Systemic Risk in the Chinese Financial System: A Panel Granger Causality Analysis*

Peter Cincinelli† Elisabetta Pellini‡ Giovanni Urga§

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Abstract

In this paper, we investigate China's changing financial interconnectedness via the presence of Granger-causality between firm level factors (*Leverage*, *Market To Book Value* and *Returns*) and systemic risk measures ($\Delta CoVaR$, *MES*, and *SRISK*). The analysis is based on 161 Chinese financial intermediaries (14 Traditional Banks, 16 Finance Services, 131 Real Estate Finance Developers) continuously listed over the period 2007:1 - 2021:1. We find that, in addition to traditional banks, finance companies and real estate financial developers pose systemic threats to the Chinese financial system, in particular during the Global Financial Crisis and the 2015 Chinese stock crash. Finally, the outbreak of COVID-19 pandemic has put under strain the Chinese financial system, in particular the finance services.

Keywords: Systemic Risk, Systemic risk measures, Granger-non causality, Panel data.

J.E.L. Classification: G01, G15, C23.

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† Department of Management, University of Bergamo (Italy).

‡ Faculty of Finance and Centre for Econometric Analysis, Bayes Business School (formerly Cass), City University of London (UK).

§ Faculty of Finance and Centre for Econometric Analysis, Bayes Business School (formerly Cass), City University of London (UK).

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1 Introduction

The Financial Crisis of 2007-2009 has generated a growing interest on the estimation and forecasting of financial systemic risk and its channels of contagion. Systemic risk, defined as the risk of threats to financial stability that impair the functioning of a large part of the financial system with significant adverse effects on the broader economy (De Bandt & Hartmann, 2000; Freixas, Laeven, & Peydró, 2015), springs from the complexity and interconnectedness in the financial system (Yellen, 2013)[1].

This paper considers systemic risk in the Chinese financial system, which experienced what Pan et al. (2016) define *"the chaos"* with the opening of the stock market to the outside world. Since then, financial systemic risk has become a topical issue in China and the 19^{th} National Congress of the Communist Party of China highlighted the need to "*improve the financial regulation system and guard against systemic financial risks*". Hence, the establishment of the Financial Stability and Development Committee under the State Council is part of the government's strategy to regulate the financial industry in a coordinated manner.

To investigate and quantify systemic risk contribution among Chinese financial institutions, we conduct a Granger causality analysis between firm-level factors (*Leverage*, *Market To Book Value (MTBV)* ratio and *Returns*) and systemic risk measures, $\Delta CoVaR$, *MES*, and *SRISK* in the Chinese financial system, which, after the liberalization reform started in 2010[2], has become the second largest market in the world, and thus has received particular attention by international investors.

Granger causality in heterogeneous panels is tested using the procedure proposed by Dumitrescu & Hurlin (2012) over the years 2007-2021. During this period, we can identify four regimes in the Chinese stock market, namely (i) the Global Financial Crisis (GFC) from 2007:1 to 2009:4; (ii) the Monetary Policy Restriction conducted by the People Bank of China (PBoC) from 2010:1 to 2014:4; (iii) the 2015 Chinese stock crash and its effects, from 2015:1 to 2019:4; and (iv) the COVID-19 pandemic, from 2019:1 to 2021:1. The different regimes allows us to test for the stability of the causal relationship.

Our sample consists of 161 publicly and continuously listed Chinese financial intermediaries: 14 Traditional Banks, 17 Finance Services, and 131 Real Estate Finance Developers, which allows to identify the contribution of the different categories of financial institutions to systemic risk.

The choice to focus on banks, finance services and real estate finance services is motivated by the strong business ties between them, many of which have emerged only in recent years (Dai & Fang, 2014;

[1]The literature provides several definitions of systemic risk: see amongst others Aglietta & Moutot (1993), Bartholomew & Whalen (1995), Davis (1995), Goldstein (1995). De Bandt & Hartmann (2000, p. 11) defined systemic risk as *"the risk of experiencing systemic events in the strong sense"*. The Group of Ten (2001) defines systemic financial risk as the risk that an exogenous shock will imply a loss of economic value in a substantial portion of a financial system causing significant adverse effects on the real economy. In relation to this definition, Adrian & Brunnermeier (2016) and Acharya et al. (2017) define a financial institution' contribution to systemic risk as the extent to which the financial institution contributes to an under-capitalization of the entire financial system.

[2]Examples include: (i) the Renminbi Qualified Foreign Institutional Investors (RQFII) scheme, which came into effect in August 2011, allows some eligible Chinese financial firms to establish RMB-denominated funds in Honk Kong to invest in the China mainland; (ii) the Qualified Foreign Institutional investors (QFII), enacted in 2002 and doubled from 80 billion U.S. dollars in 2012 to 150 billion U.S. dollars in 2013, allows foreign access to China' equity markets with restrictions on investment ratios, quotas, targets, and capital remittance controls; (iii) the launch of the Shanghai-Hong Kong Stock Connect Program in November 2014 as a new liberalization milestone that allowed investors in each market to trade shares on other markets through local brokers and clearing houses (Yu et al., 2018).

Fang et al., 2018). Traditional banks are strongly connected to finance services. They have a preference to lend to brokerage firms because these latter are perceived as relatively high-quality firms with little risks. At the same time, brokerages engage in the profitable business of helping banks transfer their loans and notes on the books into off-balance sheet financial products. This has led to the creation of bank's Wealth Management Products (WMPs) and Asset Management Products (AMPs) which are the cornerstone of China's shadow banking system and could be a hidden source of systemic risk (Wang, Jiang, et al., 2018). Traditional banks also play a crucial role both in investing idle funds from companies in the real estate supply chain and in term of loans, facilitating the functioning of the real estate sector. As reported in Beladi et al. (2021, p. 1), real estate investment is considered as a *"double-edge sword"*, in that on the one hand, the real estate assets, as collateral, may enhance corporate financing capacity while, on the other hand, it requires intensive financial resources, thus increasing the probability of excessive leverage. Bank credit has remained the most prominent channel for real estate company financing despite the opening of channels like the issuance of shares, bonds, and trust financing, because that these latter are subject to many restrictions and hence more complex to be accessed. Thus, in periods of high market volatility and when borrowers are unable to repay on time, banks may face several non-performing loans, which pose a severe threat for the capital channel and lead to liquidity risk. The relationship between traditional banks and real estate companies is also affected by that the housing market is often subject to price regulation and hence some real estate developers may incur in higher credit risk when the government introduces caps to housing prices (see for example the series of measures enacted from 2009 to 2013). Finally the risk of fluctuations in real estate prices (i.e., the risk of bubbles) could create bank credit losses. In particular, on 20^{th} September 2021, the concerns about an Evergrande default roils stock markets world widely. Major indices in America and Europe fall and yields on the dollar bonds of some Chinese borrowers outside the property sector rise. These challenges may affect the stability of the financial system.

Our paper focuses on China for three main reasons. First, the Chinese financial market grows fast since 2011 when it becomes the second largest equity market in terms of market capitalization. Second, the Chinese stock market, being young and fast-growing, is characterized by a dominance of retail traders, a large amount of trading, and changing regulations. Third, China' regulators are trying to get basic supervisory measures that provides the authorities with guidance about the amount of risk occurring within the financial system and some early warning of potential problems.

The main empirical findings can be summarized as follows. There is evidence of a rich variety of causal relationships, depending on which financial intermediaries and specific time periods are considered. Overall, we find that *Leverage* and $MTBV$ are important drivers of $\Delta CoVaR$ and MES, while only $MTBV$ plays a crucial role during and after the second Chinese stock market crash in 2015, when sharp price movements of the listed financial institutions caused severe mispricing to their market value with potential spill over effect in the financial system. The drastic adjustments experienced by the Chinese stock markets also becomes a major source of instability for worldwide financial markets (Pan et al., 2016; Pavlidis & Vasilopoulos, 2020).

For traditional banks, we find that their *Leverage* and $MTBV$ are more sensitive to systemic risk during the second Chinese stock market crash. This result confirms that, during downturns, the leverage is determined primarily by market forces, and in addition its counter-cyclicality can be explained by the fact that a large proportion of the value of a financial institution is "in the hands" of the debt holders. Regarding $MTBV$ ratio, one possible explanation is that traditional banks are expected to reduce assets in order to improve their capital or liquidity positions. The *Returns* of traditional banks are sensitive to systemic risk during the monetary policy restriction period, in contrast to finance services and real estate finance developers.

For finance services, there is evidence of strong causal relationship between $MTBV$ and the systemic risk measures $\Delta CoVaR$ and *MES*. This result can be explained by that they are able to transferring banks loans and notes on the books into off-balance sheet financial products such as WMPs and AMPs. Over the COVID-19 pandemic period, we find that *Leverage* and *Returns* show a strong causal relationship with $\Delta CoVaR$, confirming the fact that finance services are both strongly related to market dynamics and manage their balance sheets aggressively and actively (Adrian et al., 2014, 2016), and that they have become involved and more dependent on market trends during stressed economic times (Engle et al., 2015).

Finally, as far as the real estate finance developers are concerned, $MTBV$ is sensitive to both $\Delta CoVaR$ and *MES*, while *Leverage* is sensitive to *MES*, in particular during the Global Financial Crisis and the 2015 Chinese stock market crash. This is because of both their complex financing structure and the high leverage ratio, which may pose systemic threats and spillover to the financial system through multiple channels. We like to interpret this result as evidence of the multiple connections that real estate finance developers have with a range of upstream and downstream industries (particularly the banking system) which could exert an influence over their profitability and solvency conditions.

Our paper complements recent studies on the topic. Chen et al. (2014) use data on CDSs spreads and high-frequency intraday stock prices to develop a measure of systemic risk and to study the interconnectedness between banks and insurance companies with Granger causality tests. They find significant bidirectional causality between insurers and banks. Wang et al. (2018) show the special role played by small financial firms in determining systemic risk mainly due to their high level of connectedness. Fang et al. (2018) construct a tail risk network to investigate the systemic risk across Chinese financial institutions. Wang et al. (2018) investigate the interconnectedness and systemic risk of China' financial institutions by constructing dynamic tail-event driven networks finding that large traditional banks and insurers usually exhibit systemic importance. Wang et al. (2020) propose a Granger causality network procedure in order to distinguish between short-term, medium term and long-term interconnectedness using daily returns of Chinese banks, securities and insurers. Morelli & Vioto (2020) use the bootstrap Kolmogorov-Smirnov test and find that in the Chinese financial system banks contribute the most to systemic risk, followed by real estate and by insurance and brokerage companies. Finally, Cincinelli et al. (2021) find that larger financial institutions increase systemic risk, in particular traditional banks, which from 2016 started increasing shadow banking activities, and the real estate financial services with their activity closer to traditional banks.

Our paper enriches the existing literature on systemic risk by evaluating the Granger non-causality relationship in heterogeneous panels between a comprehensive set of financial and accounting variables and systemic risk measures in banks, finance services and real estate developers of the Chinese financial system, which has become increasingly important over the recent years. Our paper sheds light on the interconnectedness between traditional banks, finance services and real estate entities, outside the regulated financial system and how and to what extent financial entities behave during both financial crises and tranquil periods.

The reminder of the paper is organized as follows: Section 2 gives a review of relevant literature. Sections 3 outlines the systemic risk measures and Granger causality in panel data. Section 4 describes the data, reports the summary statistics of the variables and introduces the panel unit root tests. We discuss the empirical results from the heterogeneous panel causality test in Section 5. Section 6 concludes.

2 Background Literature

The identification of the main drivers of systemic risk has been a popular issue in the institutional and academic debate over the years since the global financial crisis of 2008. Systemic risk, by its nature, includes both a cross-sectional and a time dimension. The existing literature proposes measures that capture these two dimensions and different classifications are offered by Bisias et al. (2012), De Bandt et al. (2013) and Benoit et al. (2017). There are measures based on the single bank and on the system as a whole. Regarding the first group, the metrics rely on market data (e.g., equity returns or CDS spread) or on balance-sheet and regulatory data. With regard to the second group, there are indicators that captures the time dimension (e.g., the pro-cyclicality of credit and asset prices, specifically housing) usually measured by credit/GPD, the change in credit/GDP, the credit/GDP "gap", and measures of connectivity based on networks (graph theory) focus on the cross-sectional dimension of risk only, whereby there are common failures and so-called "domino effects" sometimes caused by a common factor or through interconnected exposures.

Benoit et al. (2017) proposes two approaches: the *"source-specific approach"* and the *"global approach"*. Within the first approach, there are methods which allow measuring various sources of systemic risk such as: (i) *systemic risk-taking* (Lehar, 2005; Acharya, 2009; De Nicolò & Lucchetta, 2011; Giesecke & Kim, 2011; Blei & Ergashev, 2014; Cai et al., 2018; He & Krishnamurthy, 2019); (ii) *contagion* between financial institutions (Upper & Worms, 2004; Markose, 2012; Elsinger et al., 2006; Allen et al., 2009; Afonso & Shin, 2011; Drehmann & Tarashev, 2011; Iyer & Peydro, 2011; Upper, 2011; Gourieroux et al., 2012; Acharya & Merrouche, 2013; Gabrieli & Georg, 2014; Acemoglu et al., 2015); (iii) *amplification mechanisms* either in traditional banks or in the shadow banking system (Brunnermeier et al., 2014; Jobst, 2014; Greenwood et al., 2015; Duarte & Eisenbach, 2021).

The *"global approach"*, instead, considers a multi-channel approach to systemic risk providing several measures (Bisias et al., 2012; De Bandt et al., 2013; Benoit et al., 2017; Abendschein & Grundke, 2018; Dičpinigaitienė & Novickytė, 2018; Grundke & Tuchscherer, 2019). Over the last decade global systemic risk measures have been proposed (see Benoit et al., 2017) accounting for specific sources such as contagion, bank runs or liquidity crises. In particular, the Marginal Expected Shortfall (MES) of Acharya et al. (2017), the SRISK of Brownlees & Engle (2016), and the $\Delta CoVaR$ of Adrian & Brunnermeier (2016) are the most central metrics in the systemic risk literature (Zhang et al., 2015; Benoit et al., 2017; Dičpinigaitienė & Novickytė, 2018; Grundke & Tuchscherer, 2019).

Among the systemic risk measures, the common theme relies on the magnitude of losses during periods when many institutions are simultaneously distressed. However, during periods of rapid financial innovation and globalization, financial intermediaries may not have experienced simultaneous losses, despite the fact that their co-movement and connectedness tend to increase implying an increase in systemic risk. For example, prior to the 2007-2009 crisis and before the Chinese stock market crash of 2015, securities firms, banks and real estate finance developers, in China, were not particularly connected. In addition, measures based on probabilities, since they depend on market volatility, during periods of economic growth (i.e., lower volatility than in periods of distress) lower estimates of systemic risk until after a volatility occurs.

Several contributions use measures to capture correlation directly and unconditionally. For example, Billio et al. (2012) propose a Granger-causality network to study the interconnectedness and systemic risk among hedge funds, brokers, banks and insurance. Diebold & Yilmaz (2014) quantify the interconnectedness of financial firms through a volatility spillover network based on variance decomposition. Balboa et al. (2015) test the Granger-causality in comovements in the left tails of returns of individual banks and the global system. Hautsch et al. (2015) develop the systemic risk beta measure based on tail risk interdependence network. Wang et al. (2017) uses an extreme risk spillover network based on the Granger-causality risk test for investigating the interconnectedness of financial firms.

In this paper, we evaluate for Granger non-causality in heterogeneous panels data models using the testing framework proposed by Dumitrescu & Hurlin (2012). The use of cross-sectional information may help to find if a casual relationship exists for an individual, and also exists for some other individuals. Moreover, it may help to consider the interconnectedness among financial institutions rather than in isolation. The measure of connectedness complement the three systemic risk measures ($\Delta CoVaR$, *MES*, *SRISK*) in providing direct estimates of the statistical connectivity of financial institutions' asset returns and firm level variables. These measures are recognized as the central metrics in the systemic risk literature (Bisias et al., 2012; De Bandt et al., 2013; Benoit et al., 2017; Abendschein & Grundke, 2018; Dičpinigaitienė & Novickytė, 2018; Grundke & Tuchscherer, 2019).

3 Measures of Systemic Risk and Granger Causality in Panel

In this section, we briefly present the three measures of systemic risk $\Delta CoVaR$, *MES*, and *SRISK*, and we describe the Granger-causality test in panel data to evaluate causality among financial institutions' characteristics and systemic risk measures.

3.1 Measuring systemic risk via CoVaR

While the Value-at-Risk (VaR) of an institution focuses on the risk of an individual entity in isolation, the CoVaR is an indicator of systemic risk that can be defined as the VaR of the financial system as a whole, conditional on another firm (or set of firms), exceeding its (their) firm specific VaR. VaR is defined as the threshold loss (in currency) that will not be exceeded at a given level of confidence. The $CoVaR_q^{system|C(X^i)}$ is defined by the q-th quantile of the conditional probability distribution:

$$Prob(X^{system|C(X^i)} \leq CoVaR_q^{system|C(X^i)}) = q\% \tag{1}$$

where X^i is the market-valued asset return of institution i, and X^{system} is the return of the portfolio, computed as the average of the X^i's weighted by the lagged market value assets of the institutions in the portfolio[3]. To obtain the time-varying VaR_t and $CoVaR_t$, we estimate the following quantile regressions on weekly data:

$$X_t^i = \alpha_q^i + \gamma_q^i \mathbf{M}_{t-1} + \varepsilon_{q,t}^i \tag{2a}$$

$$X_t^{system|i} = \alpha_q^{system|i} + \beta_q^{system|i} X_t^i + \gamma_q^{system|i} \mathbf{M}_{t-1} + \varepsilon_{q,t}^{system|i} \tag{2b}$$

where $\mathbf{M}_t$ includes the set of state variables lagged described in Section 4.5. We then use the predicted values from these regressions to obtain:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i \mathbf{M}_{t-1} \tag{3a}$$

$$CoVaR_{q,t}^i = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_{q,t}^i + \hat{\gamma}_q^{system|i} \mathbf{M}_{t-1} \tag{3b}$$

Adrian & Brunnermeier (2016) measure the contribution of each single institution to systemic risk by the $\Delta CoVaR$, namely the difference between $CoVaR$ conditional on the institution being in distress and $CoVaR$ in the median state of the institution. Formally, the $\Delta CoVaR_q^i$, i.e. the contribution to systemic risk of institution i given the choice of quartile q, is defined as follows:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_{50}^i = \hat{\beta}_q^i (VaR_q^i - VaR_{50}^i) \tag{4}$$

where the q is always set to be 5%, so that $CoVaR^i$ identifies the system losses predicted on the 5% loss of institution i, while $\Delta CoVaR^i$ identifies the deterioration in the system losses, when the institution i moves from its median state to its 5% worst scenario. As far as the estimation method is concerned, quantile regressions (q) (Koenker & Bassett, 1978) are employed to estimate the VaRs and CoVaRs (see Adrian & Brunnermeier, 2016).

3.2 Measuring systemic risk via Marginal Expected Shortfall

The second measure of systemic risk is the Marginal Expected Shortfall (MES) based on Acharya et al. (2017). The *MES* of a financial institution is defined as the contribution of that institution to the Expected Shortfall (ES) of the system. The *ES* of the system is defined as the expected value of the market return conditional to the event that the market return is lower than a certain threshold C with the market return defined as the weighted average of all financial institutions' returns:

[3] Indicating with ME_t^i the market value of a financial institution and with LEV_t^i the ratio between total assets and common equity, we can define: $X^i = \frac{ME_t^i \times LEV_t^i - ME_{t-1}^i \times LEV_{t-1}^i}{ME_{t-1}^i \times LEV_{t-1}^i}$. The sum of all the X^i of the sample gives X^{system}, namely the growth rate of the market value of the total asset of financial sector under analysis.

$$ES_{m,t}(C) = \mathbb{E}_{t-1}(r_{m,t}|r_{m,t} < C) = \sum_{i=1}^{N} \omega_{i,t}\mathbb{E}_{t-1}(r_{i,t}|r_{m,t} < C) \tag{5}$$

where $r_{m,t} = \sum_{i=1}^{N} \omega_{i,t} r_{i,t}$[4], and $\omega_{i,t}$ is the market share or capitalization of financial institution i. In the operational definition of a crisis event, the value of the threshold C is crucial[5]. The contribution of institution i to the System Expected Shortfall (the *MES* of institution i) is, therefore, defined as the partial derivative of the *ES* with respect to the weight of institution i:

$$MES_{i,t} = \frac{\partial ES_{m,t}(C)}{\partial \omega_{i,t}} = \mathbb{E}_{t-1}(r_{i,t}|r_{m,t} < C) \tag{6}$$

The *MES* of a financial institution can be interpreted as reflecting its participation in overall systemic risk. However, it is still possible to define the same statistic whenever the observed financial institution does not belong to the market index. Rather than a measure of how a particular financial institution' risk adds to the market risk, the *MES* should then be viewed simply as a measure of the sensitivity (or resilience) of this financial institution' stock price to exceptionally bad market events (Idier et al., 2014).

3.3 Measuring systemic risk via SRISK

The third measure of systemic risk is *SRISK*, based on (Brownlees & Engle, 2016). *SRISK* measures the expected capital shortage faced by a financial institution during a period of system distress when the market declines substantially. More precisely:

$$SRISK_{i,t} = max[0; \kappa(D_{i,t}) + (1 - LRMES_{i,t}W_{i,t}) - (1 - LRMES_{i,t})W_{i,t}] \tag{7}$$

where κ is the minimum fraction of capital as a ratio of total assets that each financial institution needs to hold (κ is set equal to the prudential capital ratio of 8%), and $D_{i,t}$ and $W_{i,t}$ are the book value of its debt (total liabilities) and the market value of its equity, respectively, $LRMES$ is the long-run Marginal Expected Shortfall (the MES on a six-months horizon). According with Brownlees & Engle (2016), to compute the $LRMES$, we used the non-simulation method to estimate the expected fractional loss of the financial intermediary in a crisis when the market composite indexes decline significantly in a six-month period (i.e., Long-Run Marginal Expected Shortfall or LRMES). Specifically, it is calculated as:

$$LRMES_{i,t} = 1 - exp(log(1 - d) * MES_{i,t}) \tag{8}$$

where d is the six-month crisis threshold for the market index decline and its default value is 40%, consistent with Systemic Risk Analysis with simulation. By defining leverage as $L_{i,t} = (D_{i,t} + W_{i,t})/W_{i,t}$, the formula can be transformed into the following:

[4]The risk management framework for a single institution can be extended to the whole financial system, "by letting $r_{m,t}$ be the return of the aggregate banking sector or the overall economy" (Acharya et al., 2017). In this case, the conditioning event is a systemic event, which is thought of as the 5% worst days of any given year in terms of stock returns.

[5]To ensure comparability with the other measures of systemic risk, we set the threshold at 5% level.

$$
\begin{aligned}
SRISK_{i,t} = & max[0; (\kappa L_{i,t} - 1 + (1-\kappa)LRMES_{i,t})W_{i,t}], \\
& W_{i,t}[\kappa L_{i,t} + (1-\kappa)LRMES_{i,t} - 1]
\end{aligned} \tag{9}
$$

3.4 Granger causality

The direction of the systemic risk propagation can be empirically detected by using Granger causality test. X is said to "Granger-cause" Y if past values of X contain information that helps predict Y beyond the information contained in past values of Y alone (Granger, 1969). See also the recent contribution of Lu et al. (2017).

Let X_t and Y_t be two stationary time series and for simplicity assume that they have zero mean. Their linear relationship is the following:

$$
\begin{aligned}
X_t &= \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \\
Y_t &= \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t
\end{aligned} \tag{10}
$$

where ε_t and η_t are two uncorrelated white noise processes, m is the maximum lag considered, and a_j, b_j, c_j, d_j are coefficients of the model. The definition of causality implies that Y causes X when b_j is different from zero. Likewise X causes Y when c_j is different from zero. When both of these statements are true, there is a feedback relationship between the time series. The model selection criteria of the number of lags considered for the test is base on the Bayesian Information Criterion (Schwarz, 1978). The causality is based on the F-test of the null hypothesis that coefficients b_j or c_j are equal to zero according to the direction of the Granger causality.

Dumitrescu & Hurlin (2012) propose an extension of the Granger (1969) designed to test causality in panel data. This test assumes all coefficients to vary across sections. In addition, the authors by using Monte Carlo experiments show that this test fits well enough to a relatively short span of data even in the existence of cross-sectional dependence[6]. The linear model is the following:

$$
y_{i,t} = \alpha_i + \Sigma_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \Sigma_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{11}
$$

with y and x two stationary variables observed for N individuals on T periods and $K \in \mathbb{N}^*$ and $\beta_i = (\beta_i^{(1)}, ..., \beta_i^{K})'$. The individual effects α_i are supposed to be fixed in the time dimension. The lag orders K are identical for all cross-section units of the panel and the panel is balanced. It is a fixed

[6]In addition, this causality approach can be applied in the case of both $T > N$ and $T < N$ and for unbalanced and heterogeneous panels.

coefficient model with fixed individual effects. The null hypothesis of homogeneous non causality is defined as:

$$H_0 : \beta_i = 0 \qquad \forall = 1, ..., N \tag{12}$$

with $\beta_i = (\beta_i^{(1)}, ..., \beta_i^{(K)})'$. Dumitrescu & Hurlin (2012)' test assumes that there can be causality for some individuals but not necessarily for all. Thus the alternative hypothesis is:

$$\begin{aligned} H_1 :&\beta_i = 0 \qquad \forall = 1, ..., N_1 \\ &\beta_i \neq 0 \qquad \forall = N_1 + 1, N_1 + 2, ..., N \end{aligned} \tag{13}$$

where $N_1 \in [0, N - 1]$ is unknown. If $N_1 = 0$, there is causality for all individuals in the panel. N_i must be strictly smaller than$N$; otherwise, there is no causality for all individuals, and H_1 reduces to H_0.

Dumitrescu & Hurlin (2012) propose to use the average of individual Wald statistics associated with the test of the non causality hypothesis for units $i = 1, ..., N$. The average statistic $W_{N,T}^{HNC}$ associated with the null Homogeneous Non Causality (HCN) hypothesis is:

$$W_{N,T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \tag{14}$$

where $W_{i,T}$ denotes the individual Wald statistics for the i-th cross-section unit corresponding to the individual test $H_0 : \beta_i = 0$. Under the assumption that the Wald statistics are independently and identically distributed across individuals, the standardized statistic $\bar{Z}$, when $T \to \infty$ and $N \to \infty$ follows a standard normal distribution:

$$\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \qquad \xrightarrow[T, N \to \infty]{d} \qquad N(0, 1) \tag{15}$$

where K is a lag order selection. For a fixed T dimension with $T > 5 + 3K$, the approximated standardized statistic $\tilde{Z}$ follows a standard normal distribution:

$$\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T - 3K - 5}{T - 2K - 3}} \times \left(\frac{T - 3K - 3}{T - 3K - 1} \times \bar{W} - K \right) \qquad \xrightarrow[T, N \to \infty]{d} \qquad N(0, 1) \tag{16}$$

The test of null hypothesis is based on $\bar{Z}$ and $\tilde{Z}$. If these are larger than the standard critical values, then H_0 is rejected and the Granger causality exists[7].

[7] For large N and large T panel datasets, $\bar{Z}$ can be considered. For large N and small T datasets, $\tilde{Z}$ is favored (Dumitrescu & Hurlin, 2012).

4 Data and Preliminary Analyses

Our data comes from Thomson Reuters Data Stream. We consider a representative sample of 161 continuously listed Chinese financial institutions which Traditional Banks (TBs), Finance Services (FSs) and Real Estate Finance Developers (REFDs)[8]. The sample period, at quarterly frequency, runs from December 2006 to March 2021, totaling 9,177 observations. The composition of the sample is dictated by the public availability of both balance-sheet and financial market data over the whole period. At 31/03/2021, the share of market value of financial entities composing the sample was 60%, composed as follows: TBs 76.65%, FSs 33%, and REFDs 82%. Regarding the low share of finance services market value, we noticed that starting from 2010 till 2019, the China' securities considerably grew. However, we could not consider these new entities due to the lack of their financial data during the whole time period 2007-2021.

4.1 Traditional Banks

The Chinese banking system is composed of five banks categories: (i) state owned banks; (ii) policy banks; (iii) joint-stock or commercial banks; (iv) rural banks; and (v) small cooperative banks. The state banks, controlled by the central government, are: the Industrial and Commercial Bank of China, the Bank of China, the Construction Bank of China, the Agricultural Bank of China and the Bank of Communication.

Since 1978, the Chinese Government introduced gradual reforms in order to improve capital allocation, profitability and transparency, and reduce government participation. In particular, from 1978 through 1994, the People Bank of China (PBoC) was divided into a central bank and four large state banks. During this period, banks still operated as part of a state-directed planned economy. Starting from 2004 till 2010 (i.e., the "transformational period"), the banking system was re-engineered and stabilized. Since 2010, the Chinese banking system is in an "evolutionary period" where developments have strengthened and developed banks to meet the challenges of the economy in transition. Amid this time period, in 2008, the Wall Street' crash had some consequences for Chinese banks, particularly related to the fear that demand for China' export would dry up as Western economies went into recession. As response, 4 trillion yuan stimulus was launched by Beijing Government, where most of the funds were released in the form of bank credit extension. However, since banks played a pivotal role in financing the expansion, they started to expand off-balance sheet business, both to circumvent stringent regulation on capital and liquidity, and to acquire new clients and asset classes (Liao et al., 2016).

For this analysis, we survey 14 continuously listed Chinese traditional banks. We collect the accounting and financial variables from Thomson Reuters Data Stream which provides a specific section labeled as "Banks".

[8]In the Appendix, we report the complete list.

4.2 Finance Services

Finance Services were developed from the securities departments of banks and trust companies. The securities sector plays an important role in the supporting real economic development by improving the financing efficiency of the society.

The global financial meltdown had limited impact on China' securities market. To avoid possible volatility in the domestic securities, the China Securities Regulatory Commission (CSRC) strengthened inspections and developed an extensive contingency plan (CSRC, China Securities Regulatory Commission, 2008)[9].

After the global financial crisis, till 2014 and the first half of 2015, the China' securities considerably grew amid enthusiastic market sentiment. However, during the second half of 2015, due to unusual volatility in the Shanghai and Shenzhen indices, some investors were forced to liquidate their positions when the price of underlying stocks fell below a certain threshold.

In 2018, the securities industry of China faced some challenges such as: weak stock market performance, a slowing IPO market, the increased credit risk of equity pledge, and the shrunk of Asset Under Management (AUM) influenced by the new regulations for asset management. In view of this, many brokers began exploring new organizational structure, customer strategy, talent strategy, performance appraisal, and IT system transformation (KPMG, 2018). Chinese securities generated net after-tax profits of RMB 62,4 billion, a year-on-year decrease of 44.3%. The decline in profits was caused by both decreases in operating income and increases in operating expenses. In 2018, the income of the investment banking and brokerage segments declined by 28% and 22% respectively year-on-year (CSRC, China Securities Regulatory Commission, 2018).

Since 2018, the CSRC and the China Banking and Insurance Regulatory Commission (CBIRC) have continued to implement various measures to promote the opening up of China's financial services industry. These measures include broadening the scope of foreign investment in mainland China and simplifying related investment procedures.

Comparing both the list in the CSRC 2018 report and the core business descriptions of each company available for each financial institution identified as "Finance Services" provided by Thomson Reuters Data Stream, we collected reliable data at corporate level of accounting and financial variables for only and continuously listed 16 finance services.

4.3 Real Estate Finance Developers

[9] To respond to different market conditions, the CSRC provided different measures such as: a) temporary market closure; b) trading restriction; c) and price limit adjustment. To prevent widespread fund redemptions triggered by sharp falls in equity prices, CSRC intensified daily supervision of fund purchases and redemptions, public opinion guidance and urged fund management companies to improve their liquidity management and make contingency plans for the worst scenario. To prepare for the risk of massive withdrawal of Qualified Foreign Institutional Investors (QFIIs) as the global financial turmoil worsens, CSRC strengthened monitoring of QFIIs operations in order to reduce market volatility. To avoid and to closely monitoring potential systemic risks in the domestic futures market caused by wild fluctuations in commodity prices, bankruptcy risks of futures companies, CSRC adopted corresponding measures, such as raising margin levels, expanding price range limits and forcing liquidation of positions. For greater details, see the CSRS 2008 report.

Real Estate is considered as a pillar industry of the Chinese economy and its growth over the last decade has been promoted by the deep support of financial sector, particularly, the banking sector. In 2020, the loans growth rate to the real estate sector continued. Outstanding real estate loans went up 11.7% yearly to Renminbi 49.58 trillion (PBoC, People Bank of China, 2021). The business model of Real Estate Developers relies on a higher leverage, than other sectors, and a long turnover cycle. A large share of capital, required by real estate companies, comes from bank loans causing a long-term structural unbalanced financing structure with banks bearing the majority of real estate market risk. Two main reasons explain this situation. On the one hand, real estate developers have insufficient funds of their own. On the other hand, although the development of China' capital market has opened financing channels for real estate companies (e.g., issuance of shares, bonds, trust financing), these channels are subject to many restrictions (He, 2016). In addition, the real estate sector is particularly policy-sensitive. From December 2009 to December 2013, China began a massive real estate controls in order to curb housing prices. These policy include: industrial, land, financial and tax policies.

Real Estate Finance Developers face different kinds of financial risks, all of them closely linked and interacted. At micro level, they could incur in operational, liquidity and credit risks; at macro level, policy and bubbles risk require close attention by regulatory authorities.

Recently, leverage and liquidity are major concerns in this sector. Although the demand for real estate remains resilient, their revenues are compressed from a decelerating price cycle driven by tighter regulations. In 2017, the leverage ratio of real estate companies was 79.1%, 1.9% point higher than that in 2016 (PBoC, People Bank of China, 2018). The high leverage ratio may enlarge the pro-cyclicality of their business operation, by weakening the resilience of the industry to shocks, and pose a sever threat for the capital chain by contributing to increase liquidity risk. Considering the systemic importance for the Chinese economy, appropriate economic measures are necessary for the continuity and the stability of the real estate finance market.

For the purpose of this paper, we select only continuously listed 131 Real Estate Finance Developers included in the group "Real Estate Finance & Services" provided by Thomson Reuters Data Stream.

4.4 Summary Statistics

From the balance sheets of all the financial institutions belonging to our sample, we collect the following firm-level characteristics: $Leverage_{i,t}$ is the quasi-market value of assets over the market value of equity, where quasi-market value of assets is equal to book assets minus book equity plus market equity (see Acharya et al. (2017)) of financial institution i at quarter t. This ratio is a proxy for the level of solvency of a financial institution; $MTBV_{i,t}$ is the Market-to-Book Value ratio of financial institution i at quarter t calculated as the ratio between the market value of common equity divided by book value of common equity. This ratio could capture both opportunity to growth and systemic risk due to potential asset pricing misalignments. Moreover, for each financial institution, we compute returns ($Returns_{i,t}$) as in Adrian & Brunnermeier (2016), López-Espinosa et al. (2012, 2015) and Balboa et al. (2015) considering the growth rate of market-valued total assets given by the product of the leverage ratio (defined as the total assets to equity ratio) and the market value of equity. This allows us to analyze contagion stemming from balance-sheet contractions, a most relevant case from a regulatory perspective.

Table 1: Financial institutions characteristics summary statistics.

Description	Variable	Mean	Std. Dev.	Min.	Med.	Max.
Chinese Financial System	Leverage (%)	3.93	5.39	0.24	1.85	56.89
	MTBV (%)	3.92	7.04	0.04	2.01	99.48
	Returns (%)	1.54	27.66	-88.82	-0.90	97.20
Traditional Banks	Leverage (%)	17.32	8.17	2.11	16.79	56.89
	MTBV (%)	1.27	1.11	0.24	0.92	8.13
	Returns (%)	0.47	15.80	-39.53	-0.28	49.69
Finance Services	Leverage (%)	2.12	1.26	0.27	1.67	9.64
	MTBV (%)	4.17	6.57	0.12	2.30	84.23
	Returns (%)	0.12	27.22	-88.82	-0.44	92.84
Real Estate Finance Developers	Leverage (%)	2.73	2.71	0.24	1.75	26.21
	MTBV (%)	4.18	7.39	0.04	2.13	99.48
	Returns (%)	1.82	28.69	-79.36	-1.11	97.20

The table reports summary statistics of the financial institutions characteristics computed computed over the period 1^{st} January 2007 to 31^{st} March 2021, in relation to the: a) Chinese Financial System; b) Traditional Banks; c) Finance Services; d) Real Estate Finance Developers. $Leverage_{i,t}$ is the quasi-market value of assets over the market value of equity, where quasi-market value of assets is equal to book assets minus book equity plus market equity of financial institution i at quarter t; $MTBV_{i,t}$ is the Market To Book Value ratio of financial institution i at quarter t; $Returns_{i,t}$ is the growth rate of market-valued total assets given by the product of the leverage ratio (defined as the total assets to equity ratio) and the market value of equity.

Table 1 shows the financial institutions summary statistics. We find that traditional banks show higher *Leverage* than finance services and real estate finance developers services. In relation to $MTBV$ ratio, the average is higher for real estate finance developers and finance services, 4.18% and 4.17% respectively. Traditional banks, instead, show a lower $MTBV$ (1.27%), slightly greater than one, and a lower volatility coefficient (1.11%) in comparison to the other financial institutions. Regarding the variable *Returns*, we observe a higher volatility (28.69%) in the real estate finance developers sector than traditional banks and finance services, which report a standard deviation of 15.80% and 27.22% respectively. This result may reflect the regulatory interventions by the PBoC after the global financial crisis, allowing, in the meanwhile, other non regulated financial intermediaries to take higher risks.

We also consider four sub-periods, which characterize the Chinese market in recent years: (i) the Global Financial Crisis (GFC) from 2007:1 to 2009:4, based on the classification of the Bank for International Settlements, 2010; (ii) the Monetary Policy Restriction conducted by the People Bank of China (PBoC) from 2010:1 to 2014:4, as suggested by Chen et al. (2018) and Fang et al. (2018)[10]; (iii) the second stock crash from 2015:1 to 2019:4, according to Fang et al. (2018) who refer to stock market crash and post-crash; and (iv) the COVID-19 pandemic outbreak from 2019:1 to 2021:1. Table 2 reports some useful summary statistics.

[10]Chen et al. (2018) refer the 2010-2014 period as the period of monetary policy tightening by People Bank of China. Fang et al. (2018) define the period from January 2010 to June 2014 as *"tranquil period"*.

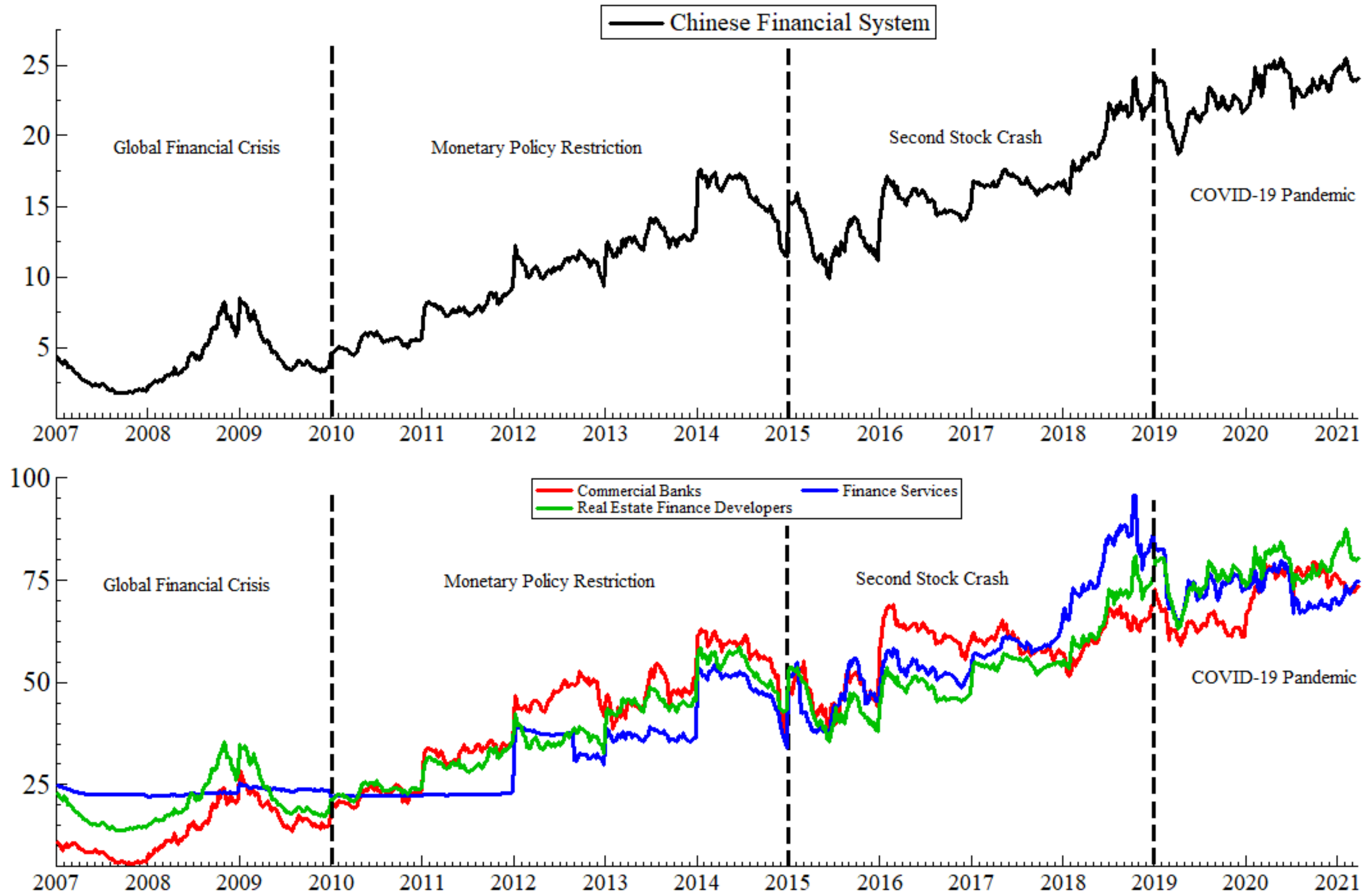
Table 2: Financial institutions characteristics for the different sub-periods summary statistics.

		Global Financial Crisis: 2007:1 - 2009:4			Monetary Policy Restriction: 2010:1 - 2014:4		
Description	**Variable**	**Mean**	**Median**	**St. Dev.**	**Mean**	**Median**	**St. Dev.**
Chinese Financial System	Leverage (%)	2.29	1.45	2.52	3.78	1.95	5.09
	MTBV (%)	5.71	3.45	7.94	3.41	2.00	5.30
	Returns (%)	4.51	2.84	38.08	2.11	0.28	23.56
Traditional Banks	Leverage (%)	8.59	7.86	4.11	18.04	17.78	6.10
	MTBV (%)	2.85	2.51	1.61	1.04	0.95	0.42
	Returns (%)	1.12	-2.71	25.23	0.38	-1.29	14.71
Finance Services	Leverage (%)	1.42	1.24	0.68	1.72	1.45	0.89
	MTBV (%)	9.76	6.82	11.24	3.59	2.56	3.11
	Returns (%)	-2.84	0.00	34.15	3.61	0.82	28.33
Real Estate Finance Developers	Leverage (%)	1.72	1.43	1.15	2.50	1.91	1.99
	MTBV (%)	5.52	3.44	7.68	3.64	2.11	5.72
	Returns (%)	5.77	4.08	39.54	2.11	0.51	23.68
		Second Stock Crash: 2015:1 - 2019:4			**COVID-19 Pandemic: 2019:1 - 2021:1**		
Chinese Financial System	Leverage (%)	4.56	2.18	5.72	5.42	1.86	7.93
	MTBV (%)	3.86	1.64	8.26	2.56	1.28	4.43
	Returns (%)	0.17	-2.18	27.84	-1.98	-1.76	4.73
Traditional Banks	Leverage (%)	19.80	18.37	6.15	22.89	21.94	9.54
	MTBV (%)	0.77	0.75	0.26	0.72	0.60	0.39
	Returns (%)	0.48	0.62	11.53	-0.42	-0.35	2.33
Finance Services	Leverage (%)	2.81	2.69	1.21	2.40	2.02	1.83
	MTBV (%)	1.99	1.66	1.07	2.18	1.40	3.80
	Returns (%)	-1.75	-3.11	24.74	-0.67	-0.92	3.67
Real Estate Finance Developers	Leverage (%)	3.15	1.90	2.96	3.94	1.46	5.61
	MTBV (%)	4.42	1.82	9.06	2.80	1.31	4.69
	Returns (%)	0.37	-2.67	29.39	-2.30	-2.22	4.98

The table reports summary statistics of the financial institutions characteristics computed computed over the period 1^{st} January 2007 to 31^{st} March 2021, in relation to the: a) Chinese Financial System; b) Traditional Banks; c) Finance Services; d) Real Estate Finance Developers. $Leverage_{i,t}$ is the quasi-market value of assets over the market value of equity, where quasi-market value of assets is equal to book assets minus book equity plus market equity of financial institution i at quarter t; $MTBV_{i,t}$ is the Market To Book Value ratio of financial institution i at quarter t; $Returns_{i,t}$ is the growth rate of market-valued total assets given by the product of the leverage ratio (defined as the total assets to equity ratio) and the market value of equity.

Leverage increases over the whole period considered, particularly for Traditional Banks and, during the second stock crash, for Finance Services and Real Estate Finance Developers (see Figure 1).

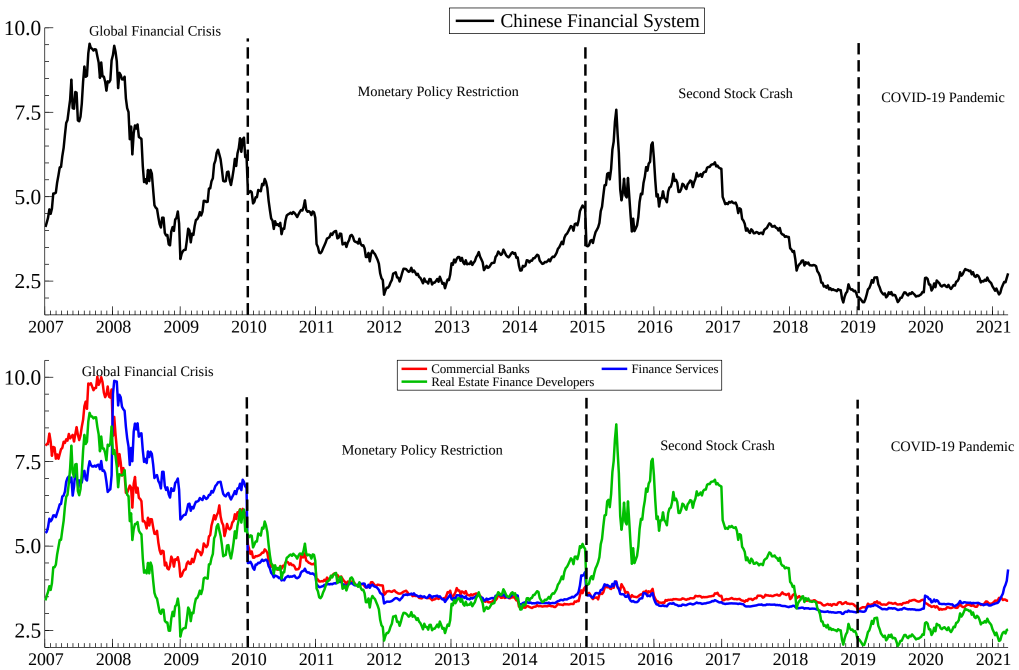
Figure 1: Leverage Chinese Financial System.



Weekly firm-level variables among 161 Chinese financial intermediaries from January 1, 2007, through March 31, 2021. $Leverage_{i,t}$ is the quasi-market value of assets over the market value of equity, where quasi-market value of assets is equal to book assets minus book equity plus market equity. The vertical lines indicate the four subsamples: (1) the Global Financial Crisis (GFC) from 2007:1 to 2009:4; (2) the Monetary Policy Restriction conducted by the People Bank of China (PBoC) from 2010:1 to 2014:4; (3) the second stock crash from 2015:1 to 2019:4; (4) the COVID-19 pandemic from 2019:1 to 2021:1.

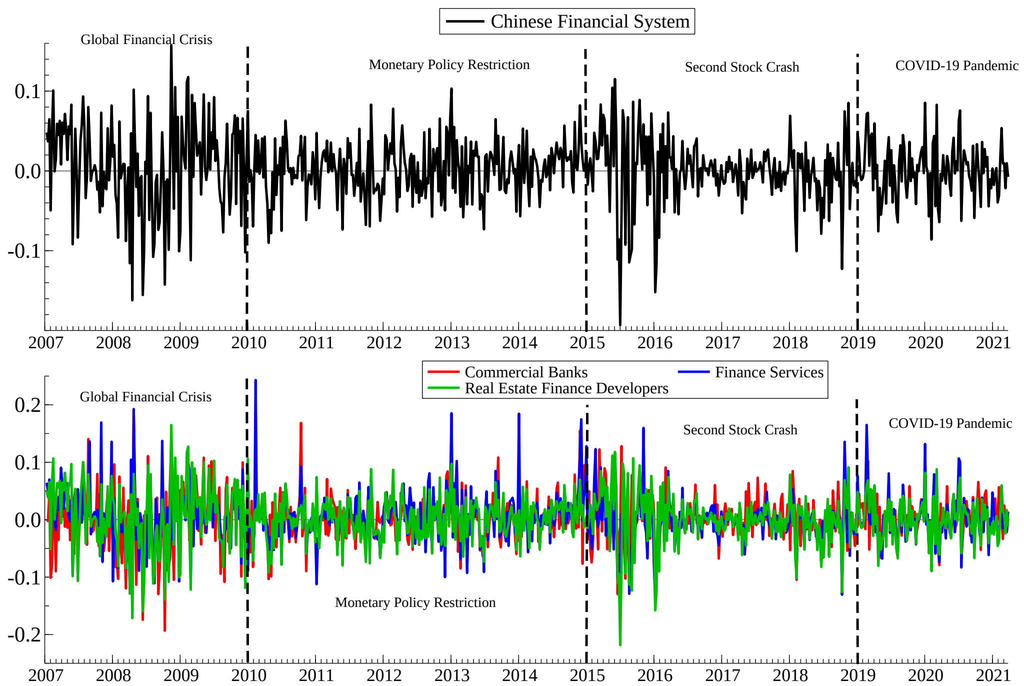
Figure 2 shows how potential asset pricing misalignments are particularly pronounced during the global financial crisis. The *MTBV* ratio shows high values during the financial turmoil with a significant reduction during the monetary policy restriction. In particular, all three entities considered present higher *MTBV* values. Figure 3 shows clearly that volatility rises dramatically and become more volatile during the global financial crises and the second stock crash. Each return series co-move throughout the sample period. Moreover, in the crisis period and during the second stock crash, rate of returns are negative only for Finance Services (-2.84%, -1.75%) and exhibit very large volatility for all the financial intermediaries considered. All financial intermediaries report negative values on *Returns* during the COVID-19 pandemic.

Figure 2: Market to Book Value Ratio Chinese Financial System.



Weekly firm-level variables among 161 Chinese financial intermediaries from January 1, 2007, through March 31, 2021. $MTBV_{i,t}$ is the Market To Book Value ratio of financial institution i. The vertical lines indicate the four subsamples: (1) the Global Financial Crisis (GFC) from 2007:1 to 2009:4; (2) the Monetary Policy Restriction conducted by the People Bank of China (PBoC) from 2010:1 to 2014:4; (3) the second stock crash from 2015:1 to 2019:4; (4) the COVID-19 pandemic from 2019:1 to 2021:1.

Figure 3: Returns Chinese Financial System.



Weekly firm-level variables among 161 Chinese financial intermediaries from January 1, 2007, through March 31, 2021. $Returns_{i,t}$ is the growth rate of market-valued total assets given by the product of the leverage ratio (defined as the total assets to equity ratio) and the market value of equity. The vertical lines indicate the four subsamples: (1) the Global Financial Crisis (GFC) from 2007:1 to 2009:4; (2) the Monetary Policy Restriction conducted by the People Bank of China (PBoC) from 2010:1 to 2014:4; (3) the second stock crash from 2015:1 to 2019:4; (4) the COVID-19 pandemic from 2019:1 to 2021:1.

4.5 $\Delta CoVaR$, MES, SRISK patterns in China

To estimate the time-varying VaR_t and $CoVaR_t$, we include a set of state variables to capture the time variation in conditional moments of asset returns. The Chinese state variables used in this analysis are: the *Shanghai Composite Index* is the weekly return of the index of the Shanghai stock exchange; the *Liquidity spread* is the liquidity spread calculated as the difference between the three-month Chinese repo-rate and the three month Chinese T-bill; the *T-Bill change* indicates the change in Chinese treasury bill three month-rate; the *Yield-Curve slope* indicates the change in slope of the yield curve represented by the five-year Chinese Government bond minus three-month interest rate on government bonds; the *5yBond* indicates the slope of the Chinese 5-year Government bond. We also include the weekly Volatility Index (*VIX*) of the Chicago Board Options Exchange (CBOE) as a measure of market risk and investors' sentiments[11]. Table 3 reports the summary statistics for the state variables[12].

Table 3: State Variables summary statistics.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Med.**	**Max.**
Shanghai Composite Index	0.03%	3.38%	-14.92%	0.11%	13.93%
Liquidity spread	0.98	1.06	-1.46	0.79	6.89
T-bill	0.0005	0.05	-0.81	0.00	0.37
5yBond	3.27	0.54	1.74	3.20	4.61
Yield-Curve slope	0.55	0.60	-1.17	0.48	1.94
VIX	19.85	9.71	9.14	17.03	79.13

Summary statistics of the state variables: *Shanghai Composite Index*: is the weekly return of the index of the Shanghai stock exchange; *Liquidity spread*: is the liquidity spread calculated as the difference between the three-month Chinese repo-rate and the three-month Chinese T-bill; *T-Bill change*: indicates the change in Chinese treasury bill three-month rate; *5yBond*: indicates the slope of the Chinese five-year Government bonds; *Yield-Curve slope*: indicates the change in slope of the yield curve represented by the five-year Chinese Government bond minus three-month interest rate on Government bonds; (*VIX*) is the CBOE option implied volatility index.

Table 4 reports the summary statistics of our three measures of systemic risk. For all the systemic risk measures ($\Delta CoVaR$, *MES*, *SRISK*), on average, traditional banks show a higher systemic risk (4.31%, 5.52%, Mln$ 765,576.2) in comparison to finance services (3.07%, 3.40%, Mln$ 18,674.21) and real estate finance services (1.61%, 1.87%, Mln$ 6,297.15)[13]. We estimate these individual institutions systemic risk measures over the period from January 2006 to December 2019[14]. Financial institutions' stock prices and state variables are taken from Thomson Reuters Eikon database. In our analysis, we take the positive value of $\Delta CoVaR$ and *MES*, and we consider the percentage of *SRISK* for each financial institution interpreted as systemic risk share (Brownlees & Engle, 2016).

[11] This state variable seems reasonable because of the strong degree of globalization in the financial industry and the predominance of the US and Chinese economies.

[12] In the Appendix, we report the correlation matrix between $\Delta CoVaR$ and the full set of state variables. The correlations do not show any extremely high value.

[13] To avoid outliers, we winsorized $\Delta CoVaR$, *MES* and *SRISK* at 1^{st} and 99^{th} percentiles.

[14] It is worth noticing that the dataset used for the estimation also includes the 31 days of December 2006 so that we can obtain an estimate of the $\Delta CoVaR$, *MES* and *SRISK* of the first week of 2007.

Table 4: $\Delta CoVaR$, MES, $SRISK$ summary statistics.

Description	Variable	Mean	Std. Dev.	Min.	Med.	Max.
Chinese Financial System	ΔCoVaR	2.00%	1.42%	-7.21%	1.67%	19.61%
	MES	2.34%	2.45%	-1.07%	1.57%	18.62%
	SRISK (mln $)	73,136.29	318,212.1	-253,668.5	2,181.72	4,411,292.00
Traditional Banks	ΔCoVaR	4.31%	0.97%	-1.46%	4.22%	11.83%
	MES	5.52%	2.92%	1.28%	4.95%	17.27%
	SRISK (mln $)	765,576.2	800,553.6	16,134.8	435,226	4,411,292.00
Finance Services	ΔCoVaR	3.07%	2.62%	-7.21%	2.50%	19.61%
	MES	3.40%	3.52%	-1.07%	2.37%	18.62%
	SRISK (mln $)	18,674.21	28,564.86	-11,232.43	8,034.71	236,878.5
Real Estate Finance Service Developers	ΔCoVaR	1.61%	0.84%	-1.13%	1.53%	8.47%
	MES	1.87%	1.87%	-0.72%	1.38%	11.27%
	SRISK (mln $)	6,297.15	22,933.52	-253,668.5	1,595.1	537,063.4

The table reports summary statistics of the three measures of systemic risk for the sample of listed Chinese financial institutions. $\Delta CoVaR$, MES, $SRISK$ (mln $) are computed over the period 1^{st} January 2007 to 31^{st} March 2021, expressed in percentages in relation to the: a) Chinese Financial System; b) Traditional Banks; c) Finance Services; d) Real Estate Finance Service Developers.

Figure 4 shows the fluctuations of the three measures of systemic risk. As expected, well identified episodes of financial distress, such as the Global Financial Crisis, second stock crash, and the outbreak of COVID-19 pandemic, are associated with a larger increase in the systemic risk. Moreover, as most available statistical measures of systemic importance, the dynamic of $\Delta CoVaR$ and MES tend to be pro-cyclical suggesting that protracted periods of financial distress are generally associated with higher $\Delta CoVaR$ and MES[15].

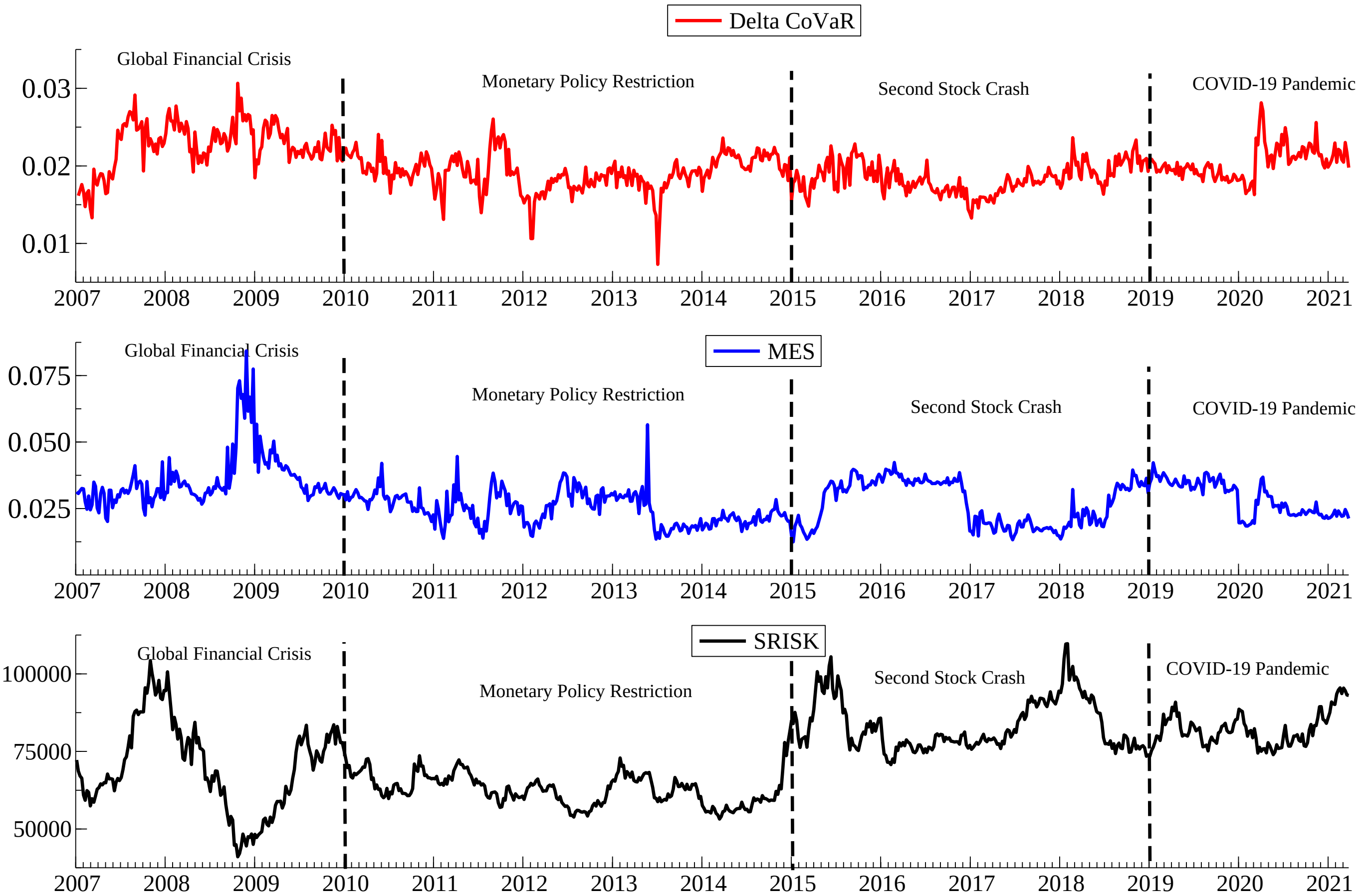
From July 2008 to January 2009, Chinese exports fallen by 18%, imports by more than 40% and Foreign Direct Investment (FDI) by 30%. The stock crash, that took place in 2008, triggered the process for the Chinese government financial stability mechanism with macroprudential approaches and effective methods. The Shanghai Composite Index (SHCI) dropped from 5,362.7 on 2007:4 to 1,806.9 on 2008:4; during the same time frame, the Shenzhen Composite Index (SZCI) fell 58.67%, from 1,261.2 to 521.19. Both the SHCI and the SZCI further dropped 29% on 2015:3, respectively, when the renminbi suffered a 1.6 and 12% depreciation in relation to US Dollar and Euro exchange rate, respectively (PBoC, People Bank of China, 2018).

Moreover, at the end of 2009, after an increase in the M2 supply, and till the end of 2015, the PBoC began to tighten the M2 supply for fear of an overblown bank credit expansion after the 2008 financial crisis. As M2 growth continued to slow down, banks became more vulnerable to unexpected deposit withdrawals, which exposed banks to the risk of violating the Loan-to-Deposit Ratio (LDR)[16].

[15] Idier et al. (2014) and Adrian & Brunnermeier (2016) also find that their MES and $\Delta CoVaR$ are pro-cyclical.

[16] As other central banks, the PBoC adopts several instruments (e.g., open market operations) to influence the amount of credit in the banking system with the harmonization of a twofold China's banking regulations related both to the quantity and the quality of banks loans: a) the LDR regulation; b) the quality-control regulation called the safe-loan regulation. The LDR regulation, established in 1994, is a 75% threshold level on the ratio of banks loans to bank deposits for each traditional bank as a way to manage the total amount of bank loans. To meet unexpected deposit shortfalls against the LDR threshold, the bank attracted additional deposits by offering a much higher rate than the official deposit rate imposed by the PBoC. However, the issue for banks is not the LDR, but the risk of surpassing the threshold due to unexpected deposit shortfalls. This is the case for non State banks, for which the LDR was above 75% on average in the earlier part of the 2006-2012 period and needed the last-minute rush to keep the ratio below the 75% threshold around the time of the PBoC audit.

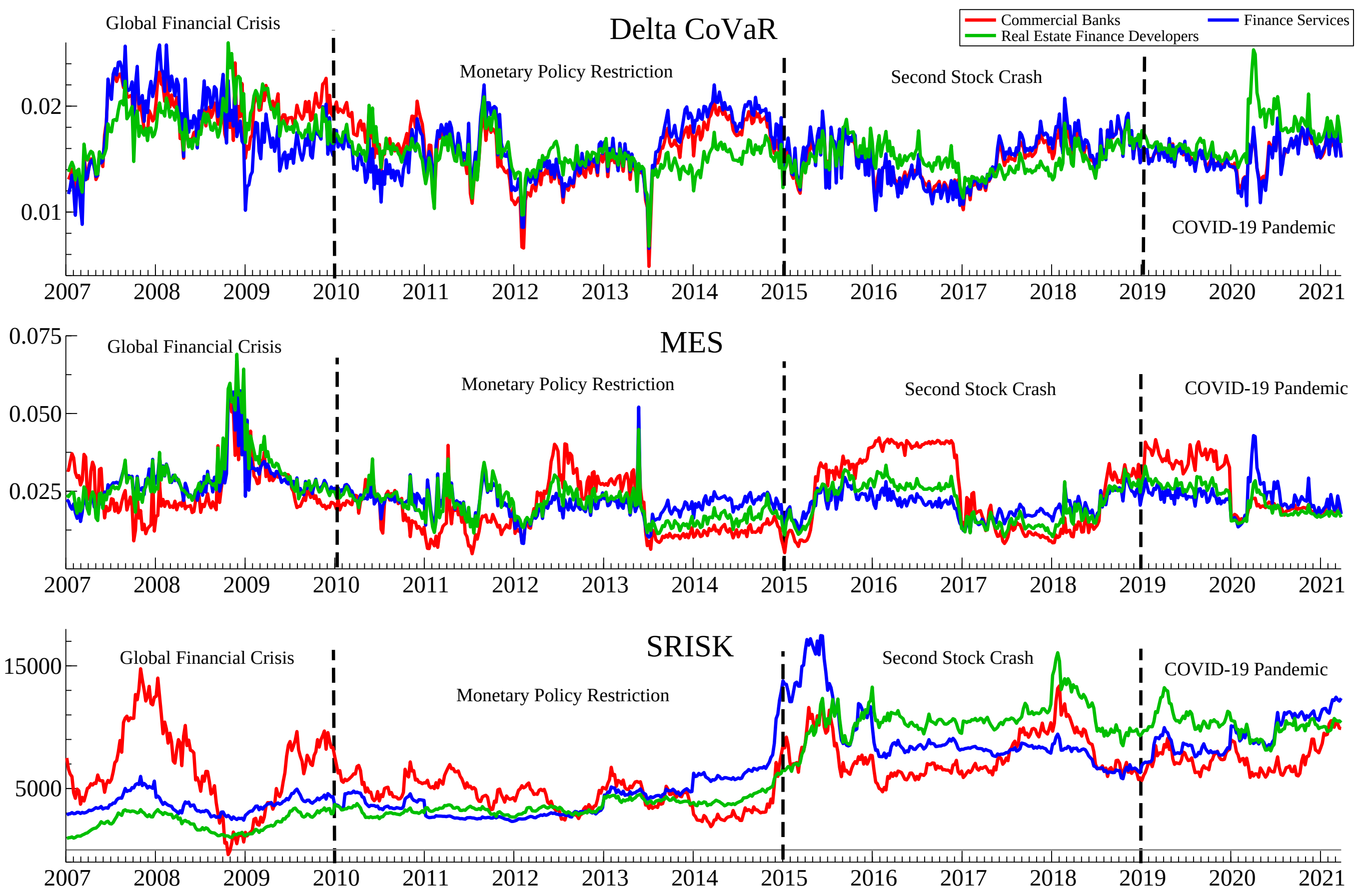
Figure 4: $\Delta CoVaR$, MES, $SRISK$ - Chinese Financial System.



$\Delta CoVaR$, MES, and $SRISK$ trend from 1^{st} January 2007 to 31^{st} March 2021. The vertical lines indicate the four subsamples: (1) the Global Financial Crisis (GFC) from 2007:1 to 2009:4; (2) the Monetary Policy Restriction conducted by the People Bank of China (PBoC) from 2010:1 to 2014:4; (3) the second stock crash from 2015:1 to 2019:4; (4) the COVID-19 pandemic from 2019:1 to 2021:1.

Figure 5 reports the evolution of the three systemic risk measures and the market capitalization for each financial entity. Between 2007 and the end of 2014, banks, finance services and real estate finance developers had similar trend in $\Delta CoVaR$ and MES. Between 2015 and 2019, traditional banks shows a higher value in MES relative to finance services and real estate finance developers. As regards $SRISK$, we notice that after the tranquil period (amid the 2014), finance services and real estate finance developers show a different trend relative to traditional banks. There is an upward trend both for finance services and real estate finance developers. Particularly, finance services rocketed to a highest value, after the period of global financial crisis and after the outbreak of COVID-19 pandemic. Same trend is emphasized by the real estate finance developers over the more recent period.

Figure 5: $\Delta CoVaR$, MES, $SRISK$ by financial entities.



$\Delta CoVaR$, MES, $SRISK$ trend from 1^{st} January 2007 to 31^{st} March 2021 for Traditional Banks, Finance Services, and Real Estate Finance Developers.

4.6 Testing for unit roots

In this study, we make use of panel data analysis to check for causality relationship between firm-level factors and systemic risk measures in the Chinese financial system. To this purpose, in this section, we report the panel unit root tests to check for order of integration of the series. This step is important to conduct correct inference of the causality relationship throughout the paper. We report the testing procedure which accounts for the presence of cross sectional dependence (Pesaran, 2007). In the Appendix, we also report the results of the implementation of (Im et al., 2003) tests valid in presence of independent units.

We perform the Pesaran (2007) test to control for cross sectional dependence. We test the following regression of the cross-section Augmented Dickey-Fuller test:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \delta_{0i}\Delta\bar{y}_t + \delta_{1i}\Delta\bar{y}_{t-1} + \varepsilon_{i,t} \tag{17}$$

where $\bar{y}_t = \sum_{i=1}^{N} y_{i,t}/N$. The null hypothesis is (homogeneous non-stationarity) $H_0 : \beta_i = 0$ for all i, versus the alternatives $H_1 : \beta_i < 0,\ i = 1, ..., N_i,\ \beta_i = 0,\ i = N_1 + 1, N_2 + 2, ..., N.$

Table 5 reports the results. Accordingly, the statistics point out that the null hypothesis of a unit root can be rejected at a 1% level of significance for all variables with the exception of SRISK. The variables are stationary and thus the level values can be used to perform the Dumitrescu & Hurlin (2012) panel causality test.

Table 5: Pesaran Panel Unit Root Test with cross-sectional.

Pesaran Panel Unit Root Test with cross-sectional - CIPS Test					
Systemic Risk Measures			**Firm-level factors**		
Variable	Critical values	P-value	Variable	Critical values	P-value
Delta CoVaR	-3.78***	<1%	Leverage	-2.67**	<5%
MES	-3.48***	<1%	MTBV	-3.48***	<1%
SRISK	-2.35	>10%	Returns	-6.27***	<1%

The table reports the critical values and the p-value for the Pesaran (2007)' test.
***, **, *, denote 1%, 5%, 10% statistical significance respectively.

5 Empirical Results from Heterogeneous Panel Causality Test

In this section, we test the existence of at least one casual relationship between firm level characteristics and the measures of systemic risk. If so, we can write *Leverage*, *MTBV*, and *Returns* $\rightarrow \Delta CoVaR$ and *MES*, where "$\rightarrow$" stands for "*variable x Granger cause variable y*". Similarly, we test causality in the opposite direction (i.e., $\Delta CoVaR$ and *MES* $\rightarrow$ *Leverage*, *MTBV*, and *Returns*), addressing the systemic vulnerability of individual financial institutions to systemic shocks. The analysis is conducted by considering: [i] the whole time period (2007:1 - 2019:4), [ii] the four sub-periods (2007:1-2009:4: the Global Financial Crisis; 2010:1-2014:4: the Monetary Policy Restriction by the PBoC; 2015:1-2019:4 the second stock crash; 2019:1-2021:1 COVID-19 pandemic), [iii] the different financial intermediaries (traditional banks, finance services, real estate finance developers). To summarize, we formulate and test the following hypotheses:

- H_1: *Do firm level characteristics Granger cause systemic risk in the whole period?*
- H_2: *Do firm level characteristics Granger cause systemic risk over four sub periods?*
- H_3: *Do firm level characteristics Granger cause systemic risk in the whole period considering each kind of financial intermediary?*
- H_4: *Do firm level characteristics Granger cause systemic risk over four sub periods considering each kind of financial intermediary?*

For each hypothesis, we obtain the p-values and critical values of $\bar{Z}$ and $\tilde{Z}$ via a bootstrap procedure[17].

Table 6 reports the results of the analysis of whether firm level characteristics Granger cause systemic risk during the period 2007:1-2021:1. When we consider the whole financial system, there is evidence of Granger causality exists between *Leverage* $\rightarrow$ *MES* and between *MTBV* $\rightarrow$ $\Delta CoVaR$, *MES*. Higher levels of *Leverage* and larger fluctuations in *MTBV* ratio may be important indicators of an increase in the systemic risk (Adrian & Brunnermeier, 2016; Acharya et al., 2017; Fang et al., 2018). Higher *MTBV* means that the market value of a financial institution is overvalued relative to its book value, causing pricing misalignments and thus leading to an increase in systemic risk. *Leverage* tends to increase systemic risk and we may argue that this causal relationship is led by higher level of leverage holds by traditional banks, 17.32% (see Table 1), relative to finance services (2.12%) and real estate finance developers (2.73%). We do not find any causal relationship in the opposite direction suggesting that, over the whole period, individual financial intermediaries are less likely to be systemically driven by the system. Systemic risk measures, instead, are unaffected by *Returns*.

Table 6: Results panel causality test - Long time period.

Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage $\rightarrow \Delta CoVaR$	1.77	6.92	6.14	No	No causality from Leverage to $\Delta CoVaR$
$\Delta CoVaR \rightarrow$ Leverage	1.08	0.70	0.31	No	No causality from $\Delta CoVaR$ to Leverage
Leverage $\rightarrow$ *MES*	1.95**	8.54**	7.64**	Yes	Unidirectional causality from Leverage to *MES*
MES $\rightarrow$ Leverage	1.07	0.68	0.27	No	No causality from *MES* to Leverage
MTBV $\rightarrow \Delta CoVaR$	1.84**	7.51**	6.67**	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
$\Delta CoVaR \rightarrow$ MTBV	1.11	0.99	0.59	No	No causality from $\Delta CoVaR$ to MTBV
MTBV $\rightarrow$ *MES*	2.18**	10.58**	9.53**	Yes	Unidirectional causality from MTBV to *MES*
MES $\rightarrow$ MTBV	1.17	1.57	1.13	No	No causality from *MES* to MTBV
Returns $\rightarrow \Delta CoVaR$	1.12	1.09	0.69	No	No causality from Returns to $\Delta CoVaR$
$\Delta CoVaR \rightarrow$ Returns	1.07	0.68	0.30	No	No causality from $\Delta CoVaR$ to Returns
Returns $\rightarrow$ *MES*	1.28	2.47	1.98	No	No causality from Returns to *MES*
MES $\rightarrow$ Returns	1.35	3.11	2.57	No	No causality from *MES* to Returns

The table reports the results from Dumitrescu & Hurlin (2012)' test. "$\rightarrow$" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\rightarrow\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\rightarrow\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.
***, **, *, denote 1%, 5%, 10% statistical significance respectively.

Table 7 reports the results for H_2. There is strong evidence of systemic risk propagation from the causal relation between *MTBV* and both the systemic risks measures ($\Delta CoVaR$ and *MES*). During and after the Chinese stock crash in 2015, many listed financial companies were hit either upward or downward price which caused severe mispricing to their market value with potential spill over effect in the financial system. This evidence confirms, on the one hand, how the Chinese financial system experienced a major turmoil during the 2015 - 2016 rather than the Global Financial Crisis (Yu et al., 2018). On the other hand, the drastic adjustments experienced by China stock markets become a major source of instability for world financial markets (Pan et al., 2016; Pavlidis & Vasilopoulos, 2020). Another possible explanation

[17]According with Dumitrescu & Hurlin (2012), computing bootstrapped critical values (rather than asymptotic) may be useful when there is cross-sectional dependence.

of this evidence is that financial companies have become involved and more dependent on market trends during stressed economic times (Engle et al., 2015). This results also confirms what Bekaert & Harvey (1997) argued, regarding that liberalization policies, on the one hand, may increase both international stock markets in providing opportunities for expansion and improve risk sharing internationally. On the other hand, however, exposures on the global financial markets may cause contagion and decrease the benefits of diversification.

Table 7: Results panel causality test - Four sub periods.

Global Financial Crisis: 2007:1 - 2009:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	2.52	13.66	6.05	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	2.43	12.81	5.57	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	2.53	13.71	5.11	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	2.17	10.47	3.48	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.43	3.84	0.13	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.44	3.97	0.19	No	No causality from Returns to *MES*
Monetary Policy Restriction: 2010:1 - 2014:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\bar{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.38	3.46	1.7	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.35	3.14	1.45	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.27	2.39	0.87	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.39	3.46	1.7	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.26	2.35	0.83	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.28	2.56	1.00	No	No causality from Returns to *MES*
Second Stock Crash: 2015:1 - 2019:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	0.00	0.00	0.00	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	0.00	0.00	0.00	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	12.25***	37.04***	12.32***	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	8.84*	21.72*	5.99*	Yes	Unidirectional causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.99	-0.04	-1.03	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.77	-2.00	-2.58	No	No causality from Returns to *MES*
COVID-19 Pandemic: 2019:1 - 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	0.00	0.00	0.00	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	0.00	0.00	0.00	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	2.24	11.13	1.54	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	0.00	0.00	0.00	Yes	Unidirectional causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.79	7.12	0.34	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.00	0.00	0.00	No	No causality from Returns to *MES*

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.
***, **, *, denote 1%, 5%, 10% statistical significance respectively.

Table 8 reports the results for H_3. Traditional banks confirm their crucial role in the economy. With their higher market capitalization and a closer relationship with finance services and real estate sector, their *Leverage* and *MTBV* Granger cause both systemic risk measures. As regards *MTBV* ratio, one possible explanation is that traditional banks, to counter the funding and capital-related pressures[18], may be expected to reduce assets in order to improve their capital or liquidity positions, or both. These measures are, however, typically comparatively costly and difficult to implement within a short time span, especially in periods of distress, causing asset pricing misalignments and thus increasing systemic risk.

As regards *Leverage*, it is worth noticing that traditional banks hold higher level of leverage relative to finance services and real estate finance developers (see Table 1). Finance services, instead, in trading securities on their own account or on behalf of customers, are usually lower leveraged than traditional banks and real estate finance developers. Therefore, there is a moderate impact on systemic risk by finance services and and real estate (Engle et al., 2015). The strong causal relationship between *MTBV* with $\Delta CoVaR$ and *MES* for finance services emphasizes that the bull market in China, in early 2015, was particularly led by these entities. In line with Fang et al. (2018), our results also confirm the strong impact of finance services on the Chinese financial market.

Table 8: Results panel causality test - Financial Intermediaries

Hypothesis	Wald Statistic	$\bar{Z}$	$\tilde{Z}$	Result	Conclusion
Traditional Banks					
Leverage → $\Delta CoVaR$	3.17**	5.74**	5.27**	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	2.76*	4.65*	4.25*	Yes	Unidirectional causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	7.11***	16.16***	14.98***	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	3.51**	6.66**	6.11**	Yes	Unidirectional causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.97	-0.08	-0.17	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	1.32	0.85	0.69	No	No causality from Returns to *MES*
Finance Services					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.78	2.20	1.96	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	2.15*	3.26*	2.94*	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	2.58*	4.47*	4.06*	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	3.22**	6.28**	5.76**	Yes	Unidirectional causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.80	-0.57	-0.63	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.59	-1.16	-1.18	No	No causality from Returns to *MES*
Real Estate Finance Developers					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.62*	5.03*	4.40*	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.84*	6.81*	6.06*	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.18	1.48	1.08	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.7	5.73	4.97	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.18	1.44	1.04	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.91	7.36	6.56	No	No causality from Returns to *MES*

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.
***, **, *, denote 1%, 5%, 10% statistical significance respectively.

[18] The pressures come from regulators and supervisors such as Basel III framework.

Tables 9, 10 and 11 test the fourth hypothesis (H_4) for traditional banks, finance services and real estate finance developers, respectively. We notice interesting empirical results coming from both different regimes and for each kind of financial intermediary. A first empirical evidence shows that during the 2008 Global Financial Crisis and the 2015 Chinese stock market crash period, higher growth opportunities, proxied by $MTBV$ ratio for all financial intermediaries, spilled over the financial system. In particular, traditional banks are the only who show a causal relationship during both time periods, whereas finance services and real estate finance developers are prominent during the second Chinese stock market crash. In addition, the monetary policy restriction and the outbreak of COVID-19 pandemic impacted the balance sheet management of traditional banks and finance services.

Looking at the monetary policy restriction period, we observe that only traditional banks have the most systemic risk contribution, ($Returns \rightarrow MES$), in contrast to finance services and real estate finance developers (see Table 9). This result is extremely important in explaining the contagion effect stemming from balance-sheet contractions, proxied by *Returns* variable, and how propagates to the global financial system. One possible explanation is that at the end of 2009, PBoC began to tighten the M2 supply for fear of a bank credit expansion after the 2007-2009 financial crisis. As M2 growth continued to slow down, banks became more vulnerable to unexpected deposit withdrawals, which exposed them to the risk of violating the Banking Disclosure Rule (BDR) regulation. To meet unexpected deposit shortfalls against the BDR ceiling, the bank attracted additional deposits by offering a much higher price than the official deposit rate imposed by the PBoC. However, higher prices decreased banks' loans returns and compelled banks to reduce issuance of new loans. Therefore, the growth in M2 and banks loans declined simultaneously. In addition to controlling the quantity of bank loans, the PBoC uses another regulation to control the quality of bank lending. In 2006, the State Council issued a notice to accelerate the restructuring process of real estate industry regarding some potential financial risks associated with bank credit to real estate sector. In 2010, the PBoC took concrete steps to curtail an expansion of bank credit to this industry. This is because the balance sheets of borrowers and lenders may deteriorate sharply in presence of financial turmoil (i.e., the asset prices fall)[19]. Moreover, according to Drakes & Retasks (2015) and Fang et al. (2018), another possible explanation for the causal relationship is that as traditional banks have higher market capitalization and a closer relationship with other sector' balance sheets, they provide the necessary liquidity to the markets and help to promote economic growth. This explains the crucial role of banks for the real economy in providing the necessary liquidity to the markets and help to promote economic growth. We also find that the leverage of traditional banks are more sensitive to systemic risk during the second Chinese stock market crash. The results confirm that the quasi-market leverage is high during downturn confirming that (i) is determined primarily by market forces, and that (ii) its counter-cyclicality comes from the fact that more of the value of the financial institution is "in the hands" of the debt holders during financial turmoil (Adrian et al., 2016).

Focusing on finance services (Table 10), *Leverage* and $MTBV$ matters during the 2015 Chinese stock crash. This evidence could be explained by the profitable business which finance services come into during

[19]According to Otaki & Moore (1997), the role of collateral amplifies the swings as a sector cycles become highly correlated with credit cycles. Within the real estate sector, the collateral role of property amplifies the swings as real estate cycles become highly correlated with credit cycles.

the monetary policy restriction, particularly, the close relationship with traditional banks in transferring their loans to off-balance sheet financial products such as MPs and Amps. In particular, we notice that both *Leverage* and *Returns* have an impact on systemic risk during the COVID-19 outbreak.

Table 9: Results panel causality test for Traditional Banks and sub periods.

Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Global Financial Crisis: 2007:1 - 2009:4					
Leverage → $\Delta CoVaR$	1.98	2.60	0.97	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.00	0.01	0.84	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	5.33*	11.45*	5.25*	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	2.10	2.87	0.91	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.56	1.49	0.22	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	2.23	3.27	1.11	No	No causality from Returns to *MES*
Monetary Policy Restriction: 2010:1 - 2014:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage $\Delta CoVaR$	1.71	1.87	1.17	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.17	0.45	0.05	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.99	2.63	1.76	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	0.65	-0.92	-1.02	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.28	0.75	0.29	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	2.44**	3.82**	2.69**	Yes	Unidirectional causality from Returns to *MES*
Second Stock Crash: 2015:1 - 2019:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	14.14**	13.42**	4.66**	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.67	1.78	1.10	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	15.18***	14.78***	5.22	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.34	0.91	0.41	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.15	0.41	0.03	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	3.27	2.38	1.20	No	No causality from Returns to *MES*
COVID-19 Pandemic: 2019:1 - 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	3.15	5.68	1.17	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.99	2.64	0.26	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	2.03	2.72	0.29	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.57	1.51	-0.07	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.25	0.66	-0.33	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.48	1.28	-0.15	No	No causality from Returns to *MES*

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.
*, **, *** denote the 10%, 5% and 1% significance level, respectively.

As for *Leverage*, the causal relationship with $\Delta CoVaR$ may be explained by the fact that finance services actively manage the behavior of leverage. Market leverage is high during downturns or financial markets turmoil; therefore, the counter-cyclicality of market leverage comes from the fact that more of the value of the financial institutions is "*in the hands of the debt holders*" (Adrian et al., 2016)[20]. The causal

[20] As suggested by Adrian et al. (2016), there is a clear difference between book and market leverage. While financial

relationship between *Returns* and $\Delta CoVaR$ show that the balance sheet management of finance services is markedly different from traditional banks and real estate financial developers; finance services manage balance sheets aggressively and actively[21].

Table 10: Results panel causality test for Finance Services and sub periods.

Hypothesis	Wald Statistic	$\bar{Z}$	$\tilde{Z}$	Result	Conclusion
Global Financial Crisis: 2007:1 - 2009:4					
Leverage → $\Delta CoVaR$	1.05	0.14	-0.45	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.99	2.80	1.05	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.28	0.81	-0.15	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.29	0.82	-0.15	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.79	-0.58	-0.86	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.05	0.14	-0.50	No	No causality from Returns to *MES*
Monetary Policy Restriction: 2010:1 - 2014:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.17	0.50	0.07	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	0.54	-1.27	-1.31	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.22	0.64	0.18	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.52	1.47	0.83	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.61	-1.10	-1.17	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.44	-1.56	-1.54	No	No causality from Returns to *MES*
Second Stock Crash: 2015:1 - 2019:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	11.96**	11.26**	3.71**	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	0.69	-0.85	-0.98	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	14.04**	14.20**	4.92**	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	10.59**	9.32**	2.91**	Yes	Unidirectional causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.58	-1.17	-1.23	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.40	-1.67	-1.62	No	No causality from Returns to *MES*
COVID-19 Pandemic: 2019:1 - 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	3.71*	7.66*	1.73*	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	2.18	3.34	0.44	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.73	2.06	0.05	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.26	0.74	-0.34	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	11.35**	29.28**	8.22**	Yes	Unidirectional causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.32	-1.93	-1.14	No	No causality from Returns to *MES*

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.
*, **, *** denote the 10%, 5% and 1% significance level, respectively.

Figure 1 shows that the finance services' market leverage decrease during the outbreak of COVID-

institutions may actively manage the behavior of book leverage (defined as the ratio between total assets and book equity), market leverage is mainly determined by market forces. This also explains that the pro-cyclicality of book leverage derives from management financial institutions by reducing their debt, i.e., deleveraging.

[21] The asset side of finance services' balance sheets is composed mainly of risky assets, while the liability side consists largely of short-term, collateralized borrowing.

19 pandemic. Therefore, a decrease in leverage is associated with a reduction in finance services assets, which consequently leads to a higher volatility and credit spreads, and a decrease in financial sector equity, increasing systemic risk (Adrian et al., 2014). These findings are also in line with Brunnermeier & Pedersen (2009), where the nexus between increases in volatility and decline in asset value (called "*margin spiral*") cause funding conditions to deteriorate, forcing therefore financial intermediaries to reduce leverage and consequently reduce their balance sheet size.

As for real estate finance developers (Table 11), during the Global Financial Crisis, particular concerns are on the causal relation between *Leverage* and *MES* of real estate finance developers. The Global Financial Crisis, coming from the US with the real estate financial crisis, posed severe threat to the business model of real estate developers. The business model of the real estate developers are characterized by a high debt ratio and complex financing structure. Real estate developers rely on borrowings to pay the earnest money for land auction, resulting in high leverage ratio which also constitutes a serious violation to the rule that only self-owned money can be used to purchase land. In addition, the causal relation between leverage and systemic risk is also associated with financing channels featuring complex structure, multiple reinvestment and debt in the guise of equity, which makes it difficult for the regulatory authorities to look through the actual money flow, and diminish the regulatory effectiveness.

Moreover, real estate risks may spread over to the financial system through multiple channels. Particularly relevant is the fact the some real estate developers, after the Global Financial Crisis, started raising money through trusts, wealth management products and other non-bank financing channels (i.e., shadow banking products), which feature complex financing structure and multiple reinvestment, and risks may spread over to the financial system through these non-bank channels.

In addition, the evidence of a strong causal relation between $MTBV$ and $\Delta CoVaR$ and MES has some interesting interpretation. On the one hand, as a large share of the credit was collateralized by real estates, shocks can spill over to the financial industry through changes in the valuation of collateral. On the other hand, as the real estate sector involves a range of upstream and downstream industries, its development exerts an influence over their profitability and solvency conditions, and further over the risk profile of the financial system.

The real estate sector also causes systemic risk due to the endogenous risk of bubbles (He, 2016). In particular, the risk of bubbles refers to the risk of fluctuations in real estate prices causing bank credit losses. The supply and demand mechanism for real estate is different from ordinary products. In the real estate, demand and price move in the same direction, while supply and price move in the opposite direction. When housing prices rise, people expect prices will continue to rise and demand for housing increases. Real estate owners, looking for higher returns, are hesitant to sell reducing therefore supply. This pushes prices upward confirming people' expectations. After the Global Financial Crisis, the excess of liquidity pumped by the Chinese Government, on the one hand, pushed up demand for real estate consumption and investment, on the other, instead, real estate become a channel of release. Participation in finance has supported the realization of housing purchase and investment demands of Chinese citizens. These forces have inflated the real estate market bubble and explains the strong causal relationship between $MTBV$ and systemic risk measures.

Table 11: Results panel causality test for Real Estate Finance Developers and sub periods.

Hypothesis	Wald Statistic	$\bar{Z}$	$\tilde{Z}$	Result	Conclusion
Global Financial Crisis: 2007:1 - 2009:4					
Leverage → $\Delta CoVaR$	2.76	14.24	6.54	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	2.63*	13.22*	5.96*	Yes	Unidirectional causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	2.38	11.17	4	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	2.28	10.38	3.61	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.49	3.98	0.37	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.40	3.28	0.02	No	No causality from Returns to *MES*
Monetary Policy Restriction: 2010:1 - 2014:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.37	3.05	1.48	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	1.46	3.78	2.05	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	1.19	1.56	0.31	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	1.44	3.62	1.93	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.34	2.74	1.24	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	1.26	2.14	0.77	No	No causality from Returns to *MES*
Second Stock Crash: 2015:1 - 2019:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	0.00	0.00	0.00	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	0.00	0.00	0.00	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	11.73***	31.27***	10.22***	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	8.89**	19.8**	5.5**	Yes	Unidirectional causality from MTBV to *MES*
Returns → $\Delta CoVaR$	1.03	0.22	-0.73	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.72	-2.22	-2.64	No	No causality from Returns to *MES*
COVID:19 Pandemic: 2019:1 - 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	0.00	0.00	0.00	No	No causality from Leverage to $\Delta CoVaR$
Leverage → *MES*	0.00	0.00	0.00	No	No causality from Leverage to *MES*
MTBV → $\Delta CoVaR$	10.73	1.60	2.32	No	No causality from MTBV to $\Delta CoVaR$
MTBV → *MES*	0.00	0.00	0.00	No	No causality from MTBV to *MES*
Returns → $\Delta CoVaR$	0.68	-2.56	-2.39	No	No causality from Returns to $\Delta CoVaR$
Returns → *MES*	0.00	0.00	0.00	No	No causality from Returns to *MES*

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.
*, **, *** denote the 10%, 5% and 1% significance level, respectively.

6 Conclusions

In this paper, we investigated China's changing financial interconnectedness via the presence of Granger-causality between firm level factors (*Leverage*, *MTBV* and *Returns*) and systemic risk measures, $\Delta CoVaR$ and *MES*. We used a sample of 161 publicly and continuously listed entities in the Chinese financial system (14 Traditional Banks, 16 Finance Services, and 131 Real Estate Finance Developers) over the 2007-2021 period and during four main sub-periods characterizing the Chinese stock markets such as the Global Financial Crisis (2007:1-2009:4), the Monetary Policy Restriction by the PBoC (2010:1-2014:4), the 2015 Chinese stock crash (2015:1-2019:4), and the outbreak of COVID-19 pandemic (2020:1-2021:1).

Over the whole period, we found that *Leverage* and *MTBV* were the prominent determinants of systemic risk. Focusing on the four sub-periods, we found that the Chinese financial system experienced a strong distress during the 2015 stock crash. This result raises interesting questions about the launch of the Shanghai-Hong Kong Stock Connect Program in November 2014 which allowed investors to trade shares on other markets through local brokers and clearing houses.

When we considered different financial institutions, there is clear evidence that traditional banks are the major players in increasing systemic risk, mainly due to their higher level of *Leverage* and *MTBV*. Regarding finance companies, their profitable business had a strong impact on financial system particularly during the 2015 Chinese stock crash and the outbreak of COVID-19 pandemic, confirming they are affected by markets dynamics during difficult economic times. We also evaluated the role played by real estate finance developers, extremely important financial player in the Chinese financial system. Their complex financing structure and high leverage ratio posed systemic threats to the Chinese financial system, in particular during the Global Financial Crisis and the 2015 Chinese stock crash.

The empirical findings in this paper provide important policy implications for regulators. First, we highlight the need to increase regulation on entities such as finance services and real estate (fully or partially outside the regular banking system) which may raise systemic risk concerns. In particular, *Leverage*, *MTBV* and *Returns* are genuine source of vulnerabilities, which may trigger systemic risk both in the finance services and in the real estate markets. Thus, regulators have the important role to closely monitor these financial institutions to ameliorate the transmission of risk across the financial system. Second, although the assessment of the impact of COVID-19 on the financial sector are at an early stage, it is important that authorities implement policy response to safeguard financial stability, preserve core financial markets functions and maintain the provision of critical financial services to the real economy.

The main findings in this paper suggest some future developments. First, in addition to finance services and real estate finance developers, there exist other financial entities, which are fully or partially outside the regulated banking system. The analysis conducted in this paper can be extended to these entities. In addition, a relevant number of Chinese financial entities are state-owned and that the People Bank of China may have more regulatory oversight over these entities, given that some of the loan portfolios may be given to state entities to foster political and social objectives. Future analyses should explore this dichotomy. We leave these interesting developments to future research.

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Appendices

Appendix A Matrix Correlation

Table A1: Correlation matrix among state variables. Dependent variable $\Delta CoVaR$.

Matrix Correlation	$\Delta CoVaR$	Shanghai Composite Index	Liquidity Spread	T-bill change	5y Bond	Yield-Curve slope	VIX
$\Delta CoVaR$	1						
Shanghai Composite Index	0.0354*	1					
Liquidity Spread	-0.0611*	-0.0176*	1				
T-bill change	-0.0220*	-0.0213*	0.0509*	1			
5y Bond	0.0698*	0.0039	0.4260*	0.1243*	1		
Yield-Curve slope	0.0143*	-0.1021*	0.6096*	0.0914*	0.4354*	1	
VIX	0.1270*	-0.0404*	-0.1617*	-0.2677*	0.0525*	-0.3168*	1

The table reports the correlations among state variables on weekly data from 2007 to 2021. The state variables are: *Shanghai Composite Index*: is the weekly return of the index of the Shanghai stock exchange; *Liquidity spread*: is the liquidity spread calculated as the difference between the three month Chinese repo-rate and the three month Chinese T-bill; *T-Bill change*: indicates the change in Chinese treasury bill 3 month rate; *5yBonds*: indicates the slope of the Chinese 5-year Government bonds; *Yield-Curve slope*: indicates the change in slope of the yield curve represented by Chinese 5-year minus three-month interest rate on Government bonds; *VIX* is the CBOE option implied volatility index.
* denotes the statistical significance at 5% level.

Appendix B Panel Unit Root Tests with Independent Units

The first step of econometric analysis is to explore the stability of series used in the analysis. We employ panel unit root tests developed by Im et al. (2003). Im et al. (2003) perform unit root test on a set of Dickey-Fuller regressions of the form:

$$\Delta y_{i,t} = \phi_i y_{i,t-1} + \mathbf{z'}_{i,t}\gamma_i + \varepsilon_{i,t} \tag{18}$$

where: i=1,...,N indexes panels, t=1,...,T indexes time, $y_{i,t}$ is the variable being tested, and $\varepsilon_{i,t}$ is a stationary error term. The $z'_{i,t}$ represents panel-specific means and, by default, $z'_{i,t}$=1, so that the term $z'_{i,t}\gamma_i$ represents panel-specific means (fixed effects). The null hypothesis is then H_0:$\phi = 0$ for all i: (includes series unit root) versus the alternative H_a:ϕ <0: (does not include series unit root).

Table E1 shows the panel unit-root test results. According with Levin et al. (2002), we subtract the cross-sectional averages from the series to mitigate the impact of cross-sectional dependence. According to the test results, for both systemic risk measures and for two firm-level factors (i.e., *MTBV*, *Returns*), we strongly reject at 1% the null hypothesis that all series contain a unit root in favor of the alternative that a nonzero fraction of the panels represents stationary processes. We can also reject the null, at 10%, for leverage variable.

We also test whether each variable contains a unit root allowing for serially correlated errors. We choose the number of lags for the Augmented Dickey-Fuller regressions by minimizing the Bayesian Information Criterion (BIC):

$$\Delta y_{i,t} = \phi_i y_{i,t-1} + \mathbf{z'}_{i,t}\gamma_i + \sum_{j=1}^{p} \Delta y_{i,t-1} + \varepsilon_{i,t} \tag{19}$$

where p is the number of lag specified using the BIC criterion. Table B2 reports the results. Both for systemic risk measures and for firm-level factors (i.e., *Leverage*, *MTBV*, *Returns*), we reject the null hypothesis that all series contain a unit root in favor of the alternative that a nonzero fraction of the panels represents stationary processes.

Table B1: Panel Unit Root Results

Panel-Unit Root Test					
Systemic Risk Measures			**Firm-level factors**		
Variable	Statistic	P-value	Variable	Statistic	P-value
Delta CoVaR	-18.84***	0.0000	Leverage	-1.80**	0.0357
MES	-25.05***	0.0000	MTBV	-16.26***	0.0000
SRISK	-10.82***	0.0000	Returns	-59.98***	0.0000

The table reports the statistic and the p-value for the Im et al. (2003)' panel unit root test.
***, **, *, denote 1%, 5%, 10% statistical significance respectively.

Table B2: Panel Unit Root Results - BIC Criterion

Panel-Unit Root Test - BIC Criterion					
Systemic Risk Measures			**Firm-level factors**		
Variable	Statistic	P-value	Variable	Statistic	P-value
Delta CoVaR	-20.57***	0.0000	Leverage	-1.37*	0.0850
MES	-29.17***	0.0000	MTBV	-19.21***	0.0000
SRISK	-21.27***	0.0000	Returns	-89.65***	0.0000

The table reports the statistic and the p-value for the Im et al. (2003)' panel unit root test allowing for serially correlated errors. The number of lags were chosen to minimize the BIC criterion.
***, **, *, denote 1%, 5%, 10% statistical significance respectively.

Appendix C Results for State and Non State Owned Banks

Table C1: Results for State Owned Banks: full time period and sub periods.

Full time period: 2007:1 – 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	6.21***	6.37***	5.91***	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → MES	6.59**	6.84**	6.35**	Yes	Unidirectional causality from Leverage to MES
MTBV → $\Delta CoVaR$	8.09***	8.68***	8.05***	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → MES	6.85**	7.16**	6.63**	Yes	Unidirectional causality from MTBV to MES
Returns → $\Delta CoVaR$	0.55	-0.54	-0.55	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	2.01	1.23	1.11	No	No causality from Returns to MES
Global Financial Crisis: 2007:1 – 2009:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	3.22	2.71	1.31	No	No causality from Leverage to $\Delta CoVaR$
Leverage → MES	0.22	-0.95	-0.77	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	14.70***	16.79***	8.23***	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → MES	0.28	-0.87	-0.69	No	No causality from MTBV to MES
Returns → $\Delta CoVaR$	0.54	-0.56	-0.53	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	0.75	-0.3	-0.4	No	No causality from Returns to MES
Monetary Policy Restriction: 2010:1 – 2014:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	0.11	-1.08	-0.98	No	No causality from Leverage to $\Delta CoVaR$
Leverage → MES	4.02	1.74	1.01	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	0.05	-1.16	-1.04	No	No causality from MTBV to $\Delta CoVaR$
MTBV → MES	7.54**	4.80**	3.16**	Yes	Unidirectional causality from MTBV to MES
Returns → $\Delta CoVaR$	2.23	1.51	1.05	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	12.04***	8.69***	5.90***	Yes	Unidirectional causality from Returns to MES
Second Stock Crash: 2015:1 – 2019:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	3.34**	2.87**	2.11**	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → MES	3.83**	3.49**	2.58**	Yes	Unidirectional causality from Leverage to MES
MTBV → $\Delta CoVaR$	12.44**	5.17**	1.72**	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → MES	3.08*	2.55*	1.86*	Yes	Unidirectional causality from MTBV to MES
Returns → $\Delta CoVaR$	3.97**	3.64**	2.71**	Yes	Unidirectional causality from Returns to $\Delta CoVaR$
Returns → MES	4.87***	4.75***	3.58***	Yes	Unidirectional causality from Returns to MES
COVID-19 Pandemic: 2019:1 – 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.55	0.67	-0.04	No	No causality from Leverage to $\Delta CoVaR$
Leverage → MES	0.82	-0.22	-0.31	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	1.72	0.88	0.02	No	No causality from MTBV to $\Delta CoVaR$
MTBV → MES	0.98	-0.02	-0.25	No	No causality from MTBV to MES
Returns → $\Delta CoVaR$	1.66	0.81	0	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	0.78	-0.27	-0.33	No	No causality from Returns to MES

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.

Table C2: Results for Non-State Owned Banks: full time period and sub periods.

Hypothesis	Wald Statistic	$\bar{Z}$	$\tilde{Z}$	Result	Conclusion
Full time period: 2007:1 – 2021:1					
Leverage → $\Delta CoVaR$	2.34**	3.14**	2.85**	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → MES	1.71	1.67	1.48	No	Unidirectional causality from Leverage to MES
MTBV → $\Delta CoVaR$	6.84***	13.70***	12.69***	Yes	Unidirectional causality from MTBV to $\Delta CoVaR$
MTBV → MES	2.61*	3.76*	3.42*	Yes	Unidirectional causality from MTBV to MES
Returns → $\Delta CoVaR$	1.08	0.19	0.09	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	1.13	0.32	0.2	No	No causality from Returns to MES
Global Financial Crisis: 2007:1 – 2009:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	1.68	1.59	0.46	No	No causality from Leverage to $\Delta CoVaR$
Leverage → MES	1.21	0.49	-0.16	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	2.55	3.65	1.37	No	No causality from MTBV to $\Delta CoVaR$
MTBV → MES	2.57	3.69	1.39	No	No causality from MTBV to MES
Returns → $\Delta CoVaR$	1.8	1.88	0.48	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	2.64*	3.85*	1.47*	Yes	Unidirectional causality from Returns to MES
Monetary Policy Restriction: 2010:1 – 2014:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	2.14	2.67	1.83	No	No causality from Leverage to $\Delta CoVaR$
Leverage → MES	1.09	0.21	-0.1	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	2.53	3.58	2.54	No	No causality from MTBV to $\Delta CoVaR$
MTBV → MES	0.36	-1.5	-1.44	No	No causality from MTBV to MES
Returns → $\Delta CoVaR$	1.07	0.16	-0.13	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	2.39*	3.27*	2.29*	Yes	Unidirectional causality from Returns to MES
Second Stock Crash: 2015:1 – 2019:4					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	15.69**	13.71**	4.88**	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → MES	2.88	1.46	0.6	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	1.38	0.88	0.43	No	No causality from MTBV to $\Delta CoVaR$
MTBV → MES	6.63	3.08	0.49	No	No causality from MTBV to MES
Returns → $\Delta CoVaR$	0.43	-1.34	-1.31	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	2.14	0.23	-0.26	No	No causality from Returns to MES
COVID-19 Pandemic: 2019:1 – 2021:1					
Hypothesis	**Wald Statistic**	$\bar{Z}$	$\tilde{Z}$	**Result**	**Conclusion**
Leverage → $\Delta CoVaR$	3.58*	6.06*	1.35*	Yes	Unidirectional causality from Leverage to $\Delta CoVaR$
Leverage → MES	2.32	3.09	0.46	No	No causality from Leverage to MES
MTBV → $\Delta CoVaR$	2.11	2.61	0.31	No	No causality from MTBV to $\Delta CoVaR$
MTBV → MES	1.73	1.72	0.05	No	No causality from MTBV to MES
Returns → $\Delta CoVaR$	1.14	0.32	-0.37	No	No causality from Returns to $\Delta CoVaR$
Returns → MES	1.67	1.58	0.01	No	No causality from Returns to MES

The table reports the results from Dumitrescu & Hurlin (2012)' test. "→" stands for "variable x Granger cause variable y" and viceversa. $WaldStatistic = W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $\bar{Z} = \sqrt{\frac{N}{2K}} \times (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} N(0,1)$; $\tilde{Z} = \sqrt{\frac{N}{2K} \times \frac{T-3K-5}{T-2K-3}} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K\right) \xrightarrow[T,N\to\infty]{d} N(0,1)$. The number of lags were chosen to minimize the BIC criterion and the p-values are computing using 50 bootstrap replications at 95% critical value. The time period is from 2007:1 to 2021:1.

Appendix D Variable definitions

Table D1: Variable definitions and data sources.

Variable name	*Definition*	*Data source*
Systemic Risk Measures		
$\Delta CoVaR$	Conditional $\Delta CoVaR$ as defined by Adrian & Brunnermeier (2016), measured as the difference difference between CoVaR conditional on the institution being in distress and CoVaR in the median state of the institution. To estimate the time-varying VaR and CoVaR, we include a set of state variables to capture the time variation in conditional moments of asset returns. The Chinese state variables used in this analysis are: Shanghai Composite Index: is the weekly return of the index of the SHANGHAI stock exchange; Liquidity spread: is the liquidity spread calculated as the difference between the three months Chinese repo-rate and the three months Chinese T-bill; T-Bill change: indicates the change in Chinese treasury bill 3 month rate; Yield-Curve slope: indicates the change in slope of the yield curve represented by Chinese 5-years minus three-months interest rate on government bonds; 5yBonds: indicates the slope of the Chinese 5-years government bonds. We also include the weekly Volatility Index (VIX) of the Chicago Board Options Exchange (CBOE) as a measure of market risk and investors' sentiments.	Datastream, own. calc.
MES	Marginal Expected Shortfall as defined by Acharya et al. (2017) as the average return on an individual institution's stock on the days the market index experienced its 5% worst outcome.	Datastream, own. calc.
SRISK	The SRISK estimate for financial institution i at time t is given by $SRISK_{i,t} = max[0; \kappa(D_{i,t} + (1 - LRMES_{i,t}W_{i,t}) - (1 - LRMES_{i,t})W_{i,t}]$ where κ is set to 8% to denote the regulatory capital ratio, $D_{i,t}$ is the financial institution's book value of debt, $LRMES$ it is the Long Run Marginal Expected Shortfall defined as $1 - exp(log(1-d) * MES_{i,t}$, MES is the marginal expected shortfall and $W_{i,t}$ is the financial institutions's market value of equity.	Datastream, own. calc.
Firm-level factors		
Leverage	Quasi-market value of assets over the market value of equity, where quasi-market value of assets is equal to book assets minus book equity plus market equity (see Acharya et al. (2017)).	Worldscope (WC02999, WC03501, WC08001), own. calc.
MTBV	Market To Book Value ratio between the market value of common equity divided by book value of common equity.	Worldscope (WC07210 and WC03501).
Returns	The growth rate of market-valued total assets given by the product of the leverage ratio (defined as the total assets to equity ratio) and the market value of equity. See as Adrian & Brunnermeier (2016), López-Espinosa et al. (2012, 2015), and Balboa et al. (2015).	Worldscope (WC02999, WC03501, WC08001, WC07210) own. calc.

The table presents definitions as well as data sources for all systemic risk measures and firm-level factors that are used in the empirical study. The financial institutions characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Appendix E List of Chinese Financial Institutions

Table E1: List of Financial Institutions.

Financial Institutions	**Type**
PING AN BANK 'A'; CHINA MERCHANTS BANK 'A'; CHINA MINSHENG BANKING 'A'; HUAXIA BANK 'A'; CHINA CON.BANK 'H'; BANK OF CHINA 'A'; INDUSTRIAL & COML.BK.OF CHINA 'A'; INDUSTRIAL BANK 'A'; CHINA CITIC BANK 'A'; BANK OF COMMS.'A'; BANK OF NINGBO 'A'; BANK OF NANJING 'A'; BANK OF BEIJING 'A'; SHAI.PUDONG DEV.BK. 'A'	**Traditional Banks**
SOUTHWEST SECURITIES 'A'; SHAANXI INTL.TRUST 'A'; SHANGHAI AJ GP.'A'; ANXIN TRUST 'A'; HAITONG SECURITIES 'A'; CITIC SECURITIES 'A'; PACIFIC SECURITIES 'A'; AVIC CAPITAL 'A'; NORTHEAST SECURITIES 'A'; GUANGDONG GLDN. DRAGON DEV. 'A'; SDIC CAPITAL 'A'; GF SECURITIES 'A'; GUOYUAN SECURITIES 'A'; SEALAND SECURITIES 'A'; CHANGJIANG SECURITIES 'A'; SINOLINK SECURITIES 'A'	**Finance Services**
SHANGHAI SHIMAO 'A'; METRO LAND 'A'; JINAN HIGH-TECH DEVELOPMENT 'A'; GZH.PER.RVR.IND.DEV.'A'; SHANGHAI GUIJIU 'A'; CHINA ENTERPRISE 'A'; CINDA REAL ESTATE 'A'; BEIJING ELECTRONIC ZONE HIGH-TECH GROUP 'A'; DONGGUAN WINNERWAY INDL. ZONE 'A'; ZHONGTIAN FINL.GP.'A'; JINYUAN EP 'A'; LANDER SPORTS DEV.'A'; WEDGE INDUSTRIAL 'A'; TIANJIN GUANGYU DEV.'A'; HAINAN JINGLIANG HOLDINGS 'A'; ZHONGRUN RES.INV.'A'; CHONGQING YUKAIFA 'A'; RONGAN PROPERTY 'A'; XUEDA (XIAMEN) ED. TGP. 'A'; LVJING HOLDING 'A'; TANDE 'A'; SHAI.CHENGTOU HLDG.'A'; SHANGHAI NEW HUANG PU INDUSTRIAL GROUP 'A'; SHANGHAI CHNGTU.HDGCO. 'A'; SHANGHAI WANYE ENTS. 'A'; SHANGHAI FENGHWA GP.'A'; SHANXI GUOXIN ENERGY 'A'; SHANGHAI TIANCHEN 'A'; EVERBRIGHT JIABAO 'A'; GUANGHUI LOGISTICS 'A'; SHANGHAI SHIBEI HI- TECH 'A'; GREENLAND HOLDINGS 'A'; TUNGHSU AZURE RENEW.EN. 'A'; SHENZHEN CENTRALCON INV. HLDG.'A'; CHIN.MRCH.PR.OPRTN. & SER.'A'; OCEANWIDE HOLDINGS 'A'; CHINA UNION HDG. 'A'; GRANDJOY HOLDINGS GROUP 'A'; SHAHE INDUSTRY 'A'; SHENZHEN PROPS.& RES. DEV.'A'; CHINA BAOAN GP.'A'; SHN.ZHENYE (GROUP) 'A'; SHN.FOUNTAIN 'A'; CHINA VANKE 'A'; HAINAN HAIDE CAPITAL MANAGEMENT 'A'; SHAI.LJZ.FN&T.ZONE DEV. 'A'; SHAI.TONGJI SCTC.INDL. 'A'; SHANGHAI LINGANG HOLDINGS 'A'; TIANJIN REALITY DEV. 'A'; NANJING CHIXIA DEV. 'A'; ZHONGCHANG BIG DATA 'A'; SICHUAN LANGUANG DEVELOPMENT 'A'; BLACK PEONY (GP.) 'A'; BEIJING CAPITAL DEV.'A'; GUANGZHOU YUETAI 'A'; GEMDALE 'A'; DELUXE FAMILY 'A'; HUBEI WUCHANGYU 'A'; VANTONE NEO DEVELOPMENT GROUP 'A'; BEIJING CAPITAL LAND 'H'; SHENYANG PUBLIC UTILITY HOLDINGS 'H'; LUSHANG HEALTH INDUSTRY DEVELOPMENT 'A'; TIANJIN SONGJIANG 'A'; TIANJIN TIANBAO INFR.'A'; YINYI 'A'; HUAFA INDUSTRIAL ZHUHAI 'A'; GUANGDONG SHIRONGZHAOYE 'A'; YIHUA HEALTHCARE 'A'; GUANGZHOU R&F PROPS.'H'; SHN.CAPSTONE INDL.'A'; POLY DEVELOPMENTS AND HOLDINGS GROUP 'A'; JIANGSU DAGANG 'A'; COSMOS GROUP 'A'; RISESUN REAL ESTATE DEV. 'A'; XINYUAN RLST.ADR 1:2; WUHAN ET.LK.HI.TECH.GP. 'A'; WUHAN DDMC CULTURE & SPORTS 'A'; BECE LEGEND GROUP 'A'; CHINA SPORTS IND.GP. 'A'; BEIJING DALONG WEIYE RLST.DEV.'A'; SHENZHEN HEUNGKONG HLDG. 'A'; GUANGDONG HIGHSUN GP.'A'; BEJ.URBAN CON.INV.DEV. 'A'; CHINA WLD.TRD.CENTER 'A'; WOLONG RLST.GP.'A'; TIANJIN JINBIN DEV. 'A'; GREE REAL ESTATE 'A'; XINHU ZHONGBAO 'A'; BEJ.CENTERGATE TECHS. (HLDG.) 'A'; CHINA CALXON GROUP 'A'; LANGFANG DEVELOPMENT 'A'; YUNNAN MET.RLST.DEV.'A'; FINANCIAL STR.HLDG.'A'; JIANGSU PHOENIX PR.INV. 'A'; ZHE JIANG DONG RI 'A'; YANGO GROUP 'A'; SHN.WONGTEE INTL. ENTER. 'A'; FUJIAN START GROUP 'A'; SUZHOU NEW DISTRICT HI- TECH INDL.'A'; SHANGHAI AIKO SOLAR ENERGY 'A'; BEIJING QIANFENG ELECTRONIC 'A'; YANG GUANG 'A'; HUA YUAN PROPERTY 'A'; CRED HOLDING 'A'; SHAI. ZHANGJIANG 'A'; SHANGHAI INDL.DEV.'A'; FJN.ORNTL.SIS.INV. 'A'; BEIJING ZODI INVESTMENT 'A'; MACROLINK CRNT.DEV.'A'; TIBET URBAN DEV.& INV. 'A'; HNA INV.GP.'A'; WINSAN (CHENGDU) MED. SCTC.'A'; CHENGDU HIGH-TECH DEV. 'A'; SHUNFA HENGYE 'A'; VANFUND URB.INVDV. 'A'; JINKE PROPERTY GROUP 'A'; MYHOME RLST.DEV.GP.'A'; RONGFENG HOLDING GROUP 'A'; BEH-PROPERTY 'A'; HAINAN YATAI INDL.DEV. 'A'; SUNING UNIVERSAL 'A'; ZHEJIANG GUANGSHA 'A'; KUNWU JIUDING INVESTMENT HOLDINGS 'A'; CCCG REAL ESTATE 'A'; BEIJING NORTH STAR 'H'; TIANJIN HI-TECH DEV.'A'; CASIN REAL ESTATE DEVELOPMENT GROUP 'A'; TAHOE GROUP 'A'; NANJING GAOKE 'A'; CHINA WU YI 'A'; SANXIANG IMPRESSION 'A'	**Real Estate Finance Services**