Assessing the contribution of China's financial sectors to systemic risk*

David Morelli[†a] and Davide Vioto[‡b]

[a]Kent Business School, University of Kent
[b]European Banking Authority

Abstract

This paper aims to assess the level of systemic risk of China's financial system along with the main systemic risk contributors over the period from January 2010 to December 2016, a period spanning the deflation of China's property bubble, the banking liquidity crisis, and the stock market crash. To this end we divide the financial system into three sectors, namely: banks, insurance and brokerage industries, and real estate, applying the $\Delta CoVaR$ introduced by Adrian and Brunnermeier (2016) as the measure for systemic risk. Our findings show that the systemic risk level of China's financial system reacted to the main systemic events covered by our sample period, reaching a major peak during the stock market crash of 2015. We further show, through the Wilcoxon signed rank test, that the systemic risk level of the financial system and sectors significantly increased after the main systemic events. In order to provide a formal systemic risk ranking of the financial sectors, we apply the bootstrap Kolmogorov-Smirnov test as developed by Abadie (2002), finding that the banking sector contributed the most, followed by real estate and subsequently insurance and brokerage industries. Finally, comparing banks systemic risk's determinants between China and the US, the reduced level of competition among banks in China is found to increase banks' systemic risk, contrary to what is found in the US.

Keywords: Systemic risk, $\Delta CoVaR$, Dominance test, Financial stability
JEL classification: G01, G15, G18, G20

*We would like to express our gratitude to the anonymous referees for their most constructive comments and suggestions. This paper should not be reported as representing the views of the European Banking Authority (EBA). The views expressed are those of the authors and do not necessarily reflect those of the EBA.

†Corresponding author: University of Kent, Kent Business School, Parkwood Road, Canterbury, CT2 7FS, United Kingdom, e-mail: D.A.Morelli@kent.ac.uk.

‡European Banking Authority (EBA), 20 Avenue André Prothin, Paris La Défense, 92927, France, e-mail: Davide.Vioto@eba.europa.eu.

1 Introduction

During 2015, with the popping of the stock market bubble, China's financial system appeared to be on the brink of a financial crisis, a crisis which would have had dramatic consequences for the major world economies given the financial linkages that many global companies have with China's markets. As contagion fears spread across the world's financial markets, one of the greatest concerns related to the size of the systemic risk of China's financial system. Given that China has experienced a very rapid and stable economic growth since the start of its reforms in 1978, the consequence of a period of financial instability could be disastrous.

Over the years China has partially opened its domestic stock markets to international capital, becoming an emerging market characterized by high returns and high volatility (Tunaru et al., 2006). Glick and Hutchison (2013) showed that the size and dynamism of China's economic activity and trading relationship have played a dominant role in linking equity markets across the Asian region, with a modest growth in the interrelationship between the mainland stock markets and the Hong Kong stock market following the Asian financial crisis (Hatemi-J and Roca, 2004). Moreover, Shu et al. (2018) using a structural vector autoregression model highlighted a growing influence, close to that of the United States, of China's financial market to the rest of Asia-Pacific, with the South China Growth Triangular markets, namely Hong Kong, Taiwan, Shanghai and Shenzhen contemporaneously correlated with the return volatility of the US market (Hu et al., 1997). Furthermore, Bekiros (2014) empirically demonstrated that the BRIC economies have become more internationally integrated following the US financial crisis, substantiating the contagion effects across the US, EU and the BRIC stock markets. Therefore, assessing the systemic risk of China's financial system and sectors is particularly critical not only for Asia but also global markets given the potential for systemic spillovers.

The International Monetary Fund (2017) stated that there are critical gaps in the functional supervision of China's financial system, recommending that regular systemic risk analyses should be undertaken by the People's Bank of China (PBoC) and China's regulatory agencies. Furthermore, using the spillover index of Diebold and Yılmaz (2014) as a measure of systemic risk, Wang et al. (2018) found that China's publicly-traded commercial banks are highly interconnected in terms of volatility shocks. Motivated by this our paper aims to investigate the main systemic risk contributors to China's financial system fragility, especially given the inevitable role they play in the quest for an effective regulatory framework. Addressing this issue requires the need to measure, not only the level of systemic risk in China's financial system, but also the contribution played by financial sectors in order to gain a better understanding of the overall systemic risk of the financial system. As discussed by Bernal et al. (2014), companies other than banks can also have a critical impact on the whole economy. For this reason, we focus on a broad range of Chinese banks, insurance and brokerage industries, and real estate companies. By comparing the systemic risk contributions of each financial sector should provide interesting insights into the existing link between systemic risk and the standards that financial institutions and sectors are expected to meet.

The empirical strategy developed in this paper examines the magnitude of the systemic risk in China's financial system over the period from the 1^{st} of January 2010 to the 31^{st} of December 2016. We apply the $\Delta CoVaR$ developed by Adrian and Brunnermeier (2016), estimated with the use of quantile regressions (Koenker and Bassett Jr, 1978), to estimate the systemic risk of a broad range of Chinese banks, insurance and brokerage industries, and real estate companies. The contribution of each financial sector to the overall systemic risk is examined. We analyse the period after the global financial crisis, an event which may have affected China's economy differently from what one observes in mature market economies (Bo et al., 2014). Indeed, the intensive state ownership of Chinese companies mitigates financial constraints during times of financial crisis (Liu et al., 2012). The period under analysis is divided into three subperiod, characterised by the deflating of China's property bubble with the stimulus program (January 1^{st}, 2010 – December 31^{st}, 2012); the banking liquidity crisis (January 1^{st}, 2013 – December 31^{st}, 2014); and the stock market crash (January 1^{st}, 2015

– December 31^{st}, 2016). Having analysed the systemic risk level of the financial system, the Wilcoxon signed rank test is applied to test the increases in the systemic risk level of the financial system and sectors during the main systemic events covered by our sample period. Moreover, the financial sectors are ranked, as per Bernal et al. (2014), by testing the systemic contribution of each sector adopting the bootstrap Kolmogorov-Smirnov (KS) test as developed by Abadie (2002).

Our study is further motivated by the fear that new systemic events at national level could trigger a new global crisis. The analysis builds on the recent literature that attempts to empirically measure systemic risk during the main systemic or high volatility episodes of the last decade (see, e.g., Acharya et al., 2017; Adrian and Brunnermeier, 2016; Bernal et al., 2014; Black et al., 2016; Brownlees and Engle, 2016; Derbali and Hallara, 2016). However, most of the existing literature is focused only on the Subprime and/or the Sovereign Debt crisis, and does not consider other episodes, such as China's recent stock market turbulence, which could have a severe systemic impact on the major global financial markets.

This paper contributes to the existing literature by attempting to estimate and assess systemic risk. Silva et al. (2017) present an analysis of the literature on systemic risk analyzing a total of 266 articles that were published no later than September 2016. The need to monitor systemic risk is largely explained by the effect that this risk could have on the real economy. The Bank for International Settlements defines systemic risk as: *"a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences on the real economy"* (Caruana, 2010). Billio et al. (2012) defined systemic risk as whatever set of events or circumstances which influence the stability of the financial system. Moreover, our paper further contributes to the growing literature adopting the $\Delta CoVaR$ as a measure of assessing the marginal contribution to the overall systemic risk. Our analysis applies the methodology proposed by Adrian and Brunnermeier (2016), which is based on quantile regressions (Koenker and Bassett Jr, 1978).

Extensions of the $\Delta CoVaR$ estimation method have been proposed in the recent literature. Girardi and Ergün (2013) proposed a multivariate GARCH estimation of $CoVaR$, a method based on a modification of the definition of financial distress, from an institution being exactly at its VaR to being at most at its VaR. This modification allows for the consideration of more severe distress events and improves the $CoVaR$ relationship with the dependence parameter. Cao (2013) introduced the $Multi-CoVaR$, where the $Multi-\Delta CoVaR$ is defined as the difference between the VaR of a financial system conditional on a given set of financial institutions being in a tail event and the VaR of the financial system conditional on this set of financial institutions being in a normal state. Reboredo and Ugolini (2015) applied this measure to assess the systemic risk in Europe, adopting a $CoVaR$ extension based on copulas. López-Espinosa et al. (2012) adopted the $CoVaR$ approach to identify the main factors behind the systemic risk in a number of large international banks, considering several econometric specifications of increasing complexity, thereby extending the basic $CoVaR$ model. Sedunov (2016) modified the $\Delta CoVaR$ to allow for forecasting, and compared the ability of this measure to forecast the performance of financial institutions with the systemic expected shortfall introduced by Acharya et al. (2017), and the Granger causality of Billio et al. (2012). His findings shows that the $\Delta CoVaR$ forecasts the within-crisis performance of financial institutions, providing useful forecasts of future systemic risk exposures.

Other systemic risk measures have also been proposed. Bisias et al. (2012) undertook a validity study examining the existing systemic risk measures, identifying thirty-one different quantitative measure for this risk.[1]

Our paper applies the $\Delta CoVaR$ to measure systemic risk given that over the last decade this measure has become one of the most widely accepted measures for systemic risk. Furthermore, this measure is strongly positively correlated with interconnectedness, and such a positive correlation mainly arises from an elevated effect of interconnectedness on systemic

[1]Bisias et al. (2012) argue that systemic risk measures can be classified according to supervisory, research, and data perspectives. For each of these they present a taxonomy of the area and concise definitions of each risk measure.

risk during recessions (Cai et al., 2018).

Our empirical results show that the systemic risk of China's financial system decreased after the deflating of the property bubble, reaching the minimum value in the second half of 2012. The banking liquidity crisis of 2013 vortically increased the systemic risk level, reaching its absolute peak with the stock market crash in the summer of 2015. This level decreased only after the restrictions upon investors introduced by the Chinese government and supervisory authorities were imposed. The statistical tests show an increase in the systemic risk level of the financial system and sectors during the major dates that characterized the Standard & Poor's (S&P) downgrade of China's developers in 2011, the banking liquidity crisis in 2013, and the China's market crash in 2015, and 2016. Moreover, our findings show that each of the financial sectors significantly contribute to systemic risk over the total and subperiods analysed. The banking sector is found to contribute the most to systemic risk, followed by real estate and subsequently insurance and brokerage industries. Such results are robust in both the Hong Kong and the Shanghai Stock Exchanges and emphasize the need for the Chinese supervisory authorities to monitor the systemic risk of the different financial sectors, as opposed to solely focusing on the regulation of the banking sector. Different financial sectors contribute differently to systemic risk, and supervisory authorities could potentially develop different courses of action depending upon the characteristics of the sectors.

Compared to the existing financial literature on systemic risk, which focuses predominantly on the US financial system, our paper provides a unique contribution by investigating systemic risk in China's financial system, a system characterized by; a strong governmental role within the banking sector (Jiang et al., 2019), its complex and confusing process for foreign investors accessing its equity markets, and an asymmetry and persistence of the business cycle compared to other developed countries as demonstrated by Dovern and van Roye (2014). Such characteristics associated with China's financial system provide a unique setting to studying systemic risk as compared to the rest of the world.

Given our results highlight the dominant role played by the banking sector to systemic risk in China, our paper also examines the question of the determinants of bank systemic risk focusing on the extent to which they differ between China and the US. We provide a detailed zoom on the different systemic frameworks of banks systemic risk between China (in both the Hong Kong and the Shanghai Stock Exchanges) and the US, analysing its relationship with bank-specific, macroeconomic and risk aversion variables. Our results show that while most of the regression estimates have the same direction and are statistically significant in both the US and China's banking sectors, the reduced level of competition among banks in China positively affects banks' systemic risk, contrary to what we find in US and as showed in Anginer et al. (2014).

The remainder of the paper is organized as follows. Section 2 outlines the systemic risk model focusing on the estimation of the $\Delta CoVaR$ and the methodology by which the financial sectors are ranked. Section 3 describes the data used for the empirical analysis. The empirical results are presented in Section 4, with Section 5 providing a reflective discussion. Section 6 provides a detailed econometric analysis of the difference between China's and US' banks systemic risk by comparing the determinants of systemic risk, and Section 7 concludes the paper.

2 Systemic risk model

Financial markets are in constant motion. Barely over a decade ago, one would have considered mortgage servicing to be an insignificant and benign component of the financial system, clearly that is not the case today (Fouque and Langsam, 2013). For this reason it is important that the empirical analysis is not constrained solely to the banking sector.

In this section, we present the methodology used in order to estimate the systemic risk of the banking, insurance and brokerage, and real estate sectors. Such a structured network is able to represent more accurately the financial system, expressing its main characteristics thereby increasing the robustness of the results. The proposed methodology relies on the estimation of the $\Delta CoVaR$ as proposed by Adrian and Brunnermeier (2016), which is based on quantile regressions (Koenker and Bassett Jr, 1978). Moreover, as in the paper of Bernal et al. (2014), we perform a formal test of significance and dominance in order to rank the sectors according to their contribution to systemic risk.

2.1 Constructing the $\Delta CoVaR$

As a measure for systemic risk, Adrian and Brunnermeier (2016) introduced the $\Delta CoVaR$. This measure is based on the most common measure of risk used by financial institutions, namely the Value-at-Risk (VaR). However, the VaR focuses on the risk of an individual institution in isolation, which does not necessarily represent its contribution to the overall systemic risk. In order to emphasize the systemic nature of this risk measure, Adrian and Brunnermeier (2016) added the prefix "Co", representing conditional, to the existing risk measure.

The $CoVaR_q^{j|i}$ is defined as institution j's VaR conditional on some event $\mathbb{C}(X^i)$ of another institution i. This event $\mathbb{C}$ is considered as institution i's equity loss being at or above its VaR_q^i level. $CoVaR_q^{j|i}$ is implicitly defined by the q% quantile of the conditional probability distribution:

$$Pr(X^j|\mathbb{C}(X^i) \leq CoVaR_q^{j|\mathbb{C}(X^i)}) = q\% \tag{1}$$

The $\Delta CoVaR$ is defined as the difference between the CoVaR of the institution j (or financial system) conditional on institution i being in distress - i.e. the 95^{th} or 99^{th} quantile, and the CoVaR of the same conditional on the normal state of institution i - i.e. the median state identified with the 50^{th} quantile:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50th}^i} \tag{2}$$

This risk measure provides the marginal contribution of the institution to the overall systemic risk.

Following the approach of Adrian and Brunnermeier (2016), we use quantile regressions (Koenker and Bassett Jr, 1978) to estimate the VaR_q^i and the related $CoVaR_q^{j|i}$. In particular, to capture time-variation in the joint distribution of X^{system} and X^i, both $VaRs$ and $CoVaRs$ are estimated as a function of the state variables. The time-varying $CoVaR_{q,t}^i$ and $VaR_{q,t}^i$ depend on time t and estimate the time variation conditional on a vector of lagged state variable M_{t-1}.

We estimate the following quantile regressions at the 50^{th}, 75^{th}, 95^{th} and 99^{th} quantile:

$$X_t^i = \alpha_q^i + \beta_q^i M_{t-1} + \varepsilon_{q,t}^i \tag{3}$$

$$X_t^{system|i} = \alpha_q^{system|i} + \beta_q^{system|i} M_{t-1} + \gamma_q^{system|i} X_t^i + \varepsilon_{q,t}^{system|i} \tag{4}$$

where α_q^i represents the constant, and $\varepsilon_{q,t}^i$ the error term, which is assumed to be i.i.d. with zero mean and unit variance and independent of the state variables M_{t-1}.

We compute the predicted VaR, for each quantile, using the estimation of α_q^i and β_q^i from Eq. (3):

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\beta}_q^i M_{t-1} \tag{5}$$

In the same way, we compute the predicted CoVaR, for each quantile, using the estimation of $\alpha_q^{system|i}$, $\beta_q^{system|i}$ and $\gamma_q^{system|i}$ from Eq. (4), and the estimates of the $VaR_{q,t}^i$ from Eq. (5):

$$CoVaR_{q,t}^i = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} M_{t-1} + \hat{\gamma}_q^{system|i} VaR_{q,t}^i \tag{6}$$

The $\Delta CoVaR_{q,t}^i$ is estimated by taking the difference between the predicted CoVaR at 99^{th}, 95^{th} or 75^{th} quantile and the one at the 50^{th} quantile. The $\Delta CoVaR_{q,t}^i$ represents the marginal contribution of the institution, or financial sector, to systemic risk:

$$\Delta CoVaR^i_{q,t} = CoVaR^i_{q,t} - CoVaR^i_{50^{th},t} \tag{7}$$

Our study considers an equity loss with positive values. For this reason, in the empirical results, we consider only positive values for $VaR^i_{q,t}$ and $CoVaR^i_{q,t}$, because the contribution of negative capital shortfall indicates a capital surplus.[2]

2.2 Testing the systemic contribution

As in Bernal et al. (2014), in order to rank the financial sectors considered in this study, we test the contribution of each sector to the systemic risk using the bootstrap KS test developed by Abadie (2002). The resampling method developed by Abadie (2002) is better suited than the standard KS test because of the so-called Durbin problem[3] (Durbin, 1973). The bootstrap KS test compares the cumulative distribution functions instead of the means, which are sensitive to outliers. Moreover, this test does not require any assumptions regarding the underlying distribution. This becomes fundamental in order to minimize the risk of errors based on assumptions. We run the hypothesis test considering the entire sample and the subperiods described in Section 3.

For the significance test, we test whether or not the cumulative distribution functions of $\Delta CoVaRs$ of each sector are systemically risky. This is determined by testing if the conditional contribution to systemic risk of each sector is statistically equal (or different) to 0. The two-sample KS statistics is defined as:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |F_m(x) - Gn(x)| \tag{8}$$

[2]We estimate positive values for $VaR^i_{q,t}$ and $CoVaR^i_{q,t}$ only at the 50^{th} quantile, which represents the median state, so the absence of a distress for the financial sector i.

[3]The distribution-free nature of the standard KS test could be jeopardized by the estimated distributions we use in the test. In particular, they could introduce an unknown nuisance parameter into the null hypothesis, which is known as the Durbin problem.

where $F_m(x)$ and $G_n(x)$ represent the cumulative distribution functions of the CoVaRs at the 95^{th} and 50^{th} quantiles, and, m and n represent the size of the two samples, respectively. The null hypothesis is defined as follow:

$$H_0 = \Delta CoVaR_{95^{th}}^{system|i} = CoVaR_{95^{th}}^{system|i} - CoVaR_{50^{th}}^{system|i} = 0 \tag{9}$$

For the dominance test, we test if sector i contributes more than sector j to systemic risk. The two-sample KS statistics is defined as:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |S_m(x) - Tn(x)| \tag{10}$$

where $S_m(x)$ and $T_n(x)$ are the cumulative distribution functions of the $\Delta CoVaRs$ at the 95^{th} related to the two sectors, and, m and n represent the size of their samples. The null and alternative hypotheses are defined as follow:

$$H_0 = \Delta CoVaR_{95^{th}}^{system|i} \leq \Delta CoVaR_{95^{th}}^{system|j} \tag{11}$$

$$H_1 = \Delta CoVaR_{95^{th}}^{system|i} > \Delta CoVaR_{95^{th}}^{system|j} \tag{12}$$

Contrary to Bernal et al. (2014), we consider the systemic contribution with a positive value only, thereby allowing us to ignore the absolute values of $\Delta CoVaR$.

As an additional test, we investigate the contribution of the financial system and sectors during the main systemic events covered by our sample period. In particular, as with Ahnert and Georg (2018) who use the Wilcoxon signed rank sum test for paired data to test whether information contagion due to counterparty risk increases systemic risk, we investigate whether or not the level of systemic risk for China's financial system and sectors h-days after a systemic event, or a period of financial instability, is greater than h-days before. We consider the horizon h as one month (22 days). As main systemic events, we examine the S&P downgrade of China's developers on June 15^{th} 2011; the banking liquidity crisis that starts on June 20^{th} 2013, with a credit crunch affecting China's banks due to a rise in the Shanghai interbank overnight lending rates to a high of 30% from its usual rate of close to 3%; and finally China's stock market crash, in which three main dates are examined, namely, July 27^{th} 2015, a day in which the Shanghai Stock Exchange (SSE) fell of 8.5%; August 24^{th} 2015, a day referred to as "Black Monday" because of losses of around 8% in all the Chinese main stock indexes; and, January 4^{th} 2016, which represents the first day of the period ending the 15^{th} of January, a period in which China's stock market fell 18%. This final event also affected global markets with the Dow Jones Industrial Average falling by 8.2%.[4] The Wilcoxon signed rank sum test is applied to the following hypotheses:

$$H_0 : \Delta CoVaR^i_{t:t+h-1} \leq \Delta CoVaR^i_{t-h-1:t-1} \tag{13}$$

$$H_1 : \Delta CoVaR^i_{t:t+h-1} > \Delta CoVaR^i_{t-h-1:t-1} \tag{14}$$

where i indicates the financial system or sector studied. The failure to reject the null hypothesis (13) implies that the systemic risk level of the financial system or sector under analysis did not increase during the systemic events previously described.

3 Data

Our data consist of daily observations. We collect daily stock prices of Chinese institutions classified as financials and all allocated within three financial sectors, namely banks, insurance and brokerage and real estate in the Hong Kong Stock Exchange Index (SEHK) – Panel A, and the Shanghai Stock Exchange Composite Index (SHCOMP) – Panel B. Considering both the SEHK and the SHCOMP allows a meaningful comparison between two Chinese Stock Exchanges that differ in terms of restrictions to foreign investors. In particular, the shares listed on the SEHK, which take the name of H-shares, can be traded freely by

[4] *"Why This Market Meltdown Isn't a Repeat of 2008: U.S. economy and financial system are in a very different place now"*, The Wall Street Journal, January 15, 2016.

non-Chinese investors without obtaining the Qualified Foreign Institutional Investor (QFII) license[5] and are denominated only in Hong Kong dollars (HKD). The SHCOMP on the other hand tracks the daily price performance of all A-shares and B-shares listed on the SSE, with A-shares being denominated in renminbi (RMB) and available to domestic investors and international participants that meet the QFII; and B-shares which are initially denominated in RMB though are traded in USD or HKD and available to foreign investors without the QFII designation.

H-shares are correlated with both domestic and foreign market factors, while A and B-shares retain significant exposure predominantly to the domestic market (Wang and Jiang, 2004). For this reason, we mainly focus on the results of the analysis based on the SEHK – Panel A, an exchange which is also free of restrictions to foreign investors[6] and includes the largest and most frequently traded companies, in terms of most liquid stocks, that are listed on the Hong Kong Stock Exchange.[7] The results related to the SHCOMP – Panel B, offer a comparison with the SEHK; however, they may be limited because of the unique institutional features that characterize the SSE. In particular, as argued by Huang et al. (2011), the share segmentation of the SSE system creates conflicts of interests between negotiable and nonnegotiable A-shares, which in turn may jeopardize results related to this equity market.

Only Chinese institutions listed in the financial market during the study period with at least 253 daily observations (1-year) prior to January 2010 are included in our data set. In particular, Panel A and Panel B are respectively composed by 54 and 138 financial firms, 18 in each financial sector in Panel A, while 28 in the banking sector, 42 in the insurance and brokerage industry and 68 real estate companies in Panel B. Panels are balanced in that all

[5]The QFII program was introduced in 2002 and permits licensed professional foreign investors to buy and sell shares on the stock exchanges in China. Prior to the introduction of QFII program trading in China's markets by foreign investors was prohibited.

[6]See Alford and Lau (2015) for a comprehensive analysis of the accessibility to the Chinese equity markets for foreign investors.

[7]A comprehensive description of the SEHK is available at: https://www.hsi.com.hk/eng/indexes/all-indexes/hsi.

companies have been trading continuously during the sample period.[8]

The empirical analysis spans the period from the 1^{st} of January 2010 to the 31^{st} of December 2016, with a total of 1712 (1684) estimates for each financial sector included in Panel A (Panel B). We divide this period into three subperiods: the period in between the property bubble and the economic stimulus package (January 1^{st}, 2010 – December 31^{st}, 2012); the period in between the banking liquidity crisis and the pre-stock market crash (January 1^{st}, 2013 – December 31^{st}, 2014); the stock market crash (January 1^{st}, 2015 – December 31^{st}, 2016).

The variables used in the quantile regressions are: the equity losses of the individual financial sector (X^i), computed as the average market equity-valued returns of the financial institutions, within the sector, weighted by their (lagged) market value of equity; the equity losses of the financial system portfolio (X^{system}), computed as the average market equity-valued returns of the financial institutions weighted by their (lagged) market value of equity; the (lagged) state variables (M_{t-1}) reported in Table 1, which represent the same variables considered by Adrian and Brunnermeier (2016). All the data used in Panel A is obtained from Bloomberg, except the S&P Hong Kong BBB Investment Grade Corporate Bond Rate Index, which is obtained from the S&P Dow Jones Indices;[9] while the unique data set for the analysis in Panel B is obtained from Bloomberg, CEIC data, SHIBOR data service and the CSI Indices.

[Table 1 about here.]

Table 2 provides summary statistics of the financial system and sectors returns, and the state variables. The 1 percent stress represents the realization of each variable in the worst 1 percent realization of the financial system returns. In Panel A, the worst realization for the banking and real estate sectors coincides with the worst 1 percent realization of the financial

[8] The company names of all the individual financial firms adopted in this study are available upon request.

[9] The S&P Hong Kong BBB Investment Grade Corporate Bond Rate Index consists of bonds in the S&P Hong Kong Investment Grade Corporate Bond Index with a rating of BBB from Standard & Poor's Ratings Services and is available; with daily frequency, at: http://us.spindices.com/indices/fixed-income/sp-hong-kong-bbb-investment-grade-corporate-bond-index.

system returns. Similarly, in both panels, the 1 percent stress level corresponds also to the worst realization of the equity return, a high level of liquidity and credit spreads, and equity volatility.

[Table 2 about here.]

4 Empirical results

This section presents the $\Delta CoVaR$ estimates with an analysis of the systemic risk in China's financial system (Section 4.1), along with the systemic contribution of each financial sector to the overall risk, reporting the results of the bootstrap KS tests (Section 4.2).

4.1 China's systemic risk

Figure 1 plots the systemic risk, measured with the $\Delta CoVaR_{95^{th}}$ of China's financial system[10] from the 1^{st} of January 2010 to the 31^{st} of December 2016 for Panel A and Panel B, respectively. Figure 1 also includes the three sectors that constitute the financial system. The time period spans three different subperiods, namely, the period in between the property bubble and the economic stimulus package (January 1^{st}, 2010 – December 31^{st}, 2012); the period in between the banking liquidity crisis and the pre-stock market crash (January 1^{st}, 2013 – December 31^{st}, 2014); and finally the period of the stock market crash (January 1^{st}, 2015 – December 31^{st}, 2016). Some major dates are included in order to label the three subperiods.

[Figure 1 about here.]

As shown in Figure 1, the systemic risk level of China's financial system peaks after the S&P downgrade of China's real estate developers in 2011 and during the stock market

[10]The $\Delta CoVaR_{95^{th}}$ of the financial system has been approximated with the average value, similar to Adrian and Brunnermeier (2016), who adopted this to compare forward and contemporaneous $\Delta CoVaR$ estimates.

turbulence of 2015 in both Panels. Other than these events the systemic risk was restrained. In particular, the first subperiod is characterized by the stimulus program of $586-billion issued by the State Council of the People's Republic of China in order to minimize the effect of the U.S. Subprime Crisis and the property bubble, which began to deflate in 2011. China was hit fairly hard by the global recession and suffered a huge drop in exports. The adverse effects on the economy were only partially offset by the stimulus program. One of the main problems associated with such a huge stimulus program was that the creation of new money caused the devaluation of the existing money, which in turn led to inflation. As with many stimulus programmes, the Chinese stimulus program created some form of immediate economic growth, though this was short lived. During this subperiod, the systemic risk level reached a first peak in the second half of 2011 due to the effect of the real estate bubble and China's declining economic growth. The peak is evident for the banking sector in Panel A, underlining the importance of this sector in the financial system as a systemic risk source, while Panel B shows a quasi-uniform co-movement of the financial sectors, which after reaching their minimum values at the beginning of 2011, all peak as a consequence of the real estate bubble. The difficult situation faced by China's financial system is underlined by the S&P downgrade of the Chinese real estate development from stable to negative in mid–2011. At the beginning of 2012, the Chinese real estate bubble completely deflated, stabilizing the financial system until the credit crunch of the Chinese commercial banks in 2013. As a consequence of market stability experienced after the deflating of the real estate bubble, low levels of systemic risk characterize 2012, in particular during the second half of the year.

During the second subperiod China's financial system was hit by the banking liquidity crisis, which began with a dramatic surge in short-term borrowing costs in June 2013. Nomura Research Institute, which is the largest Japanese consulting and IT consulting firm, argued that the credit crunch was a consequence of the PBoC refusing to inject liquidity into the system. Moreover, they found that China was displaying the same three symptoms shown by the U.S. prior to suffering their financial crises, namely, a rapid build-up of leverage, elevated property prices, and a decline in potential growth. As shown in Figure 1, in Panel A the systemic risk does not reach any remarkable peak during the period from the 1^{st} of January 2013 to the 31^{st} of December 2014, however, this period can be looked upon as the build-up to the subsequent market turbulence in 2015-16, while in Panel B, the systemic risk of the banking sector increases resulting in it being significantly higher compared to the other two industries. It is interesting to notice that during this subperiod the contribution of the real estate sector is greater than the insurance and brokerage industry in both Panels and similar to the banking sector in Panel A. This highlights the increasing systemic importance of the real estate sector prior to the stock market crash.

The dramatic increase in the systemic risk level commences early in 2015. The systemic risk of China's financial system increased dramatically after the popping of the stock market bubble on the 12^{th} June, 2015. A third of the value of Chinese shares was lost within one month of this date. By the beginning of July the stock market had fallen by 30% despite the efforts of the Chinese government to reduce the losses. In an attempt to restart the economy, the PBoC devalued the Chinese yuan on several different occasions during August 2015. As an unexpected consequence, the Chinese main stock indexes lost around 8% of their value on the 24^{th} August, a day referred to as "Black Monday". Similar events occurred in the days following. Billions were lost on international markets causing severe difficulties for the companies reliant on the Chinese market. The Nikkei index in Japan slipped by 4.6%, European markets were down 4-5% and the Dow Jones opened down more than 1,000 basis points. The peaks in systemic risk around Black Monday are evident to see from Figure 1. It is clear to see that the systemic risk reacted with an increase experienced by all three sectors between June and July due to the popping of the stock market bubble. Moreover, the reaction to this systemic event seems more evident in Panel A, showing that the financial sectors peaked prior to the 12^{th} June, 2015. In Panel B, the systemic risk builds-up only after the 27^{th} of July, 2015.

In both Panels, by the end of 2015 the Chinese systemic risk decreased due to the response of the Chinese government and the supervisory authorities, introducing restrictions, such as, limits to short selling and prohibiting shareholders with holdings of in access of 5% of a company's stock from selling shares for six months. Such measures were successful in halting the fall in stock prices which were causing disturbance to global financial markets.

[Table 3 about here.]

The results of the Wilcoxon signed rank sum test for China's financial system and sectors during the S&P downgrade of China's developers in 2011, the banking liquidity crisis in 2013, and China's stock market crash in 2015 and 2016 are illustrated in Table 3. We run this test to inspect whether or not the systemic risk level of China's financial system and sectors significantly increases after a systemic event or a period of financial instability covered by our sample period. In both Panels, the null hypothesis is rejected at 1% significance level in most of the cases. In particular, while the S&P downgrade of China's developers in 2011 seems to affect only the real estate sector with an estimate statistically significant at 10% level in Panel A, for Panel B the results are statistically significant at 1% significance level for the financial system and banking sector and at 5% and 10% significance levels for the insurance and brokerage and real estate, respectively. Moreover, combining the results from Figure 1 and Table 3, we can observe that the banking liquidity crisis did not affect the systemic risk level of the insurance and brokerage companies in Panel A, while the financial system and banking sector already reached a systemic risk peak before this event in Panel B. All the dates tested during the stock market crash between 2015 and 2016 show a statistically significant increase in the systemic risk level of the financial system and sectors in both Panels, with the exception of the 4^{th} January 2016 for the financial system and banking sector in Panel B. This result is in line with our previous analysis, which shows a major peak of the systemic risk level during China's stock market crash with some disparity in the behavioural timing of the two time-series in Panel A and Panel B.

4.2 The contribution of financial sectors to systemic risk

As in the case of the Subprime crisis, the increase in systemic risk is not solely due to the banking sector. This rationalizes our decision to examine the systemic risk of sectors outside the banking sector, namely, the insurance and brokerage, and real estate sectors. In this section we analyse the estimated values of the $\Delta CoVaR$ of the three sectors, ranking the systemically important sectors through a statistical significance and dominance test to determine the contributions to systemic risk of the different sectors.

[Figure 2 about here.]

Figure 2 plots the $\Delta^{\$}CoVaR_{95^{th}}$ of the three financial sectors over the period analysed, for Panel A and Panel B. The systemic contribution is weighted by the market equity of the companies included in the particular sector. Figure 2 clearly shows a dominance of the equity weighted marginal contribution of the banking sector for the entire period. However, what is not clear to see is the difference between the contribution of the insurance and brokerage sector and the real estate sector. For this reason, the results from the statistical tests are fundamental. Figure 2 highlights an interesting feature, namely that even though the banking sector contributes more to systemic risk, the contribution of the other two financial sectors increased after 2014. In particular, the first two subperiods analysed are characterized by a banking systemic contribution, while the systemic risk level of the market turbulence of 2015–16 is higher due to a greater contribution from the other two financial sectors. Such findings confirm the fact that studies of systemic risk should no longer be undertaken considering the banking sector in isolation, given that systemic risk threatens the functioning of the entire financial system (Martínez-Jaramillo et al., 2010).

[Table 4 about here.]

Table 4 shows the descriptive statistics of the systemic contribution of the banking, insurance and brokerage, and real estate sectors, for Panel A and Panel B, respectively. In both Panels, the absolute value of the $\Delta CoVaR$ of the banking sector, on average, has a higher contribution at the 99^{th} and 95^{th} quantiles over the entire time period of the study, moreover, the systemic contribution is less volatile compared to the other two financial sectors, with a lower volatility and slightly higher systemic risk values characterizing Panel B. However, in Panel A the insurance and brokerage and the real estate sectors both reach a higher maximum peak. It is interesting to see that, whereas prior to 2014, specifically during the first two subperiods analysed, the contribution of the banking sector is greater than the other two financial sectors, and in the last subperiod (2015–2016) the contributions of the three sectors are similar, with the prevalence of the real estate sector, in absolute value. This evidence is not repeated in Panel B, where the banking sector remains systemically dominant over the three sub-periods analysed. The finding that, in both Panels, the systemic contribution of the banking sector remains less volatile, highlights a greater consistency over time. Overall, we can confirm that all three financial sectors represent a valid source of risk for the real economy.

Figure 3 shows the relation between the VaR and the $\Delta CoVaR$ of the institutions within the three financial sector as of the 24^{th} of August, for Panel A and Panel B. Figure 3 clearly shows that across institutions there exists a very loose link between VaR_i and $\Delta CoVaR_i$, consistent with the argument put forward by Adrian and Brunnermeier (2016). Such a finding implies that the supervisory authorities cannot rely on regulation based upon individual risk measures that do not consider the systemic risk

[Figure 3 about here.]

The results above are based on average values. By using average values it is not possible to identify the sector that had the greatest risk during the entire period and subperiods analysed. Similar to Bernal et al. (2014), we implement two statistical tests: (i) a significance test to determine whether or not a sector is statistically significantly risky for the financial system; and, (ii) a dominance test in order to determine which sector has been more systemically risky. As described in Section 2.2, the bootstrap KS test is employed to test our hypothesis.

[Table 5 about here.]

Table 5 presents the results of the significance test for Panel A and Panel B, respectively. We apply this test to verify whether there is no difference between the CoVaR measured at the 50^{th} and the 95^{th} quantiles. A finding of no difference between these values, namely that the $\Delta CoVaR$ is equal to zero, would imply that the sector has no contribution to the overall systemic risk. For each of the financial sectors considered in both Panels, over all the time periods, the null hypothesis is rejected at 1% significance level, indicating that each financial sector is systemically relevant, significantly contributing to the systemic risk in China's financial system.

[Table 6 about here.]

Table 6 presents the results of the dominance test for Panel A and Panel B, respectively. In this case, the dominance test is used to compare the cumulative distribution functions of the $\Delta CoVaRs$ of two distinct financial sectors, in order to determine which of them contributes most to systemic risk. In particular, we test the null hypothesis to determine whether a sector is less (or equally) risky compared to another sector, over all the time periods. The first row of Table 6 compares the banking sector with the insurance and brokerage sector. Our results show that the null hypothesis is rejected at 1% significance level in both Panels, implying that the banking sector is systemically riskier than the insurance and brokerage sector. Such a finding is consistent across all time periods tested. The second row shows that banks are also systemically riskier than real estate companies. An interesting feature is reported in the third row, where it is found that real estate companies turn out to be systemically riskier than insurance and brokerage companies. Such a finding can be explained by the various property bubbles in China, which have made the real estate sector highly risky and volatile. The results do show that the finding that real estate companies are riskier than insurance and brokerage companies is not the case during the subperiod the 1^{st} of January 2010 to the 31^{st} of December 2012 in Panel A; while, the real estate industry is still found systemically riskier than the insurance and brokerage one in Panel B at 5% significance level. This can be explained by the fact that, as already argued in Section 4.1, during this period the Chinese government introduced the economic stimulus program, which in turn deflated the property bubble. This probably decreased the systemic contribution of the real estate sector, stabilizing it.

5 Discussion

The nonparametric statistical testing procedure proposed in this paper allows us to analyse both the absolute (Table 5) and relative (Table 6) systemic contribution of the financial sectors within the China's financial system. Our empirical results show that each financial sector significantly impacts the overall systemic risk during period of stress. This finding holds for both Panels.

Our results are consistent with previous literature examining systemic risk. In particular, our findings showing that the banking sector is systemically riskier than the insurance and brokerage sector is consistent with Bernal et al. (2014) for the Eurozone, and Girardi and Ergün (2013) for the US, where both adopted the $\Delta CoVaR$ to analyse systemic risk. Such findings are consistent with the argument put forward by Billio et al. (2012), namely the banks play a much more important role in transmitting systemic instability than other financial institutions. Given the leading role played by the banking sector to systemic risk it would be interesting to see the extent to which the determinants of bank systemic risk in China differ to that of the US. We decided to undertake this analysis, the results of which can be seen in Section 6.

Our findings showing the dominant role played by banks in transmitting systemic instability play a pivotal role in China given the government's strong role within the banking sector. In particular, government-owned banks can be bailed-out in a short period of time by the state. Such intervention by the state may avoid systemic distress even when the remaining banking system is under-capitalized (Jiang et al., 2019). The existence of such a safety net however may lead to moral hazard problems, which combined with the core business of these institutions, namely credit activity, would explain the higher systemic risk contribution of the banking sector. Another argument to explain such findings could be that the banking sector is exposed more to economic cycles compared to the other two financial sectors because of their longer-term oriented business models (Bernal et al., 2014).

Our finding that following the financial crisis of 2007 the real estate sector has become one of the main sources of systemic risk, is consistent with Li et al. (2016) who found that, in China, the real estate sector has become systemically relevant to the point that it affects bank returns. Moreover, it also highlights the increasing systemic importance of this sector, as showed also by Crowe et al. (2013), given that real estate transactions involving borrowing can have disastrous consequences on the financial system and the real economy. Given that real estate booms are often financed through borrowing, such booms are associated with rapid growth in credit levels and increases in leverage, the consequences of which when the boom abruptly ends have threatening implications for financial and macroeconomic stability, often resulting in recessions and the associated social problems that unfold.

6 Comparison of banking systemic risk's determinants: China vis-á-vis the US

Given that much of the existing empirical financial literature examining systemic risk is based upon the US financial system (See among others Adrian and Brunnermeier, 2016; Brownlees and Engle, 2016; Acharya et al., 2017), we further investigate whether the systemic importance of China's banks has a different fundamental relationship with bank-specific, macroeconomic and risk aversion variables, compared to US banks.[11] Table 7 provides a detailed description of all the variables adopted in this analysis.

[Table 7 about here.]

To undertake such an analysis a regression analysis is conducted through the following equation:

$$\Delta CoVaR_{95^{th}}^{Banks,i} = \alpha_i + \sum_{j=1}^{n} \beta_{j,i}\mathbf{X_i} + \epsilon_i \tag{15}$$

where, i is the banking sector in the Hong Kong stock exchange (Panel A), Mainland China namely Shanghai stock Exchange (Panel B), and US (Panel C), respectively; and, $\mathbf{X_i}$ represents the vector of variables used in the regression as shown in Table 7. The models are selected by considering as depended variable the systemic risk of the banking sector and simulating all the possible combinations of explanatory variables, for Panel B and Panel C, respectively.[12] The five models from each of these two markets with the highest $adjusted-R^2$ are then selected, resulting in ten different regression models as shown in Table 8.

The regression estimates for banks' systemic risk in China (Panel A: Hong Kong and Panel B: Mainland China) and the US (Panel C) are shown in Table 8. The first important insight is found looking at the $adjusted-R^2$, which estimates are found more than double in US compared to China. In particular, in Panel A, it ranges from 2.75% to 21.76%; in Panel B, from 5.18% to 48.52%; while in Panel C, from 89.62% to 96.72% – with a single exception assuming a value of 25.46%. This implies a higher explanatory power of fundamental bank-specific, macroeconomic and risk aversion variables for US banks' systemic risk.

[Table 8 about here.]

[11] We collect data on daily equity prices for all the constituent stocks of the S&P 500 Banks Industry Group GICS Level 2 from Bloomberg. The $\Delta CoVaR_{95^{th}}$ of the US banking sector is then estimated following the methodology described in Section 2.1 and using the state variables as in Adrian and Brunnermeier (2016).

[12] Due to high correlations between the independent variables of Panel A and Panel B, the models selection has been performed considering only the variables for the Chinese mainland (Panel B).

Analysing the regression estimates in Table 8, the ratio between banks' capital and reserves to total assets is found to be positively related, with high significance, to systemic risk in all three banking sectors. This common finding is coherent with Freixas et al. (2000), who argue that regulators adopt a too-big-to-fail approach to deal with large institutions, given that they represent the main source of systemic risk. Deposits as a percentage of GDP are found with a negative estimate in the only case of statistical significance in Panel A and Panel B; whereas this variable shows a positive estimate in US with high significance, highlighting a higher systemic risk exposure to deposit withdrawals for the US banks. Banks' net interest margin (and ROE) is found to be positively related to systemic risk with high significance in both Panel B and Panel C (Panel C only); while, the estimates for banks' non-interest income are found to be negative with high significance in Panel C only. The particularly high estimates for net interest margin in the US may be due to a more pronounced business model based on market interest-earning assets of US banks. As expected, regulatory capital as percentage of risk-weighted assets is associated with a negative relationship to systemic risk, reporting a greater magnitude in US. A possible explanation for this could be due to the fact that a greater number of US banks are identified as global systemically important banks (G-SIBs) and consequently are subject to higher additional regulatory capital requirements.[13]

Turning to the macroeconomic variables, Consumer Price Index (CPI) is found to be positively related to systemic risk in Panel B, whereas for the US (Panel C) the CPI not only leads to increases in systemic risk, but, in some cases also mitigates systemic risk, as shown by the negative and statistically significant estimate. Credit to governments and state-owned enterprises as percentage of GDP (GDP growth) is positively (negatively) related to banks' systemic risk in both China and US.

[13]G-SIBs included (and the assigned additional capital requirement) in Panel A and Panel B are HSBC (2.00%) – Panel A only, Bank of China, Industrial and Commercial Bank of China Limited (1.50%), Agricultural Bank of China and China Construction Bank (1.00%). In Panel C: JP Morgan Chase (2.50%), Citigroup (2.00%), Bank of America, Goldman Sachs, Wells Fargo (1.50%), Bank of New York Mellon, Morgan Stanley, State Street (1.00%).

Cost-to-income ratio and stock market volatility are found to be positively related to systemic risk in both China (Panel B) and the US, showing particularly high statistical significance in the US. Important evidence is represented by the estimates for the 5-bank asset concentration ratio, which are found to be positive in China (Panel B), though statistically significant only in one case, and negative and highly significant in US. The results found with respect to the US banks' systemic risk is in line with Anginer et al. (2014), who show a robust negative relationship between bank competition and systemic risk. Looking at the time series values, the 5-bank asset concentration ranges from 52.92% to 78.87% (with a median of 66.00%) in China (Panel B). The same ratio is lower in Panel C, with a range between 44.27% and 48.38% and a median of 47.17%. This highlights that China's banks systemic risk is positively affected by the low level of competition that exists within the banking sector in China, a sector dominated by the four big state-controlled banks, namely, Agricultural Bank of China, Bank of China, China Construction Bank, and Industrial and Commercial Bank of China Limited.

7 Conclusion

Systemic risk can be looked upon as the risk associated with the collapse of a financial system. Given that a county's financial system is essential for its economy, the need not only to accurately measure systemic risk but also attempt to determine the contribution that individual sectors within the financial system play is important. China is ideal for our investigation because of the strong role of the government in the banking sector, the restrictions to foreign investors and the asymmetry and persistence of the Chinese business cycle compared to other developed countries as demonstrated by Dovern and van Roye (2014).

As China balances on the edge of a financial crisis, with the global implications of such an event, concerns have been raised with respect to the size of systemic risk in China's financial system. This paper contributes to the literature examining systemic risk by measuring the level of systemic risk of China's financial system, and assessing the contribution that key financial sectors play, namely banks, insurance and brokerage industries, and real estate. The analysis is undertaken considering two Chinese Stock Exchanges that differs in terms of restrictions to foreign investors during the period form the 1^{st} of January 2010 to the 31^{st} of December 2016, a period spanned by the deflating property bubble, the liquidity banking crisis, and the stock market crash. The systemic contribution of each of these sectors, and the level of systemic risk of the financial system, is measured by the systemic risk measure $\Delta CoVaR$ as proposed by Adrian and Brunnermeier (2016).

We find that the systemic risk level of China's financial system is linked to key financial events that occurred during the period analysed in both equity markets. In particular, systemic risk decreased after the property bubble deflated, only to increase again after the minimum value was reached in the second half of 2012 as a result of the bank liquidity crisis. The systemic risk drastically intensified after the stock market bubble burst in the summer of 2015. The restrictions imposed on investors by the Chinese government and supervisory authorities played a fundamental role in containing the implications of the stock market crash. Moreover, a greater systemic risk co-movement among the financial sectors is found in the SSE.

During the main systemic and financial instability dates covered by our sample period, the systemic risk level of the financial system and sectors significantly increased. With respect to determining the systemic contribution of each of the sectors analysed, the significance test shows that the contribution of each sector is significantly important. The dominance test indicates that the banking sector contributes most to the overall systemic risk, this is the case in all the periods analysed. Moreover, when comparing banks systemic risk between China (in both the Hong Kong and the Shanghai Stock Exchanges) and the US, we find that while the banking sectors in both the US and China show regression variables estimates that are both significant and similar in direction, the reduced level of competition among banks in China positively affects banks' systemic risk, contrary to what we find in US.

Although our findings clearly show the dominant role played by the banking sector to systemic risk in China, the real estate sector although ranked behind the banking sector significantly exceeds the insurance and brokerage industry in the risk contribution. Given the differing contributions played by each sector, such findings suggest the need to introduce an ad-hoc systemic regulation for each sector in order to monitor and contain the systemic contribution of the key companies within the sectors.

References

Abadie, A. (2002). Bootstrap tests for distributional treatment effects in instrumental variable models. *Journal of the American Statistical Association 97*(457), 284–292.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2017). Measuring systemic risk. *Review of Financial Studies 30*(1), 2–47.

Adrian, T. and M. K. Brunnermeier (2016). CoVaR. *American Economic Review 106*(7), 1705–1741.

Ahnert, T. and C.-P. Georg (2018). Information contagion and systemic risk. *Journal of Financial Stability 35*, 159–171.

Alford, A. W. and A. W. Lau (2015). A Foreign Investor's Guide to Accessing the Chinese Equity Market. *Journal of Portfolio Management 41*(5), 31–40.

Anginer, D., A. Demirguc-Kunt, and M. Zhu (2014). How does competition affect bank systemic risk? *Journal of financial Intermediation 23*(1), 1–26.

Bekiros, S. D. (2014). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis 33*, 58–69.

Bernal, O., J.-Y. Gnabo, and G. Guilmin (2014). Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking & Finance 47*, 270–287.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics 104*(3), 535–559.

Bisias, D., M. Flood, A. W. Lo, and S. Valavanis (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics 4*(1), 255–296.

Black, L., R. Correa, X. Huang, and H. Zhou (2016). The systemic risk of European banks during the financial and sovereign debt crises. *Journal of Banking & Finance 63*, 107–125.

Bo, H., C. Driver, and H.-C. M. Lin (2014). Corporate investment during the financial crisis: Evidence from China. *International Review of Financial Analysis 35*, 1–12.

Brownlees, C. and R. F. Engle (2016). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies 30*(1), 48–79.

Cai, J., F. Eidam, A. Saunders, and S. Steffen (2018). Syndication, interconnectedness, and systemic risk. *Journal of Financial Stability 34*, 105–120.

Cao, Z. (2013). Multi-CoVaR and Shapley value: a systemic risk measure. *Bank of France Working Paper*.

Caruana, J. (2010). Systemic risk: how to deal with it. *Bank for International Settlements 12*, 1–11.

Crowe, C., G. Dell'Ariccia, D. Igan, and P. Rabanal (2013). How to deal with real estate booms: Lessons from country experiences. *Journal of Financial Stability 9*(3), 300–319.

Derbali, A. and S. Hallara (2016). Systemic risk of European financial institutions: Estimation and ranking by the Marginal Expected Shortfall. *Research in International Business and Finance 37*, 113–134.

Diebold, F. X. and K. Yılmaz (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics 182*(1), 119–134.

Dovern, J. and B. van Roye (2014). International transmission and business-cycle effects of financial stress. *Journal of Financial Stability 13*, 1–17.

Durbin, J. (1973). *Distribution theory for tests based on the sample distribution function.* SIAM.

Fouque, J.-P. and J. A. Langsam (2013). *Handbook on systemic risk.* Cambridge University Press.

Freixas, X., B. M. Parigi, and J.-C. Rochet (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, 611–638.

Girardi, G. and A. T. Ergün (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance 37*(8), 3169–3180.

Glick, R. and M. Hutchison (2013). China's financial linkages with Asia and the global financial crisis. *Journal of International Money and Finance 39*, 186–206.

Hatemi-J, A. and E. D. Roca (2004). Do birds of the same feather flock together?: The case of the Chinese states equity markets. *Journal of International Financial Markets, Institutions and Money 14*(3), 281–294.

Hu, J. W.-S., M.-Y. Chen, R. C. Fok, and B.-N. Huang (1997). Causality in volatility and volatility spillover effects between US, Japan and four equity markets in the South China Growth Triangular. *Journal of International Financial Markets, Institutions and Money 7*(4), 351–367.

Huang, J. J., Y. Shen, and Q. Sun (2011). Nonnegotiable shares, controlling shareholders, and dividend payments in China. *Journal of Corporate Finance 17*(1), 122–133.

International Monetary Fund (2017). People's Republic of China: Financial System Stability Assessment-Press Release and Statement by the Executive Director for People's Republic of China. *Country Report No. 17/358*.

Jiang, C., H. Liu, and P. Molyneux (2019). Do different forms of government ownership matter for bank capital behavior? Evidence from China. *Journal of Financial Stability 40*, 38–49.

Koenker, R. and G. Bassett Jr (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society 46*(1), 33–50.

Li, S., Q. Pan, and J. He (2016). Impact of systemic risk in the real estate sector on banking return. *SpringerPlus 5*(1), 61.

Liu, C., K. Uchida, and Y. Yang (2012). Corporate governance and firm value during the global financial crisis: Evidence from China. *International Review of Financial Analysis 21*, 70–80.

López-Espinosa, G., A. Moreno, A. Rubia, and L. Valderrama (2012). Short-term wholesale funding and systemic risk: A global CoVaR approach. *Journal of Banking & Finance 36*(12), 3150–3162.

Martínez-Jaramillo, S., O. P. Pérez, F. A. Embriz, and F. L. G. Dey (2010). Systemic risk, financial contagion and financial fragility. *Journal of Economic Dynamics and Control 34*(11), 2358–2374.

Reboredo, J. C. and A. Ugolini (2015). Systemic risk in European sovereign debt markets: A CoVaR-copula approach. *Journal of International Money and Finance 51*, 214–244.

Sedunov, J. (2016). What is the systemic risk exposure of financial institutions? *Journal of Financial Stability 24*, 71–87.

Shu, C., D. He, J. Dong, and H. Wang (2018). Regional pull vs global push factors: China and US influence on Asian financial markets. *Journal of International Money and Finance 87*, 112–132.

Silva, W., H. Kimura, and V. A. Sobreiro (2017). An analysis of the literature on systemic financial risk: A survey. *Journal of Financial Stability 28*, 91–114.

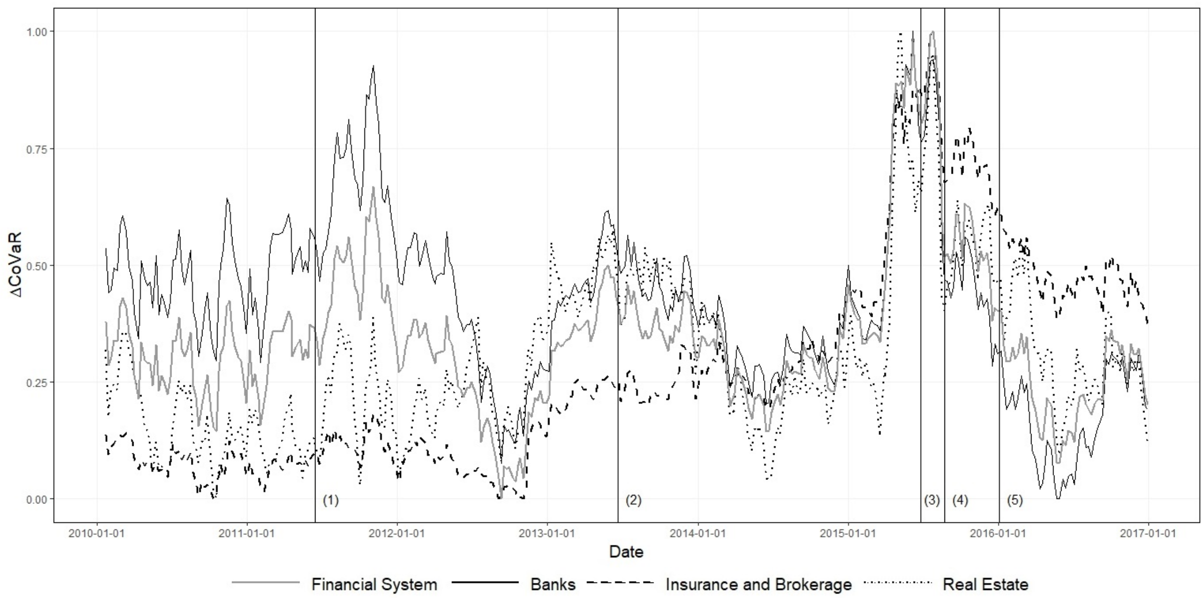
Tunaru, R., F. Fabozzi, and T. Wu (2006). Chinese equity market and the efficient frontier. *Applied Financial Economic Letters 2*(02), 87–94.

Wang, G.-J., C. Xie, L. Zhao, and Z.-Q. Jiang (2018). Volatility connectedness in the Chinese banking system: Do state-owned commercial banks contribute more? *Journal of International Financial Markets, Institutions and Money 57*, 205–230.

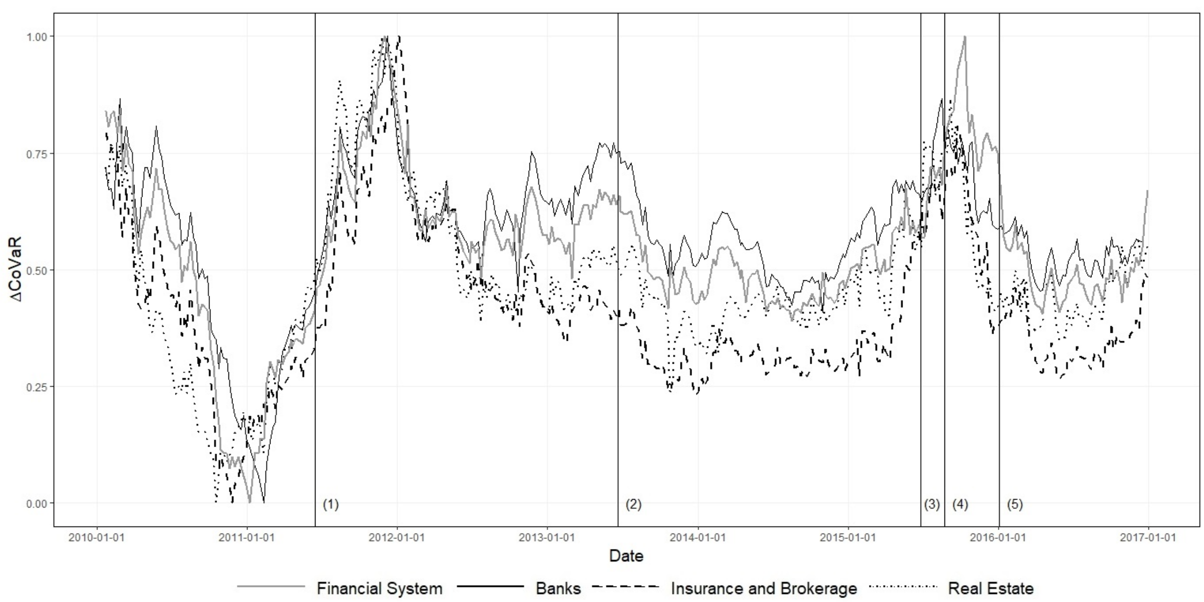
Wang, S. S. and L. Jiang (2004). Location of trade, ownership restrictions, and market illiquidity: Examining Chinese A-and H-shares. *Journal of Banking & Finance 28*(6), 1273–1297.

Figure 1: $\Delta CoVaR_{95^{th}}$ of China's financial system.

Panel A: Hong Kong Stock Exchange.



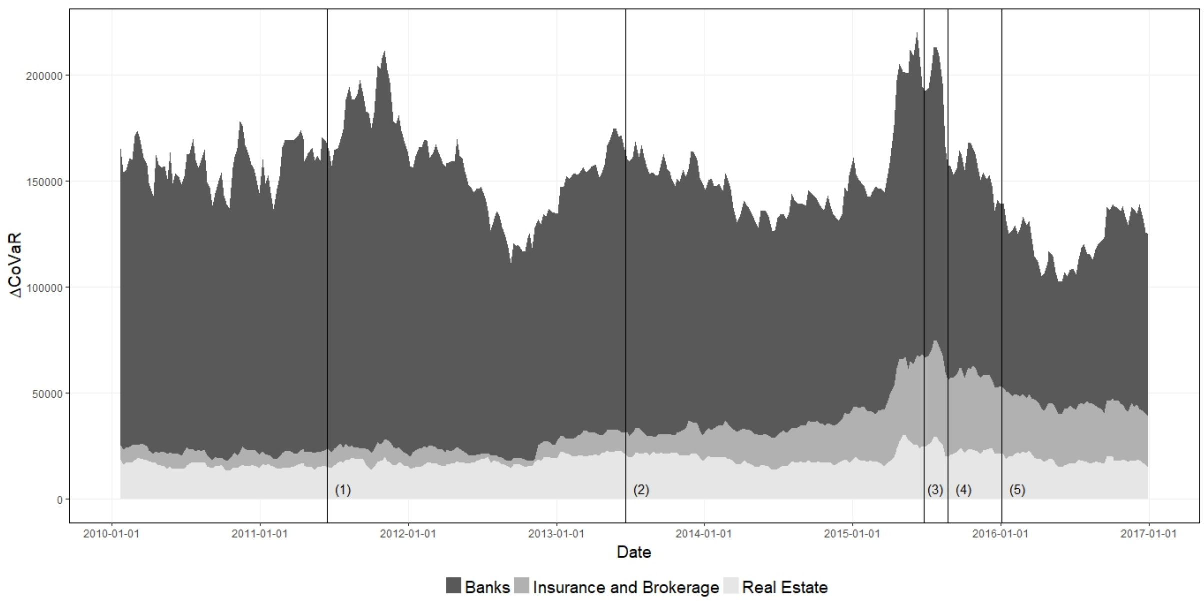
Panel B: Shanghai Stock Exchange.



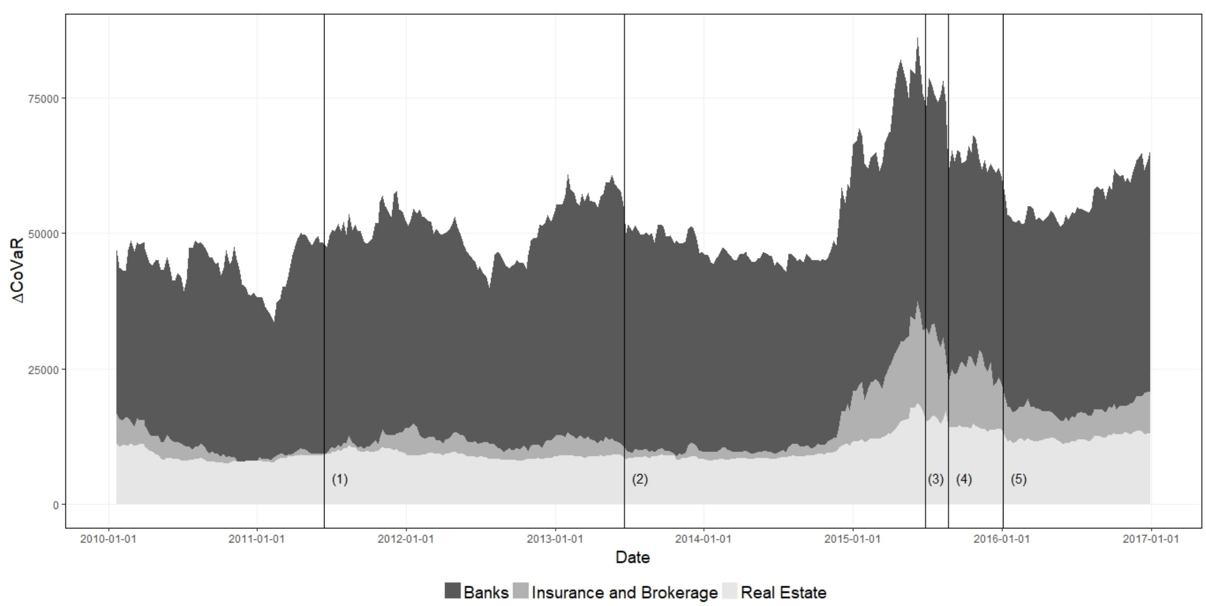
Notes: The Figure plots the $\Delta CoVaR_{95^{th}}$ of China's financial system for Panel A and Panel B. The series are normalized by their value as of December 2016. The normalized value is reported on the left vertical axis. The solid vertical lines mark: (1) the S&P downgrade of China developers in 2011; (2) the banking liquidity crisis in 2013; (3) the 27^{th} of July 2015; (4) the 24^{th} of August 2015, *("Black Monday")*; and, (5) the 4^{th} of January 2016.

Figure 2: $\Delta^{\$}CoVaR_{95^{th}}$ of China's financial sectors.

Panel A: Hong Kong Stock Exchange.



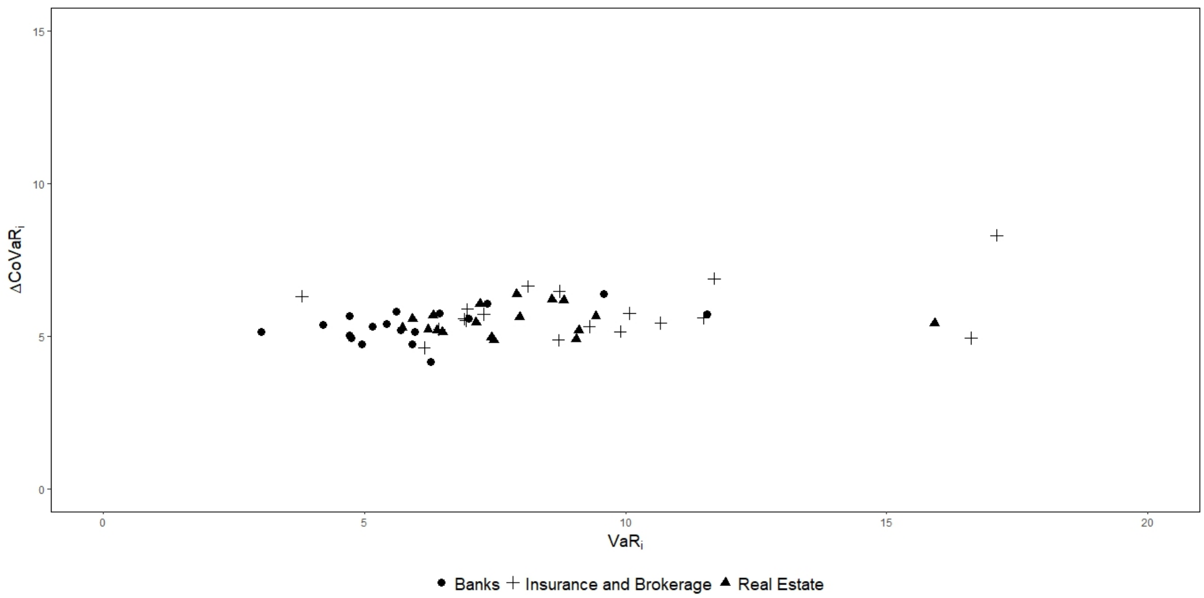
Panel B: Shanghai Stock Exchange.



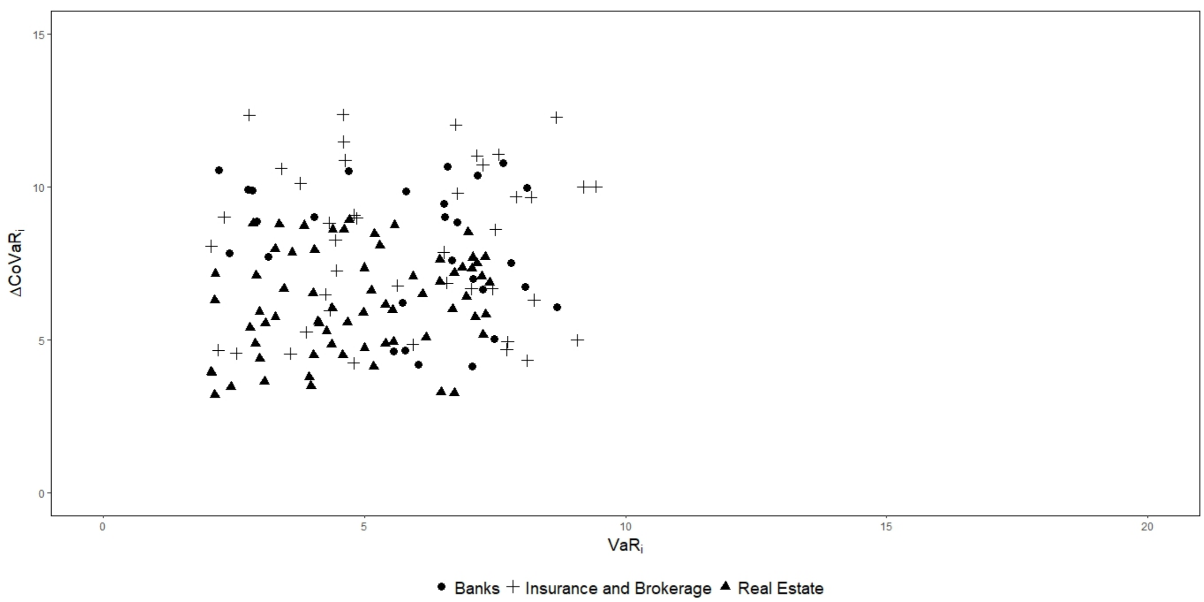
Notes: The Figure plots the $\Delta^{\$}CoVaR_{95^{th}}$ of China's financial sectors: (i) Banks; (ii) Insurance and Brokerage Industries; and, (iii) Real Estate, for Panel A and Panel B.. The solid vertical lines mark: (1) the S&P downgrade of China developers in 2011; (2) the banking liquidity crisis in 2013; (3) the 27^{th} of July 2015; (4) the 24^{th} of August 2015 *("Black Monday")*; and, (5) the 4^{th} of January 2016.

Figure 3: VaR and $\Delta CoVaR$ of the China's financial sectors.

Panel A: Hong Kong Stock Exchange.



Panel B: Shanghai Stock Exchange.



Notes: The scatter plot shows the weak correlation between the VaR (x-axis) and the $\Delta CoVaR$ (y-axis) of the Chinese financial institutions as of the 24^{th} August 2015 (*"Black Monday"*), for Panel A and Panel B. The VaR_i measures the the risk of the institution in isolation, while the $\Delta CoVaR_i$ measures the systemic risk of the same institution.

Table 1: List of the state variables used in the quantile regressions.

Panel A: Hong Kong Stock Exchange

State variable	Definition	Source
3-month Government bond spread variation	Difference between the Generic Hong Kong 3-month Government Bond rate in time t and $t-1$	Bloomberg
Yield spread change	Difference between the Generic Hong Kong 10 Year Government Bond rate and the Generic Hong Kong 3-month Government Bond rate	Bloomberg
Liquidity spread	Difference between the 3-month HIBOR rate and the Generic Hong Kong 3-month Government Bond rate	Bloomberg
Credit spread change	Difference between the S&P Hong Kong BBB Investment Grade Corporate Bond Rate Index and the Generic Hong Kong 10 Year Government Bond rate	Bloomberg and S&P Dow Jones Indices
Equity return	Hong Kong Hang Seng Index returns	Bloomberg
Real estate and Financial sector spread	Difference between the Hong Kong Hang Seng Real Estate Index returns and the Hong Kong Hang Finance Index returns	Bloomberg
Equity Volatility	22-day rolling standard deviation of the daily Hong Kong Hang Seng Index	Bloomberg

Panel B: Shanghai Stock Exchange

State variable	Definition	Source
3-month Government bond spread variation	Difference between the China 3-month Treasury Bond rate in time t and $t-1$	CEIC Data
Yield spread change	Difference between the China 10 Year Treasury Bond rate and the China 3-month Treasury Bond rate	CEIC Data
Liquidity spread	Difference between the 3-month SHIBOR rate and the China 3-month Treasury Bond rate	SHIBOR and CEIC Data
Credit spread change	Difference between the China Securities Corporate Bond Index and the China 10 Year Treasury Bond Yield	CSI Indices and CEIC Data
Equity return	Shanghai Stock Exchange Composite Index returns	Bloomberg
Real estate and Financial sector spread	Difference between the MSCI China Real Estate Index returns and the MSCI China A Onshore Financials Index returns	Bloomberg
Equity Volatility	22-day rolling standard deviation of the daily Shanghai Stock Exchange Composite Index	Bloomberg

Notes: The Table lists the state variables (M_{t-1}) used to estimate the CoVaR for the quantiles considered.

Table 2: Summary statistics of financial system, sectors and state variables.

Panel A: Hong Kong Stock Exchange							
	Mean	Std. dev.	Skewness	Min	Max	1 percent Stress	Obs.
Returns							
Financial System	0.0040	1.7797	-0.1084	-14.1806	12.9789	12.9789	2219
Banks	0.0077	1.7754	-0.2627	-16.7531	13.2618	13.2618	2219
Insurance and Brokerage	0.0002	1.9430	0.2029	-14.7156	12.2162	11.1154	2219
Real Estate	0.0077	2.4931	-0.2347	-12.3168	13.4513	13.4513	2219
State variables							
3-month Government bond spread variation	-0.0591	4.1488	-1.7398	-0.5800	0.4800	-0.0500	2219
Yield spread change	1.6533	0.6346	-0.0545	0.2250	3.3130	2.1010	2219
Liquidity spread	0.3295	0.5134	3.8100	-0.2907	4.3721	2.9386	2219
Credit spread change	4.0723	1.4151	2.0811	2.4500	9.2100	8.2100	2219
Equity return	-0.0106	1.6534	0.0643	-13.5820	13.4068	13.4068	2219
Real estate and Financial sector spread	-0.0005	1.1097	0.3417	-6.9037	8.1645	2.7357	2219
Equity Volatility	1.4177	0.8675	2.9117	0.4497	7.0043	5.2138	2219

Panel B: Shanghai Stock Exchange							
	Mean	Std. dev.	Skewness	Min	Max	1 percent Stress	Obs.
Returns							
Financial System	0.0526	2.0376	-0.6714	-10.8133	8.9654	8.9449	2190
Banks	0.0442	1.9620	0.0430	-9.5540	10.5041	10.5041	2190
Insurance and Brokerage	0.0350	2.2980	0.3015	-10.3817	9.4253	9.3234	2190
Real Estate	0.0636	2.2972	0.9325	-8.6707	16.3094	15.9594	2190
State variables							
3-month Government bond spread variation	-0.0006	0.0415	-1.7376	-0.4800	0.5200	0.4800	2190
Yield spread change	1.4532	0.7545	-0.0537	0.2550	3.3130	3.3130	2190
Liquidity spread	0.3301	0.6137	3.8009	-0.2507	4.3721	4.0098	2190
Credit spread change	4.0098	1.6748	2.0810	2.1500	9.8800	9.2100	2190
Equity return	-0.0126	1.7328	-0.5564	-8.8732	9.0345	9.0345	2190
Real estate and Financial sector spread	0.0110	0.7273	-1.0081	-5.8930	3.4640	3.4640	2190
Equity Volatility	1.5546	0.7938	1.2073	0.4930	4.1386	4.1386	2190

Notes: The Table reports summary statistics for the financial system and sectors returns and state variables. The 1 percent stress in the last column corresponds to the financial sector return and state variable realizations in the worst 1 percent of financial system returns. Note that, as stated in Section 2.1, our study considers an equity loss with positive values.

Table 3: Wilcoxon signed rank sum test during the main systemic events of 2011, 2013, 2015 and 2016.

H_0: $\Delta CoVaR^i_{t:t+h-1} \leq \Delta CoVaR^i_{t-h-1:t-1}$

Panel A: Hong Kong Stock Exchange	Financial System	Banks	Insurance and Brokerage	Real Estate
S&P downgrade of China's developers				
June 15^{th}, 2011	-0.3011	-0.7623	-0.0021	-1.5155*
Banking liquidity crisis				
June 20^{th}, 2013	-3.1488***	-3.3527***	-0.3598	-3.3527***
Stock market crash				
July 27^{th}, 2015	-2.9156***	-2.9156***	-2.9536***	-3.1888***
August 24^{th}, 2015	-2.9156***	-3.1888***	-2.5143**	-1.9147**
January 4^{th}, 2016	-4.9010***	-5.0354***	-3.2699***	-3.3527***

Panel B: Shanghai Stock Exchange	Financial System	Banks	Insurance and Brokerage	Real Estate
S&P downgrade of China's developers				
June 15^{th}, 2011	-3.1888***	-3.3527***	-1.8858**	-1.7859*
Banking liquidity crisis				
June 20^{th}, 2013	-0.9269	-0.7178	-1.6678*	-3.0307***
Stock market crash				
July 27^{th}, 2015	-4.4111***	-4.3056***	-3.7444***	-3.2266***
August 24^{th}, 2015	-3.7001***	-1.7624*	-3.5768***	-3.0788***
January 4^{th}, 2016	-0.9269	-1.0730	-2.1414**	-1.7053*

Notes: The results report for China's financial system and sectors the Wilcoxon signed rank sum test, which aims to determine whether or not the level of systemic risk h-days after a systemic event, or a period of financial instability, is greater than the same h-days before. The hypothesis tested is H_0: $\Delta CoVaR^i_{t:t+h-1} \leq \Delta CoVaR^i_{t-h-1:t-1}$, with $h = 22$–days. The failure to reject this hypothesis implies that the systemic risk level of the financial system (or sector) i did not increase during the systemic event considered. The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

Table 4: $\Delta CoVaRs$ of China's financial sectors.

Panel A: Hong Kong Stock Exchange	Banks				Insurance and Brokerage				Real Estate				
	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min	Obs.
2010-2016													
$\Delta CoVaR_{75^{th}}$	1.1373	0.1590	1.7117	0.8054	1.0884	0.1791	1.7307	0.6766	1.1504	0.1576	1.7471	0.7046	1712
$\Delta CoVaR_{95^{th}}$	3.1470	0.4734	5.2793	2.3604	2.9440	0.5268	5.7509	1.8390	3.0678	0.4940	5.6336	1.8403	1712
$\Delta CoVaR_{99^{th}}$	4.8073	0.7944	8.6386	3.3889	4.6788	0.9064	9.2327	2.9071	4.7345	0.9473	9.9318	2.8983	1712
2010-2012													
$\Delta CoVaR_{75^{th}}$	1.2173	0.1701	1.7117	0.8054	1.1765	0.1827	1.7307	0.7525	1.2012	0.1672	1.7471	0.7216	729
$\Delta CoVaR_{95^{th}}$	3.3614	0.5493	5.2793	2.3604	3.1504	0.6005	5.7509	1.8390	3.1826	0.5722	5.6336	1.8403	729
$\Delta CoVaR_{99^{th}}$	5.0739	0.9155	8.6386	3.4140	4.9249	0.9877	9.2327	2.9071	4.9562	1.0970	9.9318	2.8983	729
2013-2014													
$\Delta CoVaR_{75^{th}}$	1.0464	0.0973	1.3436	0.8446	0.9881	0.0958	1.2944	0.7845	1.0879	0.0986	1.4127	0.8392	491
$\Delta CoVaR_{95^{th}}$	2.8784	0.2296	3.6020	2.3676	2.6502	0.2675	3.5768	2.0872	2.8447	0.2692	3.7008	2.0978	491
$\Delta CoVaR_{99^{th}}$	4.3337	0.4027	5.7173	3.3889	4.1032	0.4947	5.9320	3.1381	4.2162	0.5262	5.8963	2.9608	491
2015-2016													
$\Delta CoVaR_{75^{th}}$	1.1096	0.1314	1.4853	0.8613	1.0577	0.1751	1.5053	0.6766	1.1374	0.1658	1.6078	0.7046	492
$\Delta CoVaR_{95^{th}}$	3.0975	0.3715	4.3394	2.5089	2.9313	0.4597	4.6083	2.0851	3.1204	0.4695	4.7820	2.1268	492
$\Delta CoVaR_{99^{th}}$	4.8850	0.6770	7.5578	3.6324	4.8886	0.8408	7.8740	3.0016	4.9234	0.8304	8.1573	2.9844	492

Panel B: Shanghai Stock Exchange	Banks				Insurance and Brokerage				Real Estate				
	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min	Obs.
2010-2016													
$\Delta CoVaR_{75^{th}}$	1.8959	0.4757	3.9974	1.0628	1.2682	0.4988	3.8249	0.0541	1.1436	0.5348	3.9775	0.1864	1684
$\Delta CoVaR_{95^{th}}$	4.3436	0.4801	6.4888	3.4913	3.6684	0.4981	6.2939	2.3555	3.5916	0.5322	6.8585	2.5488	1684
$\Delta CoVaR_{99^{th}}$	4.8458	0.4751	7.9142	3.9901	4.1682	0.4941	7.7531	2.9038	4.0425	0.5320	7.8055	3.0329	1684
2010-2012													
$\Delta CoVaR_{75^{th}}$	2.1083	0.5496	3.9974	1.0628	1.3764	0.5728	3.8249	0.0541	1.3521	0.6059	3.9775	0.1864	717
$\Delta CoVaR_{95^{th}}$	4.5590	0.5538	6.4888	3.4913	3.7801	0.5742	6.2939	2.3555	3.7998	0.6045	6.8585	2.5488	717
$\Delta CoVaR_{99^{th}}$	5.0596	0.5495	7.9142	3.9901	4.2801	0.5695	7.7531	2.9038	4.2512	0.6048	7.8055	3.0329	717
2013-2014													
$\Delta CoVaR_{75^{th}}$	1.6274	0.2396	2.3755	1.0663	1.0495	0.2828	2.0122	0.1521	0.8483	0.2845	1.8266	0.2773	483
$\Delta CoVaR_{95^{th}}$	4.0727	0.2442	4.8337	3.5017	3.4461	0.2843	4.3907	2.5157	3.2956	0.2799	4.3585	2.6453	483
$\Delta CoVaR_{99^{th}}$	4.5775	0.2367	5.3144	4.0625	3.9458	0.2768	4.8406	3.1143	3.7473	0.2772	4.8055	3.1235	483
2015-2016													
$\Delta CoVaR_{75^{th}}$	1.8491	0.3769	3.0752	1.1844	1.3262	0.4818	3.0912	0.2947	1.1295	0.4689	2.9021	0.2478	484
$\Delta CoVaR_{95^{th}}$	4.2949	0.3798	5.8848	3.6018	3.7247	0.4732	5.9876	2.6631	3.5786	0.4637	5.9896	2.6747	484
$\Delta CoVaR_{99^{th}}$	4.7969	0.3753	7.0339	4.1614	4.2243	0.4713	6.3773	3.2124	4.0277	0.4638	6.2338	3.1452	484

Notes: The Table shows the descriptive statistics of the $\Delta CoVaR$ related to the different quantiles for China's financial sectors. The whole sample period 2010-2016 includes three periods: the period after the Global crisis (2010-2012), the pre-Chinese market stock crash (2013-2014), the Chinese market stock crash (2015-2016). All the figures are expressed as a percentage.

Table 5: Significance test results.

	Panel A: Hong Kong Stock Exchange			
	2010–2016	2010–2012	2012–2014	2014–2016
H_0: $\Delta CoVaR$ *Banks* = 0	1.000***	1.000***	1.000***	1.000***
H_0: $\Delta CoVaR$ *Ins. and Brkg.* = 0	1.000***	1.000***	1.000***	1.000***
H_0: $\Delta CoVaR$ *RE* = 0	1.000***	1.000***	1.000***	1.000***
	Panel B: Shanghai Stock Exchange			
	2010–2016	2010–2012	2012–2014	2014–2016
H_0: $\Delta CoVaR$ *Banks* = 0	1.000***	1.000***	1.000***	1.000***
H_0: $\Delta CoVaR$ *Ins. and Brkg.* = 0	1.000***	1.000***	1.000***	1.000***
H_0: $\Delta CoVaR$ *RE* = 0	1.000***	1.000***	1.000***	1.000***

Notes: The Table reports the results of the significance test based on the two-sample Kolmogorov-Smirnov test. The null hypothesis "$\Delta CoVaR$ *Banks* = 0" determines whether or not the cumulative distribution function (CDFs) of the $CoVaRs$ at a 95^{th} quantile and at a 50^{th} quantile are different from each other. Therefore, the null hypothesis signifies that there is equality between the CDFs of the $CoVaRs$ related to the 95^{th} and 50^{th} quantile. The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 6: Dominance test results.

Panel A: Hong Kong Stock Exchange				
	2010–2016	2010–2012	2012–2014	2014–2016
H_0: *Banks* $\leq$ *Ins. and Brkg.*	0.2377***	0.2058***	0.3646***	0.2480***
H_0: *Banks* $\leq$ *RE*	0.0993***	0.1742***	0.1018***	0.0691***
H_0: *RE* $\leq$ *Ins. and Brkg.*	0.1589***	0.0549	0.2974***	0.2033***

Panel B: Shanghai Stock Exchange				
	2010–2016	2010–2012	2012–2014	2014–2016
H_0: *Banks* $\leq$ *Ins. and Brkg.*	0.7038***	0.6571***	0.9144***	0.7033***
H_0: *Banks* $\leq$ *RE*	0.6425***	0.6351***	0.7984***	0.5732***
H_0: *RE* $\leq$ *Ins. and Brkg.*	0.1653***	0.0686**	0.3014***	0.2155***

Notes: The Table reports the results of the dominance test based on the two-sample Kolmogorov-Smirnov test. The null hypothesis "*Banks* $\leq$ *Ins. and Brkg.*" means that the $\Delta CoVaRs_{95^{th}}$ related to the banking sector are lower (or equal to), in absolute value, than the $\Delta CoVaRs_{95^{th}}$ related to the insurance and brokerage sector. Therefore, the null hypothesis signifies that the banking sector is less (or equal) systemically risky than the insurance and brokerage sector. The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7: Bank-specific, macroeconomic and risk aversion variables.

Name	Description
Bank-specific variables	
Capital & Reserves (% of TA)	Ratio of bank capital and reserves to total assets (TA). Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments. Capital includes tier 1 capital (paid-up shares and common stock), which is a common feature in all countries' banking systems, and total regulatory capital, which includes several specified types of subordinated debt instruments that need not be repaid if the funds are required to maintain minimum capital levels (these comprise tier 2 and tier 3 capital). TA include all non-financial and financial assets.
Deposits (% of GDP)	Demand, time and saving deposits in deposit money banks as a share of GDP, calculated using the following deflation method: $(0.5) * [F_t/P_{e,t} + F_{t-1}/P_{e,t} - 1][GDP_t/P_{a,t}]$; where F is demand and time and saving deposits, P_e is end-of period CPI, and P_a is average annual CPI.
Net interest margin	Measure of the difference between the interest income generated by banks and the amount of interest paid out to their lenders, relative to the amount of their interest-earning assets.
Non-interest income (% of total income)	Banks income generated from the non-core activities and derived primarily from fees including deposit and transaction fees, insufficient funds fees, annual fees, monthly account service charges, inactivity fees, check and deposit slip fees.
Regulatory capital (% of RWA)	Ratio of total regulatory capital to total assets held, weighted according to risk of those assets.
ROE	Ratio of net income to total equity capital.
Macroeconomic variables	
Consumer Price Index (CPI)	Measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services.
Credit to Gov. and SOE (% of GDP)	Ratio between credit by domestic money banks to the government and state-owned enterprises (SOE) and GDP.
GDP growth	Measure of economic growth, adjusted for inflation, and expressed in real terms.
Risk aversion variables	
Cost to income ratio	Operating expenses of banks as a share of sum of net-interest revenue and other operating income.
Stock price volatility	360-day standard deviation of the return on the national stock market index.
5-bank asset concentration	Assets of the five largest banks as a share of total banking sector assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets.

Notes: The Table lists the name and description of the variables used in the regression analysis. All data are obtained from World Bank Open Data.

Table 8: Bank-specific, macroeconomic and risk aversion variables and their impact on systemic risk.

	Panel A: $\Delta CoVaR_{95th}^{Banks,\ Hong\ Kong}$									
Constant	5.2579***	5.1441	7.6029***	5.3152*	10.1959	14.2504**	4.9086*	5.9432***	5.9435***	40.4374
Bank-specific variables										
Capital & Reserves (% of TA)			0.2215**				0.2433**			
Deposits (% of GDP)					0.0007	-0.0468	-0.0023	-0.2329***		-0.0365
Net interest margin	0.1300	0.0996		0.0363	0.1410					
Non-interest income (% of total income)								0.0164		
Regulatory capital (% of RWA)		-0.0621				0.3938		0.3186	-0.0354**	0.0688
ROE							0.0738			
Macroeconomic variables										
CPI	0.1008	0.1822	0.0377	0.1336		0.2043	0.0645	0.0294**	0.0410	0.0537
Credit to Gov. and SOE (% of GDP)		0.0062*		-0.0170			0.0471			
GDP growth					-0.1135**	-0.0126			-0.0667*	
Risk aversion variables										
Cost to income ratio			-0.0075							
Stock price volatility	-0.0297**					-0.0656*			-0.0233	
5-bank asset concentration					-0.0916			-0.3524		-0.3295
$adj.R^2$	15.06%	7.16%	20.18%	2.75%	7.59%	19.23%	21.76%	23.77%	16.29%	3.72%
	Panel B: $\Delta CoVaR_{95th}^{Banks,\ Mainland\ China}$									
Constant	2.5858***	6.5339***	0.6875	3.1981***	7.1117**	4.7956	-1.0378	6.5412*	3.7026	6.8678*
Bank-specific variables										
Capital & Reserves (% of TA)			0.2561**				0.2571			
Deposits (% of GDP)					-0.0663	-0.0637*	0.0692	-0.0150		-0.0152
Net interest margin	0.5279***	0.6872***		0.3927**	0.1868					
Non-interest income (% of total income)								0.0267		
Regulatory capital (% of RWA)		-0.3637*				0.1745		-0.0997**	0.0861	-0.0417
ROE							0.0544			
Macroeconomic variables										
CPI	0.2333***	0.2599***	0.2327***	0.2229***		0.1608**	0.2688***	0.2156***	0.2003***	0.2191***
Credit to Gov. and SOE (% of GDP)		0.0487**		0.0217			-0.0311			
GDP growth					0.0509	0.0237			-0.4100**	
Risk aversion variables										
Cost to income ratio			0.0607*							
Stock price volatility	0.0185*					0.0213			0.0100	
5-bank asset concentration					0.0041			0.0064		0.1520**
$adj.R^2$	45.93%	48.52%	41.91%	41.81%	5.18%	26.85%	30.65%	27.37%	27.32%	29.11%
	Panel C: $\Delta CoVaR_{95th}^{Banks,\ United\ States}$									
Constant	1.0984	9.5274***	4.5640	-5.738*	-7.3209***	15.4613	-5.5931***	-4.2763***	8.195***	-5.6476***
Bank-specific variables										
Capital & Reserves (% of TA)			8.2955***				18.8656***			
Deposits (% of GDP)					6.5625***	0.2488	3.7243***	4.8189***		3.7481***
Net interest margin	-1.6543	69.3402***		25.4643**	45.5071***					
Non-interest income (% of total income)								-1.0824*		
Regulatory capital (% of RWA)		-31.7771***				-2.4447		-19.8278***	-3.311***	-15.7659***
ROE							1.1539***			
Macroeconomic variables										
CPI	-1.1531***	0.7242*	1.3153***	1.0792		-0.5744**	0.8893***	1.4764**	-0.5518**	0.3358*
Credit to Gov. and SOE (% of GDP)		2.2074***		2.0260			2.4272***			
GDP growth					-2.1649**	-1.2077***			-1.3117***	
Risk aversion variables										
Cost to income ratio			2.0322***							
Stock price volatility	0.6248***					0.4001***			0.3953***	
5-bank asset concentration					-6.1379***			-3.7312***		-3.3945***
$adj.R^2$	90.53%	90.72%	89.62%	25.46%	92.12%	95.41%	96.72%	96.69%	95.59%	96.29%

Notes: The Table shows the regression coefficients from the regression given by Eq. (15) for banking sectors' systemic risk of Hong Kong (Panel A), Mainland China (Panel B) and the United States (Panel C). Data are quarterly. The description of the variables is listed in Table 7. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.