\cdot \to i}^H = \sum_{\substack{j=1, \\ j \neq i}}^{N} \tilde{\theta}_{ij}^g(H)$$

Finally, the NET connectedness is the difference between the TO and FROM connectedness: $C_i = C_{i \to \cdot}^H - C_{\cdot \to i}^H$. This measure indicates whether a firm or sector generates more risks than it receives from the network.

Using a VAR model with large panel parameters may cause the overfitting problem, to minimize the estimated coefficients, we adapt the Elastic Net estimation scheme in Zou and Hastie (2005)

$$\hat{\beta} = \arg\min_{\beta} \left\{ \sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{k} \left[\alpha |\beta_i| + (1-\alpha)\beta_i^2 \right] \right\}$$

To choose the optimal parameter, we:

1. use 10-fold cross-validation to choose the optimal penalty $\lambda = 0.25$. A default value of 0.25 is leveraged to use 25% weighted penalty to the coefficients;
2. run full-sample Elastic Net with $\lambda = 0.25$, and set 20-fold cross-validation to select the optimal weighting α. An α of k would furnish a $k \times 100\%$ contribution of the Lasso penalty to the loss function.

3.2 ΔCoVaR method

In addition to overall volatility measures, quantile regression offers an alternative approach to measuring directional risk by estimating the probability of falling below critical values on the left tail of the return distribution. (Adrian and Brunnermeier, 2016) extended this concept and proposed ΔCoVaR to measure how an institute's performance deviates from the median return, given that the specific sector is in distress. This method allows us to identify which bank is most vulnerable during downturns.

Following their methodology, we estimate the quantile regression with weekly data. The regression involves the following steps: First, we calculate the weighted returns for A-shares and H-shares in the real estate sector, as well as for the banking, insurance, and securities sectors, to construct sectoral return variables. The weighted returns for banks include all banks except the one being estimated. To assess the performance of bank j under distress in sector i, we use the negative values of sector i's return variable, ensuring that the 95th percentile reflects the lower 5th percentile. We then perform a ΔCoVaR regression at the 95 percent level of the system return variables on bank j's returns, alongside control variables:

$$X_t^{j|i} = \alpha_\tau^{j|i} + \gamma_\tau^{j|i}\mathbf{M}_{t-1} + \beta_\tau^{j|i}X_t^i + \epsilon_{\tau,t}^{j|i}$$

where X_t^i denotes the value for a τ-quantile of j conditional on a return realization of sector i, $\mathbf{M}_{t-1}$ represents the independent variables at time t-1, including state variables, weighted market volatility, and any other relevant controls. When sector j is in distress, i's performance is represented by:

$$VaR_{\tau,t}^i = \hat{\alpha}_\tau^i + \hat{\gamma}_\tau^i\mathbf{M}_{t-1}^i$$

$$\text{CoVaR}_{\tau,t}^{j|i} = \hat{\alpha}_\tau^{j|i} + \hat{\gamma}_\tau^j\mathbf{M}_{t-1}^i + \hat{\beta}_\tau^{j|i}VaR_{\tau,t}^i$$

$$\Delta CoVaR_{\tau,t}^{j|i} = \text{CoVaR}_t^\tau - \text{CoVaR}_t^{0.5} = \hat{\beta}_\tau^{j|i}\left(VaR_{\tau,t}^i - VaR_{0.5,t}^i\right)$$

By repeating the regression for all banks, we can obtain the relative importance of each bank to the market risk. We constructed the directed tail risk by using real estate returns, nonbank returns, and banking sector returns separately to see each bank's performance under the extreme risks.

4 Results

4.1 GFEVD method: static analysis

We begin the empirical analysis by discussing how individual firms contribute to the connectedness of the network.

Figure 4 displays the NET connectedness of each sample firm. Each bar represents the firm's net position in terms of connectedness during the sample period. The first row of the figure shows the results of banks, which generally have a negative net connectedness, indicating that they tend to absorb more volatility than they transmit. The results of non-bank financial institutions are more varied, as shown in the second row. Some firms are net transmitters, though the amount they transmit remains relatively low. In contrast, certain real estate companies, like China-ia and Wanda, display a high positive net connectedness. This indicates that these firms are net transmitters of risk, actively spreading risks to other financial institutions during the sample period.

Overall, the figure confirms a clear pattern of volatility propagation within the financial industry: banks generally act as risk absorbers, while non-bank financial institutions, such as securities firms and insurance companies, exhibit more varied roles with differing levels of net connectedness.

4.2 GFEVD method: time dynamics

Given that the relationship among firms is not stationary, we use the rolling window to estimate the dynamic relationship of firms. First, we present the average NET connectedness during the period, then we analyze trends of each sector.

Figure 5 shows that most banks and non-bank financial institutions, including notable entities such as Ping An Bank (PinganB) and China Life Insurance (Chinalife), exhibit negative average values of NET connectedness. This negative trend suggests that these institutions are predominantly risk receivers rather than contributors, absorbing external shocks more than they spill out. Conversely, real estate firms demonstrate positive average values of NET connectedness. Among these, Evergrande stands out with a nearly unprecedented net connectedness value approaching 10. This high value underscores Evergrande's substantial role as a transmitter of risk within the industry. The positive NET connectedness of real estate firms indicates their potential to amplify and spread financial distress.

Moving to the time-varying connectedness dynamics, Figure 6 captures the evolving patterns of net connectedness for sectors over time. The values are constructed by the Elastic Net VAR estimation, with a moving window of 250-day and a horizon of 20. We find that for most of the time, for most of the sample period, banks act as risk receivers within the network. The connectedness level of the banking sector exhibited significant volatility from 2014 to 2016. Similarly, the non-bank sector displayed comparable patterns, but it became increasingly volatile than the banking sector after 2018. It is also noticeable that the NET connectedness of real estate firms (H-stock) consistently exhibits a high net connectedness, functioning as a risk transmitter in the network. Following 2020, volatility surged, with mainland-listed real estate firms showing a reversal in trend, which suggests that the risk primarily propagates within the real estate sector.

4.3 $\Delta Covar$

We perform a rolling quantile regression to assess the impact of real estate firms' tail risk on banks and non-banks, as well as the systemic risk contributions of individual banks. We measure share-price returns on a weekly basis. Figure 7 presents the maximum values from each period within the sample, calculated using a rolling window regression with a window size of 40 weeks. The results reveal significant increases in $\Delta Covar$ during the 2015 market crash, and real estate-induced non-bank risk rises sharply in mid-2020, coinciding with the onset of defaults by real estate developers. Notably, the maximum level of $\Delta Covar$ for bank's systemic risk contribution is lower than those driven by real estate firms and non-banks.

5 Regulatory interventions and contagion

We evaluate the interaction between regulatory interventions and contagion behaviors through VAR model. Regulatory interventions are represented by the dispersion of firms' classifications under the Three Red Lines policy and the required reserved ratio implemented by the PBoC.For red line classification, a smaller standard deviation indicates that most real estate firms share similar levels of risk exposure. As a safeguard of bank liquidity, the RRR can directly impact credit conditions and might amplify contagion effects by influencing the flow of credit to firms with varying risk profiles. Additionally, the contagion indices are calculated based on former Generalized Forecast Error Variance Decomposition(GFVED) and $\Delta Covar$ estimates.

5.1 GFEVD

We begin by using GFEVD matrices to quantify both within-sector and between-sector contagion behavior. Each GFVED matrix is divided into nine sub-matrices, representing interactions either between two financial sectors or within a single sector. By summing the elements within the diagonal sub-matrices, we can obtain the TOTAL connectedness within each sector. Similarly, summing the elements of off-diagonal sub-matrices allows us to quantify the amount of risk spillover from one sector to another. To determine the NET connectedness between sectors, we subtract the sum of the corresponding lower triangular sub-matrices from their symmetry upper triangular ones. Figure 8 pictures the trend of the contagion indices and intervention measures. We estimated the VAR model with 150 lags, and use lasso estimation with Cross-Validation to remove the nuisance parameters, which eliminated about 95.71 percent of coefficients. This method enables us to capture the key interactions between variables while minimizing the influence of irrelevant ones.

Figure 9 illustrates the network of the interactions among 8 variables. It is noticeable that the NET spillover from real estate to non-banks seems to be the major transmitter in the network, indicating that as this between-sector NET spillover increases, it indirectly affects the connectedness of other relations by increasing the volatility spillover within-sector and between-sector. Furthermore, we also observe that the increased risk spillover from real estate to non-banks contributes to greater divergence in real estate firms' classifications, suggesting that the Three Red Lines effectively identifies firms with different levels of exposure to contagion risk. The reserve requirement ratio is also impacted, reflecting the regulatory adjustments in response to rising contagion risk.

The bootstrapped impulse response paths in Figure 10 illustrate how contagion relationships and regulatory intervention measures respond to shocks in the NET spillover from the real estate sector to the non-bank sector over time. The first row shows the responses of TOTAL connectedness within each sector, the second row presents the response of NET connectedness between sectors, and the third row displays the effect on regulatory policy instruments.

In the first row, we see a significant initial response in the Non-bank and Real estate sectors, suggesting that when there is a shock in the NET spillover from real estate risk to non-bank, it increases the internal risk connections within these sectors, amplifying the overall contagion effect. A similar pattern occurred in the within-sector NET spillover from real estate to the banking sector, with a strong initial response and a gradual decrease after. The response is stronger than that of within-sector NET spillover, indicating that the banking sector is highly sensitive to risks in the real estate sector. The sustained positive response after the initial spike implies a prolonged sensitivity of the banking sector to contagion originating from real estate. In the third row, we see a moderate increase in the Redline dispersion, indicating that the diversification in firm classification grows in response to these shocks. The RRR, on the other hand, shows a strong initial reaction, but the influence diminishes over time, suggesting a temporary regulatory adjustment.

5.2 $\Delta Covar$

In addition to the GFEVD contagion network, we construct four contagion indices by calculating the standard deviation of $\Delta Covar$ for each of the following: banks, real estate to banks, real estate to non-banks, and non-banks to banks over the entire period. Each index represents the volatility of specific systemic risk contributions specific to one of these sectors or interactions. We then estimate the VAR with Lasso and Cross-Validation using 10 lags, while 49.12 percent coefficients are eliminated. Figure 11 presents the trends of four contagion indices and the Red Line risk index of the real estate sector. Figure 12 illustrates the network relationships among five key variables. The network reveals a strong spillover effect from real estate-induced non-bank systemic risk, impacting all variables except the RRR. This suggests that when the real estate sector experiences a downturn, the systemic risk in the non-bank sector rises and subsequently affects the banking sector, other non-bank institutions, and the dispersion of the red line classifications. This highlights the crucial role of non-banks as intermediaries in transmitting real estate risk throughout the financial system.

Furthermore, banks' systemic risk is closely tied to risks within the banking sector and to risks originating from other sectors. This underscores banks' role as risk absorbers within the broader financial network. Consistent with the GFEVD measures, the major factor affecting the dispersion of red line classification is the transmission of real estate risk through non-banks. As real estate-related shocks become more volatile, they impact non-bank systemic risk, which in turn causes greater divergence in the real estate firm classification.

This effect is further highlighted in the bootstrapped impulse response path shown in Figure 13, which demonstrates that shocks from real estate risks to non-banks can cause a greater dispersion in the default ratio among firms, as measured by the Three Red Line metric.

6 Conclusion

The directed connectedness measures of risk contagion were constructed to assess how shocks transmitted through stock markets affect banks within the financial network, represented by 82 Chinese listed firms. Banks, non-banks, and real estate firms play different roles in this financial network as transmitters or receivers of risk. By examining decomposed variance matrices, we identify that banks primarily act as risk receivers in the financial system. In the recent context of Chinese real estate developers' default incidents, banks have been significantly affected through indirect transmission. The risk from the real estate sector directly spills over to the non-bank sector, which subsequently propagates that risk to banks.

We find that spillover from real estate to non-banks is a critical factor influencing the broader contagion dynamics. As extreme events in the real estate sector increase in volatility, they heighten the systemic risk exposure of non-banks, which, in turn, propagate this risk to banks. This interconnectedness amplifies the volatility within the banking sector, as observed in the contagion indices and the network of interactions between sectors.

The VAR estimation supports these findings, particularly highlighting the importance of non-banks in the contagion network. The impulse response paths further confirm that shocks from real estate to non-banks have significant, lasting effects on systemic risk transmission, increasing uncertainty in bank risk exposure and impacting real estate firms' classification under the Three Red Line policy.

Our results highlight that as real estate-related risks become more volatile, their spillover effects on non-banks lead to greater divergence in firm classifications and a wider dispersion of default ratios, particularly among real estate firms. This reflects the growing systemic risk posed by real estate to both non-banks and banks, emphasizing the need for careful regulatory interventions to mitigate these spillover effects and ensure financial stability.

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full_net.jpg

Figure 4: Static Network Connectedness Estimation

Notes: This figure illustrates the static estimation results of network NET connectedness for all 82 institutions over the entire sample period. NET connectedness is the difference between the total volatility sent out and the total volatility received.

average_netvol.jpg

Figure 5: Dynamic Network Connectedness Estimation

Notes: This figure displays the mean values of net connectedness across all rolling window periods. The values are constructed by the Elastic Net VAR estimation, with a moving window of 250 days and a horizon of 20.

Figure 6: Median value of rolling window estimation

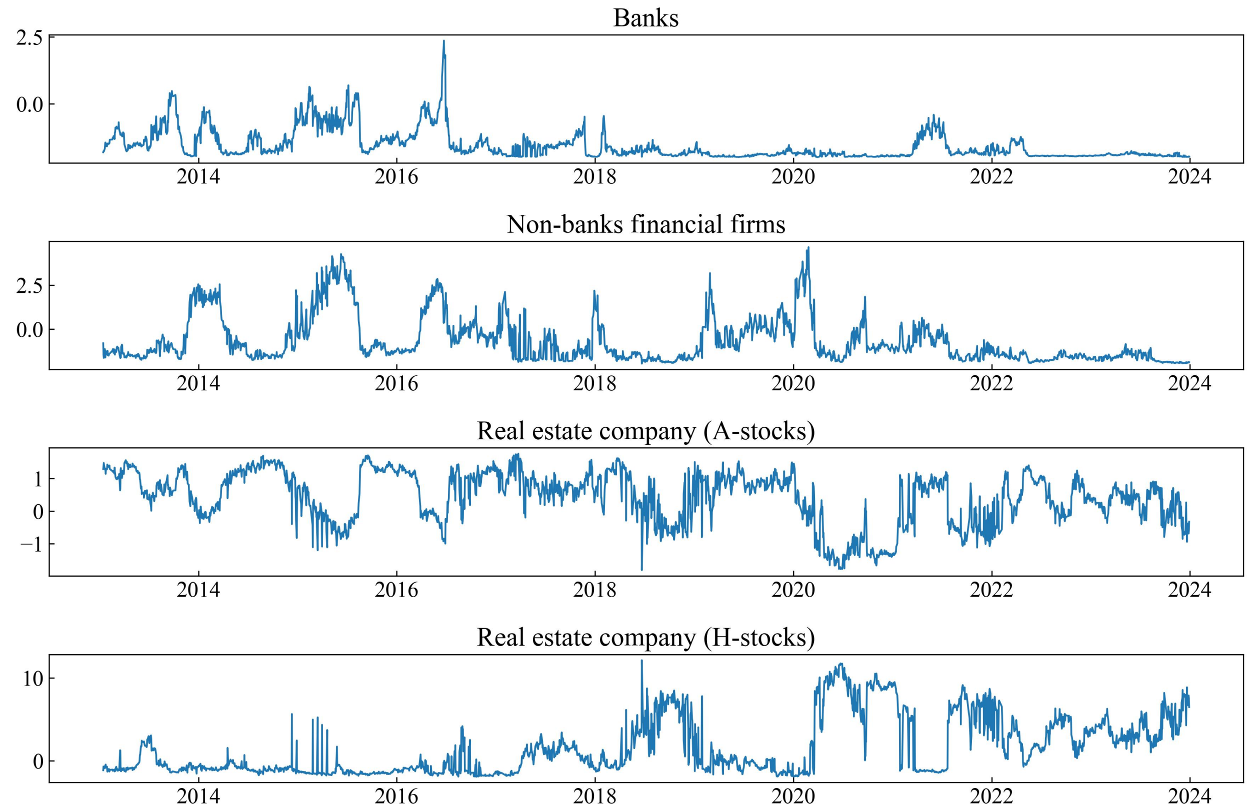

Figure 7: Maximum values of $\Delta Covar$ with rolling regression estimation

max_Dcovar.jpg

Figure 8: GFEVD contagion indices and regulatory intervention

dy_trend.jpg

Figure 9: Network map of contagion index and policy interventions

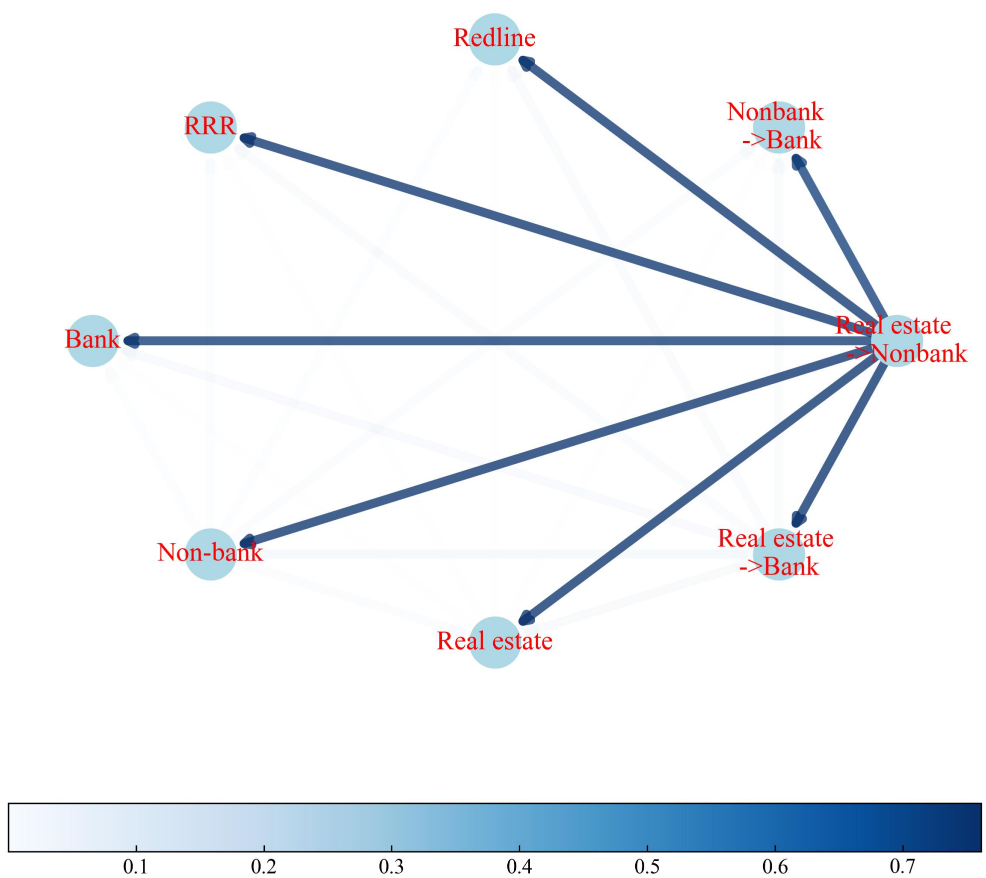

Figure 10: Impulse Response Path: Response of Real Estate→Non-bank

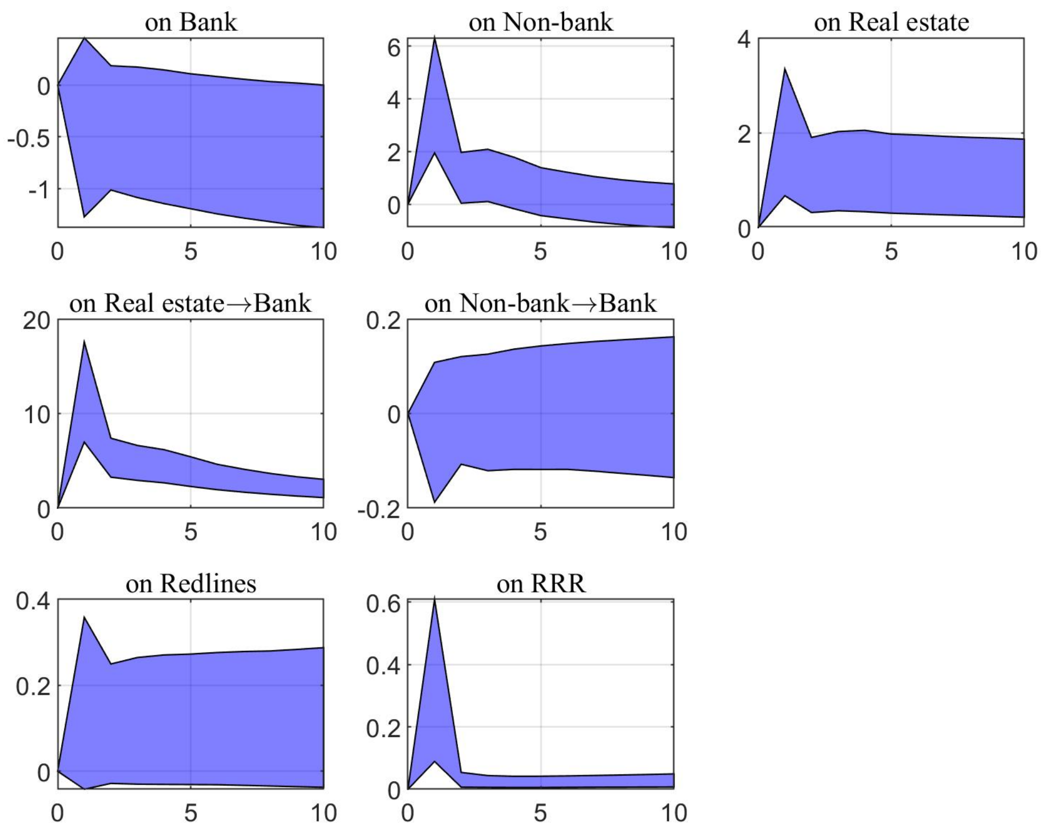

Figure 11: $\Delta Covar$ contagion indices and default ratio

dcovar_trend.jpg

Figure 12: Network map of contagion index and policy interventions

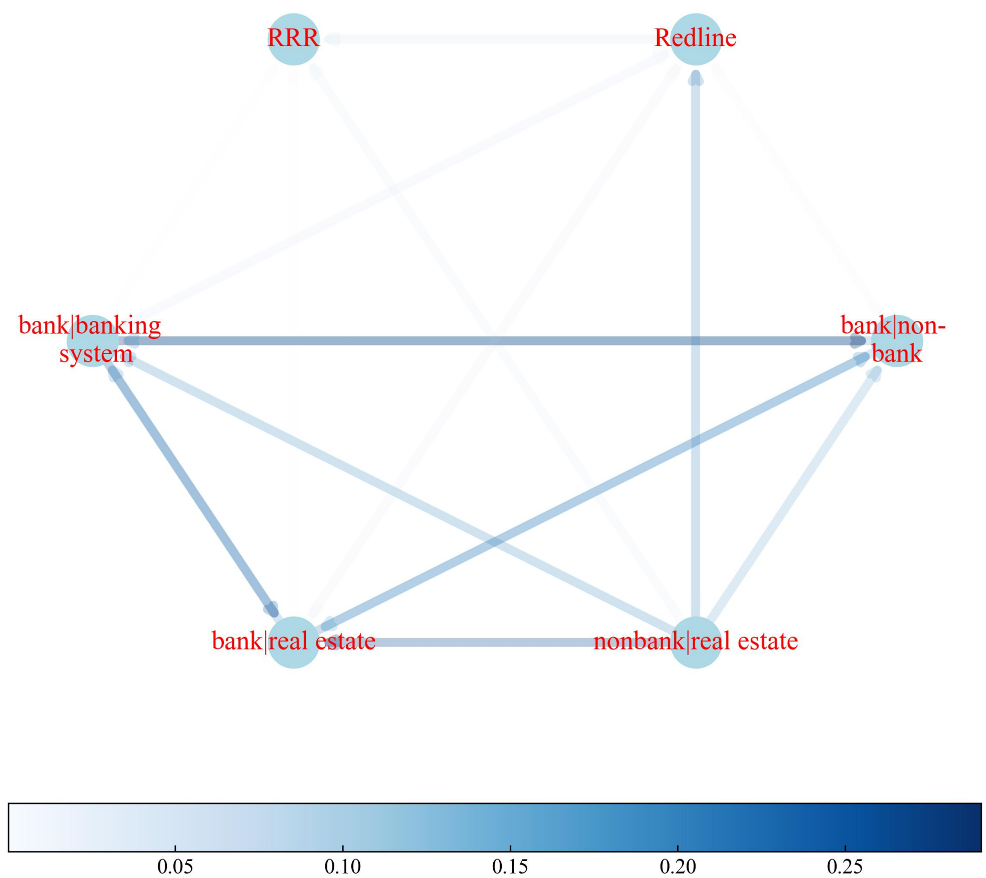

Figure 13: Network map of contagion index and policy interventions