



SYSTEMIC RISK IN THE CHINESE STOCK MARKET UNDER DIFFERENT REGIMES: A SECTOR-LEVEL PERSPECTIVE



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ABSTRACT

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This study's aim is to investigate systemic risk in the Chinese stock market. To this end, we analyze risk contributions to the Chinese stock market from 2007 to 2018 at the sector level using the Conditional Value at Risk (CoVaR) approach proposed by Adrian and Brunnermeier (2016). For the full sample period, we find that the information technology sector is the top contributor to systemic risk in the Chinese stock market. To distinguish the risk contribution of each sector under different market regimes, we propose an adjusted Bry-Boschan program to identify turning points in the stock market, which captures regime shifting between bull and bear markets. We find that the risk contribution of each sector in a bear market is significantly higher than that in the following bull market. We also find that the top contributor to systemic risk in the Chinese stock market changes across market regimes. Our findings have important policy implications. First, policymakers may use the early identification of systemically risky sectors of the stock market to improve the pertinence of economic policy-making. Second, it may allow security regulators to foster an environment in which incentives for risk taking by financial practitioners are reduced.

Contribution/ Originality: This study is one of very few studies which have investigated the systemic risk in the stock market by employing the systemic risk method to estimate ten stock sectors' risk contributions to the Chinese stock market.

1. INTRODUCTION

The Chinese stock market has become one of the largest worldwide in terms of market capitalization of its listed companies, but it is still relatively vulnerable and has faced numerous challenges in recent years. For instance, it became the second biggest stock market globally in late 2014 and then soared to an all-time high of more than \$10 trillion in June 2015, which was followed by a crash in the second half of the year. Because of the uncertainties of trade negotiation with the United States and concerns about slowing economic growth, the benchmark Shanghai Composite Index slumped 24.59% in 2018, making 2018 a bad performance year for the Chinese stock market. The instability of the Chinese stock market has been a deep concern for not only the investors but also the regulatory authorities. Protecting against systemic financial risk has been a main task for the Chinese government and the regulatory authorities, as highlighted in the Government Work Reports by Premier Li Keqiang and emphasized by

the former Governor of the People's Bank of China Zhou Xiaochuan.¹ Under these circumstances, a study on systemic risk in the Chinese stock market seems to be an urgently needed and valuable undertaking.

We study systemic risk in the Chinese stock market from the sector-level perspective, examining which sector contributes the most to systemic risk and whether the riskiest sector changes across market regimes. To this end, we apply the CoVaR approach proposed by Adrian and Brunnermeier (2016) to estimate the systemic risk contributions of stock sectors during the 2007-2018 period. Our results suggest that information technology is the systemically riskiest sector during the full sample period. In addition, we apply Pagan and Sossounov (2003) adjusted BB program to identify the bull and bear periods and examine the systemic risk rankings of stock sectors under different market regimes. We find that (i) the systemic risk contributions of stock sectors are overall higher in bear markets than in bull markets; (ii) stock sectors with low systemic risk contributions in bull markets can become the systemically riskiest sectors in bear markets; (iii) the systemic risk ranking of stock sectors in a bull market is insignificantly correlated with the ranking in the subsequent bear market.

Our findings have important policy implications. First, policymakers may use the early identification of systemically risky sectors to improve the pertinence of economic policy-making. For example, the empirical results show that the information technology sector is the top systemic risk contributor to the stock market. This conclusion reflects the major challenges faced by China's real economy. For policymakers, relevant policies should be formed to actively promote the real economy to achieve high-quality and sustainable industrial development. Second, the identification of systemically risky sectors can help security regulators foster an environment in which incentives for risk taking by financial practitioners are reduced. For example, when risk-aware firms and investors in the stock market build an asset portfolio, they will select companies that can defuse extreme risk shocks and not instigate extreme risk spillovers, thus reducing the accumulation of risk in the system.

Our study contributes to the academic literature on systemic risk in the Chinese financial system. To name a few, Huang *et al.* (2017) and Fang *et al.* (2018) study the systemic risk ranking of Chinese banks under various measures (e.g., the CoVaR and the systemic risk measure (SRISK) approaches). Wang *et al.* (2018) investigate the interconnectedness and systemic risk of Chinese financial institutions by constructing dynamic tail-event driven networks. Xu *et al.* (2018) estimate systemic risk in the Chinese banking industry using an improved CoVaR approach. Wang *et al.* (2018) investigate the volatility connectedness of Chinese listed banks and find that they are highly interconnected. These studies focus on systemic risk in the Chinese banking system and estimate systemic risk from the bank-level perspective. We contribute to this body of literature papers by estimating systemic risk in the Chinese stock market from the sector-level perspective.

There are only a few papers that study systemic risk in the stock market at the sector level (Wu, 2018; Van Vu and Tran, 2019). Van Vu and Tran (2019) apply the VaR and Δ CoVaR method to study ten stock sectors systemic risk in the Vietnam stock market in the period from the first quarter of 2010 to the second quarter of 2017. The results show that Δ CoVaR is a more suitable measure in considering the level of company contribution to the systemic risk of the whole market. The most closely related paper is Wu (2018) who also investigate systemic risk in the Chinese stock market. Our study differs from Wu (2018) in three ways. First, we employ the CoVaR approach to measure systemic risk contributions of stock sectors while Wu (2018) uses the marginal expected shortfall and component expected shortfall approaches. Second, our sample covers the period from January 2007 to December 2018 which includes the 2008 global financial crisis and the two major stock market crashes in the Chinese stock market. This enables us to compare the systemic risk contributions of stock sectors across the global financial crisis and stock market crash periods. Wu (2018) does not study systemic risk during the global financial crisis period. Third, we examine which sectors contribute the most to systemic risk in the Chinese stock market and

¹ See www.gov.cn/premier/2017-03/16/content_5177940.htm and www.gov.cn/premier/2018-03/22/content_5276608.htm for Premier Li's reports and www.ccpp.com.cn/ywrd/index_rdzt/fddb/201711/P020171122321676465404.pdf for the Governor Zhou's report.

whether the top contributors remain the same across different market regimes (i.e., bull and bear markets), while Wu (2018) only performs the former analyses. To the best of our knowledge, this study is the first to examine systemic risk contributions of stock sectors under different regimes.

The remainder of this article is structured as follows. Section 2 presents a review of the relevant literature on stock market sectors. Section 3 illustrates the CoVaR approach and the adjusted BB program and discusses our data. Section 4 presents estimation results for the sample data ranging from January 4, 2007 to December 29, 2018. Then a subsample of bull and bear market data is used to compute systemic risk contribution of each stock sector. Concluding remarks are given in Section 5.

2. LITERATURE REVIEW

In the literature on stock market sectors, one thread of studies investigates the transmission of volatility and shocks among major sectors. Ewing (2002) examines five major S&P stock indexes to determine their interrelationships and how shocks to one index are transmitted to the others. He establishes a vector autoregression (VAR) model and employs the newly developed technique of forecast error variance decomposition to find the profit spillover effect between industries. The results provide important information about the transmission of shocks among these indexes. Hassan and Malik (2007) use multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models to simultaneously estimate the mean and conditional variance of the daily sector index returns of the financial, industrial, consumer, health, energy, and technology sectors. Their results show significant transmission of shocks and volatility among all these sectors. Hammoudeh *et al.* (2009) examine the dynamic volatility and volatility transmission in a multivariate setting using the VAR(1)–GARCH(1,1) model for three major sectors, namely, the service, banking, and industrial/or insurance sectors, in four economies of the Gulf Cooperation Council (Kuwait, Qatar, Saudi Arabia, and the UAE). The results suggest that past volatilities matter more than past shocks, and there are moderate volatility spillovers between the sectors within individual countries, with the exception of Qatar. Majumder and Nag (2018) examines how shocks and volatility are transmitted across sector indexes. The study uses daily data from India's National Stock Exchange from January 2004 to January 2014 and employs the autoregressive asymmetric BEKK–GARCH model. The study finds evidence of asymmetric spillover in most cases: shock and volatility spillovers inside the pro-cyclical sectors, from the non-cyclical fast-moving consumer goods to pro-cyclical sectors, and to fast-moving consumer goods from the other sectors were bidirectional, unidirectional, and unaffected, respectively.

Another stream of the extensive empirical studies attempts to examine systemically important institutions within the financial sector of the stock market using the econometric and complex network methods. Econometric methods focus on public market data or accounting book data to identify systemically important institutions. Five prominent examples of market-data based measures are marginal expected shortfall and systemic expected shortfall proposed by Acharya *et al.* (2010), SRISK proposed by Brownlees and Engle (2012) delta conditional value-at-risk (ΔCoVaR) proposed by Adrian and Brunnermeier (2016) and distress insurance premium proposed by Huang *et al.* (2009;2012). Over the past five years, hundreds of research articles have discussed, implemented, and sometimes generalized, these systemic risk measures. López-Espinosa *et al.* (2012) propose a variant of ΔCoVaR that captures risk spillovers from a financial institution to the rest of the financial system. Castro and Ferrari (2014) develop a test of significance using ΔCoVaR . Bernal *et al.* (2014) employ the ΔCoVaR approach to determine which financial service industries were the most systemically important in the Eurozone from 2004 to 2012. Their empirical results reveal that the other financial service sectors contribute the most to systemic risk. In turn, the insurance sector appears to contribute less to systemic risk than the banking sector does, in contrast with the United States, where the insurance industry is the systemically riskiest financial sector. Bierth *et al.* (2015) employ marginal expected shortfall, SRISK, and ΔCoVaR to estimate each insurers' systemic risk, using daily stock market data. They find systemic risk in the international insurance sector to be smaller in comparison with previous findings in the

literature for banks. In a related vein, [Billio et al. \(2012\)](#) propose principal components analysis and Granger causality tests to identify systemically important institutions. Using monthly returns of hedge funds, banks, brokers, and insurance companies, they find that four sectors had become highly interrelated over the past decade, and the banking and insurance sectors may be even more important sources of systemic risk than other sectors.

The complex network methods used to identify systemically important institutions are based on network structures. They consider the architecture of economic and financial networks as a complex network, financial institutions are the nodes, and financial dependencies are the links. Systemically important financial institutions can be identified by calculating the eigenvector centrality and PageRank, a recursive centrality measure ([Battiston et al., 2012](#)). Following this intuition, DebtRank was introduced, which is relevant to the field of complex networks in general and can be applied to detect systemically important nodes in any directed and weighted network. [Van De Leur et al. \(2017\)](#) propose a measure based on average pairwise correlations (CorrRank) that is much simpler than SIFI Rank (based on Google's PageRank), showing that direct (rather than indirect) connections in the network determine the systemic risk contributions. [Silva et al. \(2018\)](#) simulate shocks to the real sector and evaluate how the financial system reacts and amplifies these events using unique Brazilian loan-level data between banks and firms. Their result suggests that government-owned banks are the most susceptible to receiving shocks from firms of any economic sector. [Tian et al. \(2016\)](#) introduce a network approach to estimate systemic risk in the Chinese shadow banking system which consists of five sectors, including commercial banks, security companies, trust companies, fund management companies, and insurance companies. They found that trust companies were the main initiator of financial instability during the 2007-2012 period.

In summary, previous related research on stock market sectors mainly focus on the correlation between stock sectors and the measurement methods to identify the systemic risk contribution of financial institutions to the financial sector. Measurement of the systemic risk contributions of all stock sectors to the stock market is rarely studied. Thus, this study uses the CoVaR method to conduct an in-depth examination of the contribution of all sectors to the systemic risk of China's stock market for the full sample period and under different market regimes.

3. METHODOLOGY AND DATA

This section illustrates the methodology for measuring the risk contributions of sectors to the stock market and the adjusted BB program to identify bull and bear markets. We also discuss the data in this section.

3.1. The Application of the CoVaR Approach

There is a plethora of literature on identifying institutions' risk contributions to the overall financial system (e.g., ([Huang et al., 2009;2012](#); [Adrian and Brunnermeier, 2016](#); [Acharya et al., 2017](#))). [Huang et al. \(2009\)](#) propose an indicator, called the distress insurance premium, to model systemic risk as the price of insurance against financial distress. [Zhou \(2010\)](#) presents the systemic impact index and the vulnerability index to measure systemic risk under the framework of multivariate extreme value theory. [Acharya et al. \(2017\)](#) propose the marginal expected shortfall to determine each financial institution's contribution to systemic risk when the financial system is in distress. In other words, these measures look at the returns of an institution when the financial system was in distress and experiencing losses. Contrary to these measures, **CoVaR** looks at the returns of the financial system when an institution is in financial distress. In fact, for both measures it is possible and straightforward to reverse the analysis ([Girardi and Ergün, 2013](#)). In that case **CoVaR** would correspond to the **VaR** of an institution conditional on the financial system being in distress, that is, being at its **VaR**. This reverse **CoVaR** would be more meaningful than other measures as it would measure the exposure of an institution that causes distress in the

financial system. However, in the definition given above, systemic risk is the failure of an institution that is the cause of distress for the financial system. Therefore, we only consider $CoVaR_t^{system|i}$ where *system* is the stock market, and is conditional on the distress of a stock sector *i* (Girardi and Ergün, 2013).

Recall that the unconditional *VaR* computes the risk of an individual asset *i* (or the financial system) at the *q*-th percentile. *VaR* is defined as:

$$\Pr(R^i \leq VaR_q^i) = q\% \tag{1}$$

where R^i denotes the daily return of the asset *i*. VaR_q^i is typically a negative number.

According to Adrian and Brunnermeier (2016) we estimate the most extremely negative return of an asset *i* within the *q*-th confidence interval using *CoVaR*, when the financial system is in a state of distress. In mathematics, that is

$$\Pr(R_i \leq CoVaR^{system|R^i=VaR_q^i} | R_{system} = VaR^{R^i=VaR_{50\%}^i}) = q\% . \tag{2}$$

We use $\Delta CoVaR_q^{i|system}$, which is called “exposure *CoVaR*”, to capture one particular asset *i*'s exposure to system wide distress. By definition, $\Delta CoVaR$ is the difference between the *CoVaR*'s when the financial system (denoted by *system* hereafter) is, or is not, in distress (extreme state)

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|R_i=VaR_q^i} - CoVaR_q^{system|R_i=VaR_{50\%}^i} . \tag{3}$$

A negative (positive) $\Delta CoVaR$ indicates a positive (negative) contribution to systemic risk in the stock market.

We have the following three-step procedure to estimate *CoVaR*:

Step 1 First, the *VaR* of each stock sector *i* and stock market *system* are computed by estimating the following univariate model

$$R_t^i = \mu_t^i + \varepsilon_{i,t} \tag{4}$$

where $\mu_t^i = \alpha_0 + \alpha_1 R_{t-1}^i$, $\varepsilon_{i,t} = z_{i,t} \sigma_{i,t}$, $z_{i,t}$ is independently and identically distributed with zero mean and unit variance, and the conditional variance $\sigma_{i,t}^2$ follows the standard GARCH (1,1) model

$$\sigma_{i,t}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t-1}^2 + \beta_2^i \sigma_{i,t-1}^2 . \tag{5}$$

Given a distributional assumption for z and, hence, the q -th quantile of the estimated conditional distribution, we can compute, the VaR of each stock sector i and stock market *system* for each period (see (Duffie and Pan, 1997; Giot and Laurent, 2004)) for the VaR calculations from univariate GARCH models) of the Equation 1.

Step 2 Next, $CoVaR_q^{system|i}$ is estimated by quantile regressions. Consider the predicted value of a quantile

regression of the stock market return $\hat{R}_q^{system|i}$ on a particular stock sector return i for the q -th quantile

$$\hat{R}_q^{system|i} = \hat{\alpha}_q^i + \hat{\beta}_q^i R^i. \tag{6}$$

In principle, this regression could be extended to allow for nonlinearity by introducing higher order dependence of the stock market's value at risk as a function of the stock sector's value at risk. The specific

$CoVaR_q^{system|i}$ measure is given by

$$CoVaR_q^{system|R_i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{7}$$

Step 3 Once we estimate the VaR_q^i and VaR_q^{system} in Step 1 and $CoVaR_q^{system|i}$ of each stock sector in Step 2,

we proceed to obtain $\Delta CoVaR_q^{system|i}$ as follows:

$$\Delta CoVaR_q^{system|R_i=VaR_q^i} = CoVaR_q^{system|R_i=VaR_q^i} - CoVaR_q^{system|R_i=VaR_{50\%}^i}. \tag{8}$$

3.2. The Application of the Adjusted BB Program

We identify the bull and bear market regimes by adopting the adjusted BB program procedure (Pagan and Sossounov, 2003). The BB program originates from the work of Bry and Boschan (1971) which aims to detect turning points in the business cycle to isolate the patterns using a sequence of rules. The related application of this method can be found in studies by King and Plosser (1994) and Harding and Pagan (2003). In the definition of bull and bear markets in stock market terminology, a bull (bear) market corresponds to periods of generally increasing (decreasing) market price (Chauvet and Potter, 2000). Based on previous work, Pagan and Sossounov (2003) develop an adjusted BB program that extends the rules of identifying the turning point from a bull market to a bear market phase (and conversely).

The empirical literature on identifying bull and bear markets is generally based either on the equity price or the stock returns. The former considers the movement from a bull market to a bear market phase (and conversely) involving a turning point in the market (Pagan and Sossounov, 2003; Yan *et al.*, 2006) while the latter relates the bull and bear market with different return states and conditional variances (Maheu and McCurdy, 2000; Lv *et al.*, 2015). The literature suggests that the adjusted BB program framework facilitates the study of extreme events such

as large increases in stock values during bull markets and is also useful in evaluating Value at Risk (Pagan and Sossounov, 2003) which is related to CoVaR method analysis.

We classify the stock market state into bull and bear markets by adopting the adjusted BB program on the basis of CSI 300 index. It accelerates the calculation of the stock sector risk contribution under different regimes. This method was previously employed by Yan *et al.* (2006) who divided China's stock market into two regimes on the basis of the Shanghai Composite and Shenzhen Component Indexes. The daily data were converted to monthly data. The detailed procedure for determining the turning points is as follows:

First, finding the initial turning points. In this step, we identify local peaks (troughs) when the CSI300 monthly data are the highest (lowest) values in a window five months on either side of the date t . Then we enforce alternation of turns by selecting the highest of multiple peaks (or the lowest of multiple troughs).

Second, deciding the minimum time one can spend in any phase. We set this to at least five months for one regime duration and at least twelve months to complete a cycle, and then eliminate the turning points not satisfying this condition.

Finally, an extra constraint was appended such that the minimal length of a phase (five months) and a cycle (twelve months) is disregarded if the stock price falls by 20% in a single month.

In our robustness test, we find that the stock returns during the bull and bear market are significantly different.

Thus, we regress the monthly stock return with dummy variable D_t :

$$R_t = \alpha_0 + \alpha_1 D_t + \varepsilon_t \quad (9)$$

where R_t represents the CSI300 monthly return; $D_t = 1$ if the regime is in the bull market state, and 0 if the regime is in the bear market state. In the regression equation, the intercept term α_0 in the represents average monthly stock returns in the bear market, and α_1 denotes the difference in stock returns in the two market regime states.

3.3. Data

Our analysis is based on daily data of China's Shanghai and Shenzhen 300 stock index (CSI 300 Index) and 10 stock sectors indices. The CSI 300 Index consists of the 300 largest and most liquid A-share stocks and aims to reflect the overall performance of China's A-share market. The 10 stock sectors are energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services, and utilities according to the Wind classification. During 2005–2006, the Chinese government implemented the split share structure reform, aimed at eliminating non-tradable shares, that is, the shares typically held by the State or by politically connected institutional investors that were issued in the early stage of financial market development (Beltratti *et al.*, 2012). Upon completion of the split-share structure reform, the Chinese stock market reflects the price and valuation efficiently (Liao *et al.*, 2014). Therefore, our sample period ranges from January 4, 2008 to December 31, 2018, and there are 2,919 observations for each stock index. The data were downloaded from the Wind financial database.

Figure 1 illustrates the trajectory of the daily level series over the sample period. This subfigure of the CSI300 clearly shows that the stock market has experienced two distinct periods of ups and downs. One is the period around 2008 when a spectacular rise of the CSI 300 index was followed by a significant decline after the global financial crisis broke out in 2008. The other starts on June 12, 2015 and ends in early February 2016 when the stock market turbulence began with the popping of the stock market bubble.

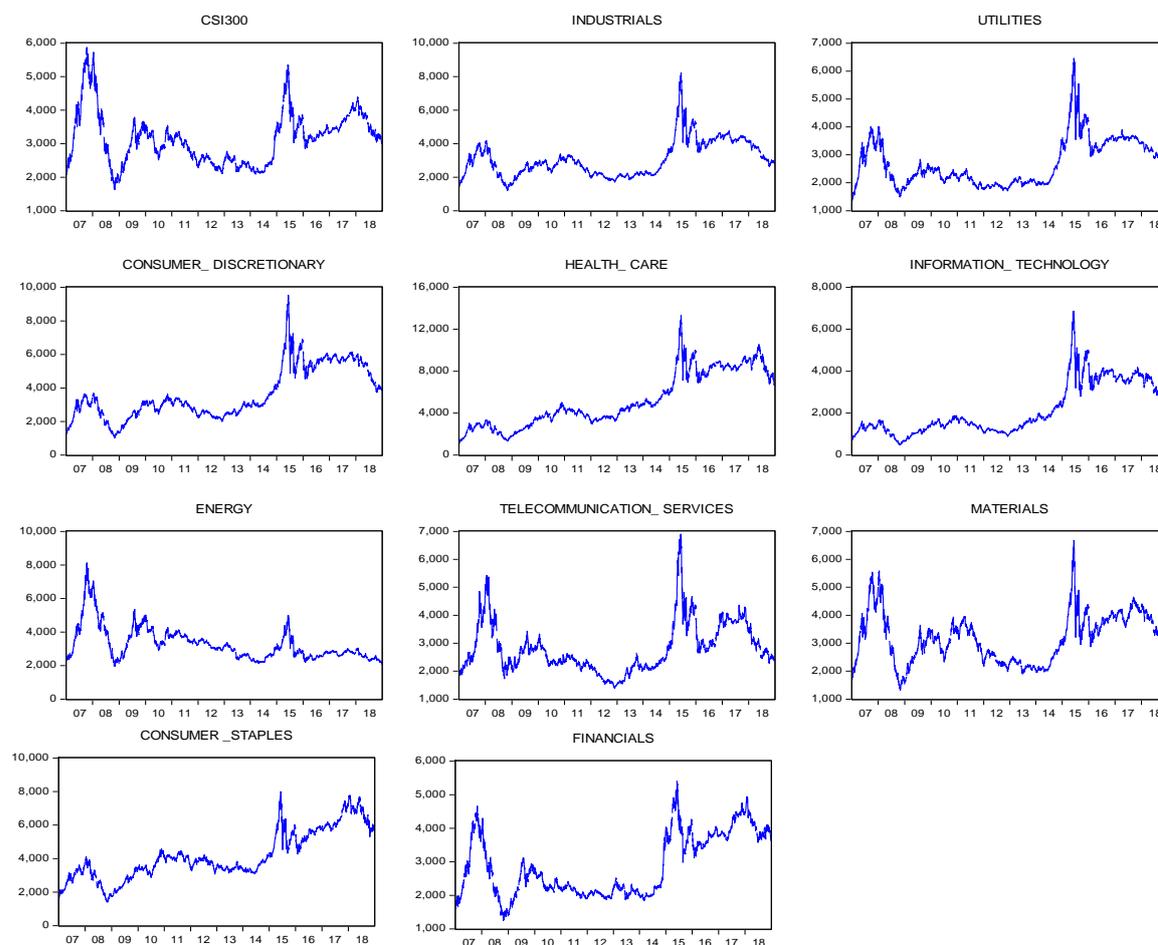


Figure-1. Daily level of CSI 300 index and the 10 stock sector indexes.

Source: Organized according to Wind database.

Table 1 presents the descriptive statistics of the CSI 300 index and the 10 stock sector indexes from January 2007 to December 2018. The average return of most sectors is positive except for the energy sector. More precisely, the healthcare sector has the highest average return, whereas the energy sector displays the lowest. The unconditional volatility of each sector is very close to the others. Specifically, the telecommunication services sector is a little more volatile than the other sectors. The negative values of skewness are common for all the sectors, in which the skewness of the utilities sector is more pronounced than other sectors. All return series exhibit excess kurtosis, which means that the daily returns of all sectors have a heavy tail. Moreover, the Jarque-Bera test in the last column of Table 1 strongly rejected normality of unconditional distribution for all series.

Table-1. Descriptive statistics of stock sector returns.

	Mean (%)	Max (%)	Min (%)	Std. Dev.	Skewness	Kurtosis	J.B.
Health_Care	0.06	0.95	-0.10	0.02	-0.63	6.56	1730.58***
Consumer_Staples	0.04	0.93	-0.10	0.02	-0.62	6.56	1732.05***
Information_Technology	0.04	0.95	-0.10	0.02	-0.66	5.68	1084.38***
Consumer_Discretionary	0.04	0.94	-0.10	0.02	-0.76	6.71	1955.96***
Financials	0.03	0.95	-0.99	0.02	-0.32	6.75	1756.61***
Utilities	0.03	0.95	-0.10	0.02	-0.80	8.15	3528.95***
Industrials	0.02	0.94	-0.10	0.02	-0.76	6.94	2164.09**
Materials	0.02	0.94	-0.10	0.02	-0.71	6.14	1444.79***
Telecommunication	0.00	0.96	-0.11	0.02	-0.22	6.48	1495.90***
Services Energy	-0.00	0.94	-0.10	0.02	-0.42	6.47	1553.75***
CSI300	0.01	0.89	-0.97	0.02	-0.54	6.59	1707.79***

Notes: *denotes significance at the 10 percent level; **denotes significance at the 5 percent level; and *** denotes significance at the 1 percent level.

4. EMPIRICAL RESULTS

In this section, we discuss our estimation results of the systemic risk contributions of the stock sectors. We first present the results of the systemic risk contributions at the sector level over the full sample period. Then we examine whether and how the systemic risk rankings of stock sectors change across the bull and bear market regimes.

4.1. Sectoral Contributions to Systemic Risk in the Chinese Stock Market

We first estimate $Var_{q,t}^i$ of Equation 1 for each stock sector i in time period t using the GARCH model at the 5% quantile according to Equation 1; Equation 4 and Equation 5. The second and third steps consist of estimating $CoVaR_{5\%}^{system|R_i=VaR_{5\%}^i}$ and then $\Delta CoVaR_{5\%}^{system|R_i=VaR_{5\%}^i}$ of the stock market for each time period t conditional on the distress of stock sector i based on 5%- estimates for the overall sample period according to Equation 2 Equation 6, Equation 7, and Equation 3, Equation 8. Table 2 shows the results of $CoVaR$ and $\Delta CoVaR$, $\Delta CoVaR$ values are negative, indicating that stock sectors have positive contributions to systemic risk in the stock market when they are in distress. Columns 2 and 3 of Table 2 rank the stock sector index according to the ascending order of $\Delta CoVaR$ and $CoVaR$, respectively, (i.e., contribution to systemic risk from large to small) during the full sample period. The sectors' systemic risk contribution to the stock market increases in the following order: information technology, health care, telecommunication services, consumer staples, energy, consumer discretionary, utilities, materials, financials and industrials. The information technology sector contributes the most systemic risk to the stock market with the $\Delta CoVaR$ of -1.38%, and the industrials sector contributes the least with the $\Delta CoVaR$ of -0.92%—a difference of 0.46%.

Table-2. Results of $\Delta CoVaR$ (%) and $CoVaR$ (%) during the full sample period.

10 stock sectors	$\Delta CoVaR$ (%)	$CoVaR$ (%)
Information_ Technology	-1.38	-4.14
Health_ Care	-1.31	-4.07
Telecommunication_ Services	-1.26	-4.02
Consumer_ Staples	-1.21	-3.97
Energy	-1.10	-3.86
Consumer_ Discretionary	-1.07	-3.83
Utilities	-1.06	-3.82
Materials	-0.99	-3.75
Financials	-0.98	-3.74
Industrials	-0.92	-3.68

Note: The $\Delta CoVaR$ and $CoVaR$ are based on 5%- estimates for overall sample period.

4.2. Systemic Risk under Bull and Bear Markets

As stated in Section 2.3, Figure 1 shows that the stock market index experienced extensive periods during which it rose and fell. Therefore, it is necessary to calculate the systemic risk contribution of a sector considering the time difference. Zhao *et al.* (2019) focus on the systemic risk of China's stock market during two typical stock market crashes, one in 2008 and the other in 2015. In contrast to his study, we identify the stock market as bull and bear markets using the adjusted BB program, which actually includes the two stock market crashes.

The result of the BB program to identify bull and bear markets for the CSI 300 index from January 2007 to December 2018 is depicted in Figure 2. The shaded areas in the figure represent the bear market regimes and the white areas represent the bull market regimes. To be specific, the bull market regimes are: January 2007 to September 2007, December 2008 to October 2009, April 2014 to May 2015, and March 2016 to December 2017. The bear market regimes are: October 2007 to November 2007, November 2009 to March 2014, June 2015 to February 2016, and January 2018 to December 2018.

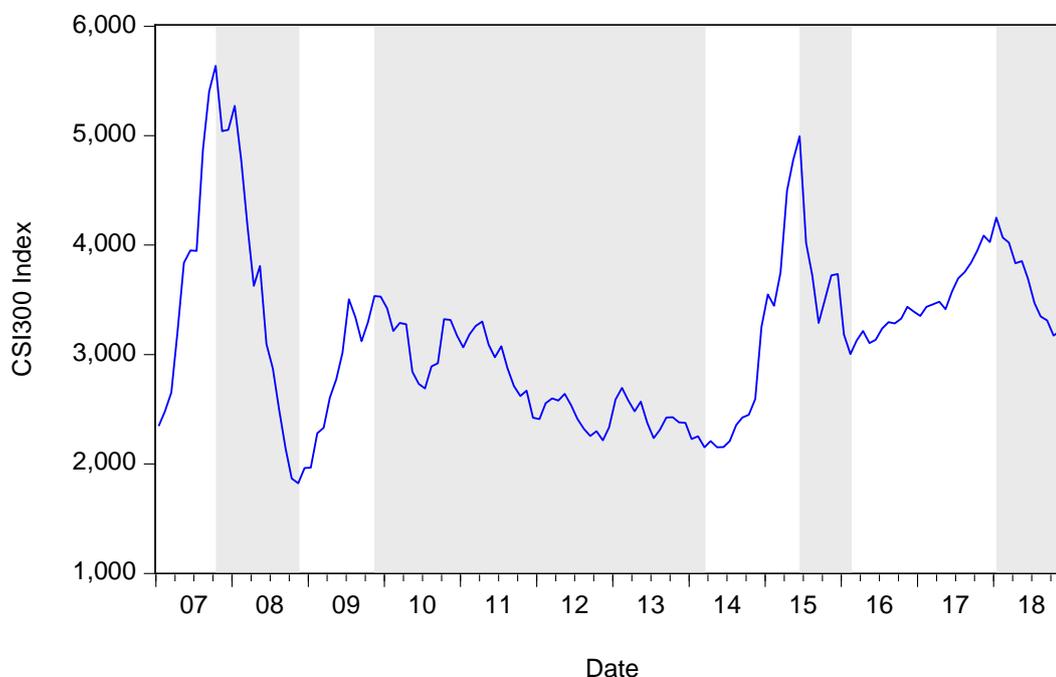


Figure-2. The results of the identification of the bull and bear markets.

Source: Organized according to Wind database.

The results of the robustness test are reported in Table 3 according to Equation 9. The results show that our previous work of bull and bear market classification of the stock market is statistically significant at the 5% level. The coefficient of constant is $-1.24e-03$ and the coefficient of the dummy variable (bull market = 1, bear market = 0) is $3.67e-03$.

Table-3. Empirical results of the robustness check.

Variable	Coefficient	t-Statistic	Prob.
α_0	$-1.24e-03$	-2.85	0.00
$D_t(\text{bull market}=1, \text{bear market}=0)$	$3.67e-03$	5.22	0.00

Note: $R^2 = 0.161170$, F-statistic=27.28350 ($p=0.000001$).

The results on the analysis of the changes in $\Delta CoVaR$ are presented in Table 4. Two observations are worthy of special remarks.

First, the risk contributions of stock sectors under the bear market regime are in general significantly higher than those under the bull market regime with several exceptions. Specifically, the average systemic risk contribution of the sector to the stock market under the bear market increased significantly from $\Delta CoVaR_{Bear} = -1.05\%$ to $\Delta CoVaR_{Bull} = -1.49\%$ in our full sample. The same pattern can be observed in the bull-bear market cycle: first cycle ($\Delta CoVaR_{Bull} = -1.65\%$ and $\Delta CoVaR_{Bear} = -1.65\%$), second cycle

($\Delta CoVaR_{Bull} = -1.99\%$ and $\Delta CoVaR_{Bear} = -1.19\%$), third cycle($\Delta CoVaR_{Bull} = -1.52\%$ and $\Delta CoVaR_{Bear} = -0.95\%$) and fourth cycle ($\Delta CoVaR_{Bull} = -0.83\%$ and $\Delta CoVaR_{Bear} = -0.43\%$).

To explain this, according to a large number of empirical studies, the stock market in China not only acts in the role of economic barometer, but also reflects the obvious characteristics of a policy driven market. This means that in the operation process of China's stock market, the bull market is often driven by the major economic policies instead of basic fundamentals. This fact leads to the continuous accumulation of systemic risk in the bull market. When the policy effect ends, a systemic crash of the stock market is inevitable (Wei, 2016). To be more specific, systemic risk is accumulated in the bull market and released in the bear market. Therefore, the systemic risk under a bull market is more significant than under a bear market.

Second, the most significant contributors to the systemic risk, or the systemically important stock sectors, change frequently under different stock market regimes. This is because of the risk spillover effect of international financial market and the effect of the domestic policies and industry characteristics. To be more specific,

- i) During the first bull-bear market cycle from January 2007 to December 2008, the financials sector made the highest risk contribution to the stock market under the bull market regime. This because in the beginning phase of the United States subprime crisis, the financials sector was most threatened. Furthermore, with respect to financial liberalization and international market interdependence after its accession to the WTO in 2001, China's stock market with witnessed increasing interdependence of equity markets among developed and/or developing economies (Sahabuddin *et al.*, 2018). As market co-movement has popularly observed (He *et al.*, 2014) this has resulted in the financials sector being the most affected in the Chinese stock market and the top systemic risk contributor. The telecommunication services sector under the bear market regime contributes most to the systemic risk because the restructuring of the telecommunications industry in 2008 aggravated the uncertainty of this sector.
- ii) During the second bull-bear market cycle from December 2008 to March 2014, the consumer staple sector is the most significant risk contributor to the stock market. This is because, after the global financial crisis in 2008 that resulted from the American subprime mortgage crisis, the European debt crisis brought unrest to the whole world and the finance sector. Pointed out that financial shocks have plunged China's economy into a prolonged recession, which has led to a sharp decline in output, consumption, investment and employment. Thus the consumer staple sector is affected by this recession and making it the most systemically risky contribution to the stock market at this stage.
- iii) During the third bull-bear market cycle from April 2014 to February 2016, the materials sector made the highest risk contribution to the stock market under the bull market regime. The fundamental reason for this result is that the general rise in commodity prices in the international market has led to a sharp decline in the performance of listed companies related to materials. Whereas under the bear market regime, because the government began to call for "mass entrepreneurship and innovation", the information technology sector was significantly affected by the "double innovation policy," and contributed the most to the risk of the stock market during this period.
- iv) During the fourth bull-bear market cycle from March 2016 to December 2018, the energy sector made the highest risk contribution to the stock market under the bull market regime whereas industrials sector contributes most under the bear market regime. For the energy sector, the process of destocking and reducing excess capacity brought the significant risk contribution of this sector to the stock market. The industrials sector, was affected by a series of internal and external factors such as deleveraging, the trade war, and dollar appreciation, and consequently contributes the most risk to the stock market.

Table-4. Results of $\Delta CoVaR$ (%) under bull and bear markets.

	2007.1 - 2007.9	2007.10 - 2008.11	2008.12 - 2009.10	2009.11 - 2014.3	2014.4- 2015.5	2.15.6- 2016.2	2016.3- 2017.12	2018.1- 2018.12
	$\Delta CoVaR_{Bull}$	$\Delta CoVaR_{Bear}$	$\Delta CoVaR_{Bull}$	$\Delta CoVaR_{Bear}$	$\Delta CoVaR_{Bull}$	$\Delta CoVaR_{Bear}$	$\Delta CoVaR_{Bull}$	$\Delta CoVaR_{Bear}$
Financials	-1.91 (1)	-1.28 (9)	-1.14 (7)	-1.88 (5)	-0.77 (7)	-0.74 (10)	-0.44 (4)	-0.71 (8)
Information_ Technology	-1.74 (2)	-1.33 (8)	-1.27 (5)	-1.97 (4)	-0.91 (6)	-2.12 (1)	-0.40 (8)	-0.81 (5)
Energy	-1.63 (3)	-2.22 (2)	-1.23 (6)	-1.87 (6)	-0.62 (8)	-1.36 (9)	-0.55 (1)	-0.54 (9)
Utilities	-1.50 (4)	-1.75 (3)	-0.86 (9)	-2.36 (2)	-0.60 (9)	-1.60 (4)	-0.44 (5)	-0.51 (10)
Industrials	-1.49 (5)	-1.47 (6)	-0.98 (8)	-2.32 (3)	-1.17 (4)	-1.53 (6)	-0.52 (3)	-1.23 (1)
Materials	-1.40 (6)	-1.12 (10)	-0.74 (10)	-1.85 (7)	-1.38 (1)	-1.87 (2)	-0.42 (7)	-0.77 (6)
Health_ Care	-1.39 (7)	-1.41 (7)	-1.32 (2)	-1.83 (8)	-1.34 (2)	-1.61 (3)	-0.37 (9)	-0.91 (3)
Consumer_ Discretionary	-1.27 (8)	-1.72 (4)	-1.28 (4)	-1.70 (9)	-1.25 (3)	-1.42 (7)	-0.43 (6)	-0.72 (7)
Telecommunication _ Services	-1.39 (9)	-2.47 (1)	-1.29 (3)	-1.31 (10)	-0.41 (10)	-1.57 (5)	-0.23 (10)	-0.86 (4)
Consumer _Staples	-0.93 (10)	-1.69 (5)	-1.80 (1)	-2.49 (1)	-1.00 (5)	-1.37 (8)	-0.51 (2)	-1.19 (2)
Mean	-1.65	-1.65	-1.19	-1.96	-0.95	-1.52	-0.43	-0.83
Correlation With Previous Ranking		0.36 (-0.31)	0.31 (0.04)	-0.20 (0.58)	-0.13 (0.73)	0.30 (0.41)	-0.71* (0.02)	

Note: The number in brackets is the rank of sector systemic risk contributions under different regimes. The last row presents the Spearman correlation.

5. CONCLUSIONS

This study aims to identify the risk contribution of each stock sector to China's stock market using daily data from January 4, 2008 to December 31, 2018. We employ the systemic risk measure proposed by Acharya *et al.* (2010), Conditional Value-at-Risk ($CoVaR$). The ten sectors used in the analysis are energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services and utilities. Our empirical results show that information technology, health care, telecommunication services contribute significantly to the stock market in the full sample. In order to uncover the hidden dynamics of risk contribution to China's stock market, this study applied the adjusted BB program to the CSI 300 index in order to capture bull and bear market regime. We find that sector risk contributions are significantly higher under bull markets than the bear market regime with several exceptions. We also find that the most significant contributors to systemic risk, or the systemically important stock sectors, changed frequently under different stock market regimes. In addition, our empirical results on the full sample and sub-samples under different market regimes suggest that, although there is widespread agreement that systemic risk was triggered and propagated by the financial sector, we should also pay attention to the risk contributions of other stock sectors.

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