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The Risk Spillover Effects of Securities Companies in China's Capital Market with the *CoVaR* Method

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Abstract

In China's capital market, securities companies are not only converging but also intertwined in business. Once in crisis, their risks may not only infect one another but also impact the whole market. Based on the *CoVaR* method, from both static and dynamic dimensions, this paper uses the quantile regression and principal component analysis to quantify the risk spillover effects between securities firms and the contributions of individual securities firms to the systemic risk of capital market, and studies the factors influencing the contributions. The results show that when in crisis, CITIC Securities contributes the most to the systemic risk, followed by Haitong Securities and others. Characteristics of securities firms have great influence on their risk contributions as well, such as leverage ratio, maturity mismatch, market scale and price-to-book ratio.

JEL Classification Numbers: G11, G24, G28
Keywords: Risk Spillover Effect; Securities Companies; Capital Market; *CoVaR*

1 Introduction

In 2015, stock market crash caused total market capitalization to lose 22 trillion yuan in just three weeks. During the stock market crash, the total value of equity assets in stock market eliminated exceeded 25 trillion yuan, accounting for 36% of GDP in 2015. China's capital market cannot be ignored for accumulating systemic financial risk. Since the 1970s, systemic risk exposure events such as financial crises triggered by asset price fluctuations have become more frequent. Systemic risk has gradually entered the eyes of the public, attracting the attention of regulators, and industrial and academic circles, especially after the subprime mortgage crisis. In July 2017, The Fifth National Financial Work Conference in China clearly stated that "preventing systemic financial risks is the eternal theme of financial work," and in October, the

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report of the 19th Congress of the Communist Party of China called for “improving the financial supervision system and maintaining the bottom line of systemic financial risks.” There have been abundant studies on systemic risks, but they mainly focused on the entire financial system or banking system. There is relatively little systemic risks research on capital market. The events of systemic risk exposure in China's capital market such as stock market crashes happened frequently, and there have been 9 stock market crashes in the past 28 years since the establishment of the stock market. Although the previous stock market crashes did not cause devastating impact on the real economy or even the financial system, they had a major negative impact on the funding function of the capital market. As the size of China's capital market continues to grow, the influence on the financial system and real economy has increased significantly. If the stock market crash occurs again, it is likely to jeopardize the stability of the financial system and even become an important channel or fuse for the transmission of systemic financial risk to the real economy. As intermediaries of the capital market, securities companies play an important role in the direct investment and financing system, and are likely to become key nodes in the process of systemic risk transmission. Therefore, studying the role of brokers in the process of systemic risk accumulation and exposure and analyzing the influencing factors of their risk contributions has important significance for improving the supervision of capital market.

A profound lesson learned from the financial crisis in 2008 is that the steady operation of a single financial institution does not guarantee the stability of the financial system. The same is true of the capital market as a subsystem of the financial system. In the capital market, brokers, as the most important intermediary, not only link investment and financing, but also participate in investment and financing, and play an important role in enhancing market liquidity. It can be seen from the previous stock market crashes that the steady operation of individual brokerages cannot ensure the continued stability of the capital market; instead they may become a booster for stock market crashes, especially brokers with systemic importance. During the stock market crash in 2015, the performance of securities companies was relatively stable, and there was no bankruptcy liquidation event. Before the stock market crash, brokerages provided a large number of leveraged funds for stock market through margin financing, stock pledge and channels of shadow margin financing, which greatly increased systemic risk accumulation while improving their own performance. When the stock market crashed, the liquidity of the market was sharply aggravated by forced liquidation, raising the counterparty's margin and cutting off the channels.

There was no brokerage bankruptcy during the stock market crash in 2015, in which the government rescuing the market played an important role. From a macro perspective, if government bailouts cannot fundamentally improve the efficiency of capital allocation, the inherent risks of the entire market will not be eliminated by the bailouts, but more likely be hidden. The accumulating risk exacerbates the risk exposure of brokers. In extreme cases, it may even lead to “group” operation failure of most brokers, which triggers systemic risk exposure in the capital market and has a huge negative impact on the economic and financial system. From a micro perspective, Chinese brokerages' business is relatively convergent, their investment products are similar, and most of their shareholding structure is state-owned or state-shared, which make them rely heavily on the government's rescue route, easily cause moral hazard and enhance the risk preference of brokerage managers under the market-based compensation incentive mechanism. In addition, brokers have close relationship with each other, which enables them to act as a buffer against risk, enhancing the risk tolerance of the entire system. On the other hand, their close relationship may become a booster for capital market stock crash when systemic risk is exposed, and the risk of one broker may be transmitted to related brokers in terms of business and asset, which will aggravate market panic.

Based on the effective market concept, this paper uses market data such as stock price, macro state variables and micro-features of securities firms to conduct empirical analysis, and attempts to study the risk spillovers between listed brokers and their contributions to capital market risk from a static perspective. In addition, we analyze the changes in the risk contributions of brokers to capital market and the factors that cause such changes from a dynamic perspective.

2 Literature Review

The theoretical basis for studying the risk spillover effects of capital market securities companies is market externality. Excessive risk taking and high leverage of securities companies will inevitably lead to an increase in their own risks. They will also cause risk spillovers through channels such as business transactions or asset price linkages. When the stock market prospers, the excess returns are owned by brokers themselves. However, when the stock market crashes, the risks borne by brokers are shared by all market participants. This is typical negative externality. If financial institutions do not bear the corresponding costs of risk spillovers, it will encourage other financial institutions to adopt the same risk behavior, and thereby increase systemic risk. In a fierce competition environment, the negative externality is particularly prominent among brokers with similar business in China's capital market.

In 1994, investment bank J. P. Morgan introduced Value at Risk (*VaR*) into the risk control model to quantify the maximum potential loss faced by financial institutions as an indicator. *VaR* exported through institutional operation data is very explicit and less theoretically confined, and is widely used by financial institutions in the field of risk management. However, *VaR* mainly measures the risks of individual financial institutions regardless of the risk spillovers among institutions or the contributions of individual institutions to systemic risks. In reality, when some institutions, particularly large or highly connected ones (commonly known as "Too big to fall, too relevant to fall") are in crisis, their risks are bound to be transmitted to other institutions or markets, causing a chain reaction throughout the system. Investigating risk against a single institution rather than the entire financial system will be negative incentive for financial institutions to take excessive risk. In addition, it is difficult to fully consider the risk spillover in times of crisis when measuring risk for individual financial institution by *VaR*. In view of the limitations of *VaR*, Adrian and Brunnermeier (2008) proposed *CoVaR* method (Conditional Value at Risk, "Co" includes condition, contagion and comovement), which overcomes the shortcomings of the traditional *VaR* method and regards the financial system as a whole, quantifying the risk contribution of individual financial institutions to the entire system in crisis and the risk spillover effects between different financial institutions. Adrian and Brunnermeier (2016) refined the *CoVaR* method, using the quantile regression technique to study the tail risk spillover effects between financial institutions from the two dimensions of cross section and time series. In the cross-sectional dimension, they analyzed the inter-institutional risk contagion and the agency's risk contribution to the system. In the time series dimension, they used the macro state variables to study the dynamic changes in the contribution of institutions to systemic risk, and to analyze the institutional characteristics that influence the dynamic changes of risk contributions. This method also captures the risk characteristics of the tail of financial time series data, which considers the risk spillover effects under extreme conditions and conforms to the "spike and thick tail" characteristics of financial time series data. At present, the *CoVaR* method has been widely used in the fields of quantitative evaluation and financial supervision as an effective indicator for investigating inter-institutional risk conduction trends, and has gradually become the mainstream method for studying systemic risks.

There are many measurement methods of *CoVaR*, and the quantile regression method is only one of them. Many scholars have proposed new estimation methods or innovative methods based on quantile regression. Mainik and Schaanning (2014) used the copulas method to estimate *CoVaR* and compared the characteristics of alternative systemic risk measures. Oh and Patton (2018) used Copulas method to estimate *CoVaR* and other related systemic risk measurement based on CDS spreads. The advantage of the copulas method lies in its ability to estimate the overall joint distribution of features, including fat tail and heteroscedasticity. Girardi and Ergun (2013) used the multivariate GARCH model to estimate *CoVaR*, which can describe the dynamics of institutions' contribution to systemic risk in more details. This method of making assumptions about the distribution can more accurately measure the *CoVaR* of institutions. White et al. (2010) proposed dynamic *CoVaR* estimation in combination with the quantile regression and GARCH methods. Chinese scholars have also conducted innovative research on *CoVaR*. By integrating the EVT-Copula and *CoVaR* models, Liu et al. (2011) constructed the EVT-Copula-*CoVaR* model to study the risk spillover effects of the US stock market. Chen and Wang (2014) evaluated the systemic risk of financial institutions based on an extreme quantile regression technique, which approximates the tail features of the real conditional quantile model. Based on the EVT-GARCH-*CoVaR* model, Zhang et al. (2015) measured the contributions of individual financial institutions to the systemic risk of the financial system and their time variation under extreme market condition. Dai and Yin (2017) used the five factors in the Fama five-factors model as risk factors for measuring *CoVaR* and statistically analyzed the risk comovement between individual stocks and industries. Chen and Zhou (2017) combined the single factor MSV model and *CoVaR* model to analyze the risk spillover effect between China's stock market and ETF market. Zhang and Li (2017) adopted the DCC-MGARCH method to construct the time-varying covariance coefficient *CoVaR* and conditional β index, and measured the degree of risk spillover between banks.

In addition to the *CoVaR* approach, there are many other ways to measure systemic risk. After the subprime mortgage crisis, international institutions such as the International Monetary Fund (IMF), the Financial Stability Board (FSB), and the Basel Committee (BIS) have used the regulatory data and proposed the indicator approach highlighting scale, relevance, substitutability, complexity, and global activities. Liu and Zhu (2011) combined the financial system vulnerability assessment framework to analyze the factors of financial structure vulnerability, and constructed a measurement framework suitable for the systemic risk of China's banking industry. The indicator method has the advantages of simplicity, clarity, and easy supervision, but also has some shortcomings such as data unavailability and metric lag. In recent years, many scholars have developed different risk measurement methods using market data. Huang et al. (2012) proposed a disaster insurance premium (DIP) model that used CDS spreads to evaluate the systemic importance of financial institutions by assessing the premiums that major financial institutions need to survive in crisis. Billio et al. (2012) used principal component analysis and Granger causality test to construct a systemic risk measurement method based on the correlation among hedge funds, banks, brokers and insurance companies. On the basis of cross-sectional distribution of systemic risk metrics, such as marginal expectation shortage, Δ*CoVaR* and network connectivity, Billio et al. (2016) used different entropy methods to analyze the temporal evolution of European systemic risk and put forward a new banking crisis early warning indicator. Dube (2016) examined the nature of stock market returns using a t-DCC model and investigated whether multivariate volatility models can characterize and quantify market risk. Acharya et al. (2017) proposed a systemic expected loss (SES) and marginal expected loss (MES) method based on expected loss (ES). By the use of marginal expected loss (MES), Brownlees and Engle (2017) measured the systemic risk of financial institutions by Monte Carlo simulation experiment with such data as scale, leverage and risk. Chinese scholars are paying more attention to systemic risk measurement as well. Ma et al. (2007) used the matrix method to estimate the bilateral infection risk of banking system. He believed that the impact of inter-bank market crisis mainly depend on the types of inducing factors, the change in the loss rate and the inter-bank linkages. Jia (2011) analyzed risk diffusion mechanism with the financial network model, incorporated financial network structure into systemic risk measurement, and evaluated the systemic importance of financial institution in terms of "direct contribution" and "indirect participation". Zhao et al. (2013) compared the relationship between marginal expected loss (MES) and conditional risk value (*CoVaR*) by theoretical and empirical analysis of Chinese banking. Meng and Wei (2018) measured the systematic correlation level risk and systematic correlation shock risk with mixed vine copula method and investigated their relationship with stock return.

Based on Adrian and Brunnermeier (2016), the present study focuses on the systemic risk of capital market and takes capital market brokers as the research object. We introduce principal component analysis method innovatively, attempting to avoid the over-fitting of macro state variables and autocorrelation problem among variables. Using the public data of brokers listed on A-share market, we study the risk spillover effects between brokers and their risk contributions to the capital market from the cross-sectional dimension, and analyze the dynamic changes and influencing factors of brokers' contributions to the systemic risk of the capital market from the time series dimension.

3 Research design

3.1 Sample and data

Considering the availability of data, listed brokers are selected as representatives, and the weekly logarithmic yield of the stock closing price are used in the study, as stock price can reflect not only a lot of information about brokers, but also market information such as market risk and liquidity risk. According to the industry classification of CSRC (China Securities Regulatory Comission), there are 34 capital market service institutions in the A-share market. Taking into account the time of listing, scale, business structure, property and other factors, we select 19 institutions of them as research samples. The time interval is from October 2006 to May 2017, with a time span of 10 years and 8 months. Among them, Shenwan Hongyuan Securities' pre-merger data is replaced by Hongyuan Securities data. Huatai Securities data began on February 26, 2010, China Merchants Securities data began on November 17, 2009, Founder Securities data began on August 10, 2011, Everbright Securities data began on August 18, 2009, Western Securities data began on May 3, 2012, Industrial Securities data began on October 13, 2010, Soochow Securities data began on December 12, 2011, Shanxi Securities data began on November 15, 2010, and Pacific Securities data began on December 28, 2007. Capital market data as a system is represented by the brokerage index (stock code: 886054). All data come from the Wind database.

3.2 Model Design

1. Static estimation method of $\Delta CoVaR$

VaR_q^i represents the maximum potential return loss of brokerage *i*'s stock price in the next week under certain confidence level. The mathematical expression is: $\Pr(X^i \leqslant VaR_q^i)=q\,(0<q<1)$, which is similar to the *q*-quantile of yield distribution. Among them, X^i represents the weekly logarithmic yield of the closing price of brokerage *i* stock, mathematically expressed as: $X^i=100\times\mathrm{Ln}(P_t^i/P_{t-1}^i)$, and P_t^i represents the closing price of brokerage *i* stock at time *t*.

$CoVaR_q^{j/i}$ denotes the VaR_q of securities firm *j* in the condition that securities firm *i* is under state $C(X^i)$. It is referred to as the conditional value at risk, mathematically expressed as: $\Pr(X^j/C(X^i))\leqq CoVaR_q^{j/C(x^i)})=q$. As can be seen from the *CoVaR* calculation method, like *VaR*, *CoVaR* is actually similar to a quantile. In order to simplify calculation, $C(X^i)$is divided into two states: crisis state ($X^i=VaR_q^i$) and normal state ($X^i=VaR_{50\%}^i$). The $\Delta CoVaR_q^{j/i}$ formula is as follows:

$$\Delta CoVaR_q^{j/i} = CoVaR_q^{j/X^i=VaR_q^i} - CoVaR_q^{j/X^i=VaR_{50\%}^i} \quad (1)$$

$\Delta CoVaR_q^{j/i}$ represents the difference between the *CoVaR* of securities firm *j* under the condition that securities firm *i* is in crisis state VaR_q^i and in normal state $VaR_{50\%}^i$. It is referred to as the increment of *CoVaR*, which reflects the risk increase of brokerage *j* when brokerage *i* is in crisis. Considering the size of institutions, the increment can be expressed as:

$$\Delta^{\$}CoVaR_q^{j/i} = {}^{\$}Size^i \times \Delta CoVaR_q^{j/i} \quad (2)$$

${}^{\$}Size^i$ is represented by the market value of brokerage *i*'s equity. The size of the brokerage is considered to better examine the risk spillover of the brokerage and its contribution to systemic risk.

When *j* represents the capital market, $\Delta CoVaR_q^{system/i}$ indicates the difference between the *CoVaR* of the capital market under the condition that securities firm *i* is in crisis state VaR_q^i and in normal state $VaR_{50\%}^i$, that is, the risk spillover increment for the capital market when brokerage *i* is in crisis, which is mathematically calculated as:

$$\Delta CoVaR_q^{system/i} = CoVaR_q^{system/x^i=VaR_q^i} - CoVaR_q^{system/x^i=VaR_{50\%}^i} \quad (3)$$

Considering the size of institutions, the increment can be expressed as:

$$\Delta^{\$}CoVaR_q^{system/i} = {}^{\$}Size^i \times \Delta CoVaR_q^{system/i} \quad (4)$$

We mainly calculate *CoVaR* by quantile regression. The quantile regression is a new method for estimating *VaR*. Instead of focusing on the probability distribution of yield, it is simple and clear to estimate *VaR* based on a quantile. Compared with the mean regression of the least squares method, the quantile regression can better analyze the tail effect of variables, and is suitable for describing the "spike and thick tail" features that are common in financial time series data. Unlike the analysis of specific quantile points, the quantile regression can perform more comprehensive data analysis on different quantile segments of data. The fitting results are more robust, especially when there are outliers in the data. We assume a linear relationship between the explained variables and the explanatory variables. Using the linear quantile regression, the conditional cumulative distribution function of *y* is denoted as $F_y(y/x)$ given *x*. The inverse function of the overall *q* ($0<q<1$) quantile can be expressed as:

$$F_y^{-1}(q \mid x) = \inf\{y : F_y(y \mid x) \geq q\}\text{, and } F_y^{-1}(q \mid x) = x^T \beta_q(q) \text{。} \quad (5)$$

Where β_q is the *q*-quantile regression coefficient, and its estimator $\hat{\beta}_q$ is defined by the following equation minimization problem:

$$\min_{\beta_q} \left(\sum_{y \geq x^T \beta_q} q \left| y_i - x_i^T \beta_q \right| + \sum_{y < x^T \beta_q} (1-q) \left| y_i - x_i^T \beta_q \right| \right) \quad (6)$$

The crisis state is represented by a very small *q* value (such as 5%, 2.5%, 1%). In order to measure the risk spillover effects between brokers in the capital market and their contributions to the systemic risk, the following model is established:

$$X^{j} = \alpha_q^{j/i} + \beta_q^{j/i} \times X^{i} + \varepsilon \quad (7)$$

The estimated result of the above equation (7) is:

$$\hat{X}_q^{j/i} = \hat{\alpha}_q^{j/i} + \hat{\beta}_q^{j/i} \times X^{i} \quad (8)$$

X^i and X^j represent the logarithmic yield of brokers *i* and *j*, and ε is a random disturbance term. The estimated parameters $\hat{\alpha}_q^{j/i}$ and $\hat{\beta}_q^{j/i}$, and regression estimated value $\hat{X}_{\mathrm{q}}^{j/i}$ are obtained by performing *q*-quantile regression on equation (7). To simplify calculation, all samples' sequences are arranged in order from small to large, and the corresponding value of *q* quantile is selected as the approximate substitute value of the $VaR_q^{\,i}$ of broker *i*. According to the definition of $\Delta CoVaR_q^{\,j/i}$, the measurement values are obtained from the following equations:

$$CoVaR_q^{j/i} = \hat{X}_{\mathrm{q}}^{j/i} \quad (9)$$

$$CoVaR_q^{j/i} = CoVaR_q^{j/x^i = VaR_{\mathrm{q}}^i} = \hat{\alpha}_q^{j/i} + \hat{\beta}_q^{j/i} \times VaR_q^i \quad (10)$$

The following equation are derived from equation (9) and (10):

$$\Delta CoVaR_q^{j/i} = CoVaR_q^{j/x^i = VaR_{\mathrm{q}}^i} - CoVaR_q^{j/x^i = VaR_{50\%}^i} = \hat{\beta}_q^{j/i} \times (VaR_q^i - VaR_{50\%}^i) \quad (11)$$

Similarly, when *j* represents the capital market, $\Delta CoVaR_q^{\,system/i}$ and $\Delta^{\$}CoVaR_q^{\,system/i}$ can be calculated.

2. Dynamic estimation method of Δ*CoVaR*

The risk contribution of brokerage *i* to the capital market can be characterized by the conditional distribution of X^i and X^{system}, and the conditional distribution of X^i and X^{system} can respectively be represented by a conditional distribution containing state variables. To consider the time-varying feature, a vector *M* (consisting of state variables) is introduced to estimate $VaR_{q,t}^{\,i}$ and $CoVaR_{q,t}^{\,j/i}$. Assuming that the relationships between the variables are still linear and considering that the risk conduction has hysteresis, the estimation is performed using the lag phase 1 of the state variables. X_t^i and X_t^{system} respectively represent the logarithmic yield sequences for the t-week in institution *i* and the brokerage index (representing the capital market). The parameters are obtained by the following quantile regression:

$$X_t^{\,i} = \alpha_q^{\,i} + \gamma_q^{\,i} M_{t-1} + \varepsilon_{q,t}^{i} \quad (12)$$

$$X_t^{\,system/i} = \alpha_q^{\,system/i} + \gamma_q^{\,system/i} M_{t-1} + \beta_q^{system/i} X_t^i + \varepsilon_{q,t}^{system/i} \quad (13)$$

Estimated results can be obtained from quantile regression:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \quad (14)$$

$$CoVaR_{q,t}^i = \hat{\alpha}_q^{\,system/i} + \hat{\gamma}_q^{\,system/i} M_{t-1} + \hat{\beta}_q^{system/i} VaR_{q,t}^i \quad (15)$$

Since the principal component analysis method is introduced in this paper, the state variable M_t is converted into M_t', so (12) (13) (14) (15) are transformed into:

$$X_t^{\,i} = \alpha_q^{\,i} + \gamma_q^{\,i} M_{t-1}' + \varepsilon_{q,t}^{i} \tag{16}$$

$$X_t^{\,system/i} = \alpha_q^{\,system/i} + \gamma_q^{\,system/i} M_{t-1}' + \beta_q^{system/i} X_t^{\,i} + \varepsilon_{q,t}^{system/i} \tag{17}$$

$$VaR_{q,t}^{i} = \hat{\alpha}_q^{i} + \hat{\gamma}_q^{i} M_{t-1}' \tag{18}$$

$$CoVaR_{q,t}^{i} = \hat{\alpha}_q^{\,system/i} + \hat{\gamma}_q^{\,system/i} M_{t-1}' + \hat{\beta}_q^{system/i} VaR_{q,t}^{i} \tag{19}$$

Finally, calculating $\Delta CoVaR_{q,t}^{i}$ of each institution *i*, the formula is as follows:

$$\Delta CoVaR_{q,t}^{i} = CoVaR_{q,t}^{i} - CoVaR_{50\%,t}^{i} = \hat{\beta}_q^{system/i}(VaR_{q,t}^{i} - VaR_{50\%,t}^{i}) \tag{20}$$

Considering the size of institutions, the increment can be expressed as:

$$\Delta^{\$}CoVaR_{q,t}^{i} = {}^{\$}Size_t^{\,i} \times \Delta CoVaR_{q,t}^{i} \tag{21}$$

By the equations above we get the weekly time series data of $\Delta CoVaR_{q,t}{}^{i}$ and $\Delta^{\$}CoVaR_{q,t}{}^{i}$. It should be noted that the unconditional loss risk $VaR_{q,t}{}^{i}$ and the conditional loss risk $\Delta CoVaR_{q,t}{}^{system/i}$ gained from the quantile regression of state variables are not a causal relationship, but a tail correlation based on statistical analysis.

4 Static empirical results and analysis

4.1 The analysis of data feature

The data selected in this paper includes two stock market crashes (2008 and 2015), as well as the international financial crisis (subprime mortgage crisis in 2007 and European debt crisis in 2011), so the empirical results can better capture the risk spillover effects between brokers and the risk contributions of brokers to capital market under extreme cases. The descriptive statistics of the sample data are shown in Table 1. EVIEWS8.0 software is used for analysis.

Table 1: Summary of the statistics of weekly logarithmic yield of the samples

No.	Securities firm	Mean	Maximum	Minimum	S.D.	Skewness	Kurtosis	J-B Statistics	P-Value
1	Securities index	0.262	31.42	-20.92	6.64	0.56	5.94	223.48	0
2	CITIC	0.019	32.55	-41.73	7.26	-0.21	8.49	684.95	0
3	Haitong	0.177	47.60	-88.21	8.79	-1.44	24.93	11071.05	0
4	Huatai	-0.035	38.65	-22.21	5.08	1.39	13.31	2579.97	0
5	Guangfa	0.080	155.69	-73.81	9.10	8.43	167.41	618031.90	0
6	Shenwan Hongyuan	0.041	37.31	-83.07	8.33	-1.43	22.84	9088.67	0
7	China Merchants	-0.125	36.19	-28.07	4.87	1.08	15.96	3907.15	0
8	Founder	0.071	35.96	-16.96	4.71	1.61	16.35	4269.26	0
9	Everbright	-0.088	36.43	-23.21	5.35	0.83	11.59	1733.01	0
10	Western	-0.016	35.55	-66.09	5.97	-1.61	36.36	25417.08	0
11	Changjiang	0.050	135.19	-75.80	9.52	4.45	84.04	150375.40	0
12	Industrial	-0.163	26.51	-67.81	5.71	-2.57	41.17	33557.80	0
13	Guoyuan	0.038	118.51	-38.65	8.67	4.72	67.87	97230.38	0
14	Soochow	0.070	26.67	-23.31	4.60	0.44	9.63	1011.87	0
15	Guojin	0.091	78.26	-72.76	9.85	-0.45	20.68	7092.67	0
16	Shanxi	-0.058	29.21	-21.71	4.79	0.40	10.53	1298.69	0
17	Southwest	0.139	47.68	-74.22	7.87	-0.79	20.41	6918.71	0
18	The Pacific Ocean	-0.433	43.68	-40.14	6.83	0.03	12.03	1844.06	0
19	Guohai	0.087	110.16	-82.95	8.11	2.72	85.31	153960.60	0
20	Northeast	0.002	127.59	-73.89	9.59	3.64	66.35	92008.80	0

Data source: Organized according to Wind database

It can be seen from the statistics that the distribution of the sample data are in line with the “peak and thick tail” characteristics of the financial time series data. For the time series of the yield, we use the quantile regression to estimate the risk spillover effects between brokers and their risk contributions to the capital market, and *q* value takes 1%.

4.2 Risk spillover effects between brokers

We select six brokers including CITIC Securities, Haitong Securities, Changjiang Securities, Guojin Securities, Southwest Securities and Northeast Securities for research (excluding suspension data) as they represent large-, medium- and small-scale brokerages respectively. $^{\$}Size^{i}$ represents brokerage i's market value (unit: 100 million yuan) calculated by the closing price on May 31, 2017. The empirical results are shown in Table 2 (the intercept is not considered). The values in parentheses are the corresponding *t* statistics, and all statistical results are significant.

Table 2: Measurement results of the risk spillover effects among six listed brokers

j	i	$x^i = VaR_q^i$	$x^i = VaR_{50\%}^i$	$\hat{\beta}_q^{j/i}$	$\Delta CoVaR_q^{j/i}$	$^{\$}Size^i$	$\Delta^{\$} CoVaR_q^{j/i}$
CITIC	Haitong	-23.69	-0.21	0.72 (72.41)	-16.95	1630.28	-276.40
Haitong	CITIC	-19.90	-0.01	0.82 (97.98)	-16.39	1945.35	-318.76
CITIC	Changjiang	-20.45	-0.24	0.67 (58.62)	-13.47	518.66	-69.87
Changjiang	CITIC	-19.90	-0.01	0.73 (68.47)	-14.58	1945.35	-283.62
CITIC	Guojin	-20.75	0.16	0.52 (39.89)	-10.80	361.71	-39.05
Guojin	CITIC	-19.90	-0.01	0.54 (10.00)	-10.65	1945.35	-207.18
CITIC	Southwest	-19.39	-0.12	0.57 (48.39)	-10.97	308.79	-33.89
Southwest	CITIC	-19.90	-0.01	0.58 (52.64)	-11.51	1945.35	-223.84
CITIC	Northeast	-19.89	-0.05	0.67 (53.32)	-13.28	226.79	-30.11
Northeast	CITIC	-19.90	-0.01	0.78 (72.38)	-15.59	1945.35	-303.23
Haitong	Changjiang	-20.45	-0.24	0.69 (60.19)	-13.94	518.66	-72.28
Changjiang	Haitong	-23.69	-0.21	0.63 (52.06)	-14.81	1630.28	-241.37
Haitong	Guojin	-20.75	0.16	0.49 (45.44)	-10.15	361.71	-36.70
Guojin	Haitong	-23.69	-0.21	0.60 (40.79)	-14.16	1630.28	-230.84
Haitong	Southwest	-19.39	-0.12	0.60 (48.58)	-11.50	308.79	-35.51
Southwest	Haitong	-23.69	-0.21	0.53 (38.45)	-12.39	1630.28	-201.95
Haitong	Northeast	-19.89	-0.05	0.63 (64.33)	-12.53	226.79	-28.41
Northeast	Haitong	-23.69	-0.21	0.63 (46.26)	-14.87	1630.28	-242.44
Changjiang	Guojin	-20.75	0.16	0.48 (33.85)	-10.06	361.71	-36.39
Guojin	Changjiang	-20.45	-0.24	0.67 (53.06)	-13.46	518.66	-69.79

Changjiang	Southwest	-19.39	-0.12	0.69 (45.26)	-13.27	308.79	-40.98
Southwest	Changjiang	-20.45	-0.24	0.65 (65.77)	-13.03	518.66	-67.61
Changjiang	Northeast	-19.89	-0.05	0.73 (76.97)	-14.43	226.79	-32.73
Northeast	Changjiang	-20.45	-0.24	0.81 (82.39)	-16.42	518.66	-85.14
Guojin	Southwest	-19.39	-0.12	0.61 (38.24)	-11.68	308.79	-36.06
Southwest	Guojin	-20.75	0.16	0.37 (25.82)	-7.63	361.71	-27.61
Guojin	Northeast	-19.89	-0.05	0.69 (56.68)	-13.66	226.79	-30.97
Northeast	Guojin	-20.75	0.16	0.52 (33.55)	-10.86	361.71	-39.27
Southwest	Northeast	-19.89	-0.05	0.59 (47.06)	-11.66	226.79	-26.44
Northeast	Southwest	-19.39	-0.12	0.67 (57.64)	-12.86	308.79	-39.71

Data source: Organized according to Wind database

The empirical results show that the $\Delta CoVaR_q^{j/i}$ values of all brokers are less than the corresponding VaR_q^i values, indicating that when a broker is in crisis, the risk spillover effect is less than the risk impact the broker has suffered. It is well understood that when a broker is in crisis, the risk born by it must be the greatest, and the impact of risk spillover on other institutions is relatively small. In addition, we can see that when a broker is in crisis, the risk spillover effects on other brokers are different. For example, CITIC Securities has a risk spillover effect of about -31.876 billion yuan on Haitong Securities, about -28.362 billion yuan on Changjiang Securities, about -20.718 billion yuan on Guojin Securities, about -22.384 billion yuan on Southwest Securities, and about -30.323 billion yuan on Northeast Securities. The same is true for other brokers. This is because different brokers have different relevance and different influence capabilities, so the risk spillover effects are unequal. In addition, the mutual spillover effects between any two brokers are different, that is, $\Delta CoVaR_q^{j/i} \neq \Delta CoVaR_q^{i/j}$ and $\Delta^{\$}CoVaR_q^{j/i} \neq \Delta^{\$}CoVaR_q^{i/j}$, which shows that regardless of a broker's scale, the risk spillover effect of brokerage *i* in crisis on brokerage *j* is different from that of brokerage *j* in crisis on brokerage *i*. This is because when different brokers are in crisis, the risks transmitted to other institutions are inevitably different due to their own characteristics and environmental factors.

Regardless of scale, observing from the average value of the risk spillover intensity $\Delta^{\$}CoVaR_q^{i/j}$ of broker *i* to other brokers, we can see that larger brokers have relatively stronger risk spillover intensity. When CITIC Securities, Haitong Securities, Changjiang Securities, Guojin Securities, Southwest Securities and Northeast

Securities are in crisis respectively, the average risk spillover intensity of each one of them to other brokers are -13.74%, -14.64%, -14.06%, -9.9%, -12.06%, -13.11%, respectively. This may be because the larger a brokerage is, the stronger influence it has on other brokers and the entire market. However, the risk spillover intensity and broker scale are not completely correspondent, indicating that there are other factors that influence the risk spillover intensity. Considering scale, observing from the average value of the risk spillover intensity $\Delta^{\$}CoVaR_q^{i/j}$ of broker i to other brokers, we can see that the larger a broker in crisis is, the greater its risk spillover intensity is. When CITIC Securities, Haitong Securities, Changjiang Securities, Guojin Securities, Southwest Securities and Northeast Securities are in crisis respectively, the average spillover intensity of each one of them to other brokers are -26.733 billion yuan, -23.86 billion yuan, -7.294 billion yuan, -3.581 billion yuan, -3.723 billion yuan, and -2.973 billion yuan, respectively. It can be seen that the risk spillover intensity of large-scale brokerages is further amplified when the impact of scale is considered.

Generally speaking, there is a significantly positive correlation between the scale of securities firms and risk spillover effects, as when brokerages with a larger size are in trouble, they have a greater impact on the entire market and their spillover effects are greater. Secondly, the tail correlation between brokers is also an important aspect that affects risk spillover effects, as brokers have different risk spillover impacts on others due to their difference in correlations of business, asset price, and shareholding structure with other brokers.

4.3 The risk contributions of individual brokers to the capital market

We select 19 listed brokers as research samples (excluding suspension data). $^{\$}Size^i$ represents the brokerage i's market value (unit: 100 million yuan) calculated by the closing price on May 31, 2017. The empirical results are shown in Table 3 (the intercept is not considered). The values in parentheses are the corresponding t statistics, and all statistical results are significant.

Table 3: Measurement results of the risk contributions of individual brokers to the capital market

System	i	$x^i = VaR^i_{1\%}$	$x^i = VaR^i_{50\%}$	$\hat{\beta}_q^{system/i}$	$\Delta CoVaR_q^{system/i}$	$^{\$}Size^i$	$\Delta^{\$}CoVaR_q^{system/i}$
Securities index	CITIC	-19.90	-0.01	0.95 (391.68)	-18.93	1945.35	-368.28
Securities index	Haitong	-23.69	-0.21	0.78 (78.19)	-18.21	1630.29	-296.86
Securities index	Huatai	-13.20	-0.42	0.77 (143.88)	-9.84	1189.26	-117.08
Securities index	Guangfa	-14.72	-0.51	0.71 (49.95)	-10.12	1227.78	-124.23
Securities index	Shenwan Hongyuan	-20.49	-0.15	0.77 (110.44)	-15.74	1143.23	-179.94
Securities	China	-14.90	-0.59	0.88	-12.62	1076.02	-135.78

index	Merchants			(110.47)			
Securities index	Founder	-15.56	-0.14	0.80 (103.27)	-12.41	741.71	-92.05
Securities index	Everbright	-15.54	-0.25	0.81 (138.64)	-12.35	673.43	-83.17
Securities index	Western	-20.10	-0.02	0.58 (40.11)	-11.60	478.00	-55.43
Securities index	Changjiang	-20.45	-0.24	0.74 (73.64)	-14.95	518.66	-77.53
Securities index	Industrial	-14.63	-0.52	0.80 (84.11)	-11.26	497.56	-56.03
Securities index	Guoyuan	-21.49	-0.07	0.74 (93.61)	-15.79	355.89	-56.21
Securities index	Soochow	-16.38	-0.08	0.74 (92.89)	-12.06	335.70	-40.50
Securities index	Guojin	-20.75	0.16	0.54 (51.19)	-11.37	361.71	-41.11
Securities index	Shanxi	-17.11	-0.30	0.73 (67.43)	-12.35	262.22	-32.39
Securities index	Southwest	-19.39	-0.12	0.67 (62.90)	-12.84	308.79	-39.65
Securities index	The Pacific Ocean	-20.13	-0.37	0.87 (97.70)	-17.19	274.02	-47.11
Securities index	Guohai	-22.90	-0.30	0.53 (32.20)	-11.97	227.22	-27.19
Securities index	Northeast	-19.89	-0.05	0.73 (77.61)	-14.44	226.79	-32.75

Data source: Organized according to Wind database

The empirical results show that all $\Delta CoVaR_q^{system/i}$ and $\Delta^{\$}CoVaR_q^{system/i}$ are negative, indicating that listed brokers in crisis have increased the systemic risk of capital market. Judged from the risk spillover intensity, when brokers are in crisis, CITIC Securities has the largest risk contribution to the capital market regardless of broker size; $\Delta CoVaR_q^{system/i}$ and $\Delta^{\$}CoVaR_q^{system/i}$ are -18.93% and -36.828 billion yuan, respectively. CITIC Securities is followed by Haitong Securities; $\Delta CoVaR_q^{system/i}$ and $\Delta^{\$}CoVaR_q^{system/i}$ are -18.21% and -29.686 billion yuan, respectively. This is basically in line with the actual situation. At present CITIC Securities and Haitong Securities are among the top ones in China in terms of scale, market influence and business. If one of them is in crisis, it will have a huge negative impact on the capital market. CITIC Securities and Haitong Securities are followed by Shenwan Hongyuan Securities, China Merchants Securities, Guangfa Securities and Huatai Securities, which have similar influence on the market, not only large in size, but also prominent in certain business areas. It can also be seen that although the scale of brokers are very important for their risk contributions to the capital market, the correlation between brokers and the capital market cannot be neglected. For example, the scale of Guangfa Securities is larger than that of Shenwan Hongyuan and China Merchants Securities, but it has less risk contribution to the capital market. Therefore, when considering the risk contribution of securities firms to capital market, it is necessary to consider not only scale but also correlation.

5 Dynamic empirical results and analysis

5.1 Principal component

To estimate dynamic $\Delta CoVaR_{q,t}^{system/i}$ and $VaR_{q,t}^{i}$, we select state variables vector M_t as common factors for measuring the *VaR* of brokers and capital market. The selected state variables should not only reflect the state of the capital market and be easy to observe, but also effectively capture the tail risk characteristics of the stock yield loss. Considering the abundance of the sample and the availability of data, we select the weekly data from the beginning of October 2006 to the end of May 2017 as the research object. The selected state variables include the following:

1. Market Return (MR): It is expressed by the weekly logarithmic yield of the CSI 300 Index, which is used to reflect the stock market income level.

2. Stock Volatility (MV): It is expressed by the GARCH volatility of the weekly logarithmic yield of the CSI 300 Index, which is used to characterize the volatility changes in the capital market.

3. Market Liquidity (ML): It is expressed by the March SHIBOR rate, used to reflect market liquidity supply.

4. TED Spread (TED): It is the difference between the interbank borrowing weighted average interest rate and the six-month fixed-rate government bond maturity yield, used to measure short-term liquidity risk.

5. Credit Spread (CS): It is expressed by the difference between the 10-year treasury yield and the 10-year corporate bond yield to reflect market risk premium and investment preference.

6. Term Spread (TS): It is expressed by the difference between the maturity yield of 10-year government bond and the maturity yield of 1-year government bond, which is used to reflect market risk and liquidity risk.

7. Bond market return (BMR): It is expressed by the weekly logarithmic rate of return of the CSI fully-debt (net) index, used to reflect the bond market's income level.

8. Dow Jones Industrial Average Return (DJIR): It is expressed by the weekly logarithmic rate of return of the Dow Jones Industrial Average, used to reflect the level of return of overseas stock markets.

9. Willingness to cross border capital arbitrage (WCA): It is expressed by the difference in the yield to maturity of the 10-year government bond between China and

the United States, used to reflect the risk of cross-border capital flow.

To estimating time-varying $CoVaR_t$ and VaR_t, state variables that have a systemic impact on the capital market are introduced. These variables are not factors that cause systemic risk, but conditional variables that vary with the conditional mean and conditional volatility of the risk measure. In order to avoid over-fitting, considering the availability of data, we strictly limit the number of state variables and further reduce the dimensionality of state variables vector M_t by principal component analysis. According to the results of principal component analysis, the nine state variables are reduced to three principal components Z_1, Z_2 and Z_3, and the analysis results are shown in Table 4. It can be seen that the eigenvalues of these three principal components are all greater than 1, which can explain more than 60% of the information contained in all state variables.

Table 4: The statistical analysis result of state variable principal component

Number	Value	Difference	Proportion	Value	Proportion
Z_1	3.04	1.63	0.34	3.04	0.34
Z_2	1.40	0.39	0.16	4.44	0.49
Z_3	1.01	0.13	0.11	5.45	0.61
Z_4	0.89	0.14	0.10	6.34	0.70
Z_5	0.75	0.03	0.08	7.09	0.79
Z_6	0.72	0.10	0.08	7.81	0.87
Z_7	0.62	0.22	0.07	8.43	0.94
Z_8	0.40	0.23	0.04	8.83	0.98
Z_9	0.17	---	0.02	9.00	1.00

Data source: Organized according to Wind database

According to the factor load matrix (see Table 5), after obtaining the eigenvectors of the original correlation coefficient matrix, the expressions of the three principal components are obtained:

$$Z_1=0.50*ML-0.28*MV-0.1*MR-0.03*DJIR+0.1*BMR-0.43*TS+0.34*TED+0.38*CS+0.46*WCA$$

$$Z_2=-0.04*ML+0.42*MV-0.38*MR-0.49*DJIR+0.56*BMR+0.14*TS+0.23*TED+0.17*CS-0.12*WCA$$

$$Z_3=-0.04*ML+0.19*MV+0.61*MR+0.45*DJIR+0.4*BMR+0.15*TS+0.42*TED+0.15*CS-0.07*WCA$$

Table 5: Factor loading matrix for principal component analysis

Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
ML	0.50	-0.04	-0.04	-0.12	-0.12	0.32	0.22	-0.32	0.68
MV	-0.28	0.42	0.19	0.10	-0.04	0.75	0.19	0.31	-0.02
MR	-0.10	-0.38	0.61	-0.53	0.40	0.06	0.16	0.07	0.01
DJIR	-0.03	-0.49	0.45	0.54	-0.51	0.02	0.10	0.03	0.00
BMR	0.10	0.56	0.40	-0.20	-0.37	-0.49	0.24	0.15	0.11
TS	-0.43	0.14	0.15	0.41	0.42	-0.24	-0.11	-0.05	0.60
TED	0.34	0.23	0.42	0.07	0.06	0.15	-0.76	-0.19	-0.10
CS	0.38	0.17	0.15	0.41	0.46	-0.04	0.48	-0.26	-0.36
WCA	0.46	-0.12	-0.07	0.15	0.21	-0.06	-0.08	0.82	0.16

Data source: Organized according to Wind database

It can be seen from the principal component expression that the positive factors influencing the principal component Z_1 are market liquidity, cross border capital arbitrage, credit spread, liquidity spread, etc. The negative influence factors mainly include term spread, stock volatility, etc. So it can be inferred that the principal component Z_1 mainly represents the overall liquidity of the market. The main factors affecting the principal component Z_2 are bond market yield and stock market volatility. The negative factors mainly include the Dow Jones index yield and stock market yield. So the principal component Z_2 mainly represents the bond market's rate of return. The main positive factors of Z_3 are stock market yield, overseas stock market yield, liquidity spread, bond market yield, etc. There is basically no negative influence factor. So the principal component Z_3 represents the overall market income level. The main components Z_1 (market liquidity), Z_2 (bond market income) and Z_3 (market overall income) constitute a new state variable vector M_t', and the lag phase 1 M_{t-1}' is selected for quantile regression.

5.2 Estimated coefficient matrix

In this section, 19 listed brokers are selected as research samples, and the principal components are introduced into the state variables and analyzed by the quantile regression. The empirical results are shown in Table 6. The values in parentheses are the corresponding *t* statistics, and all statistical results are significant. The first three columns $\gamma^{i,1}$, $\gamma^{i,2}$, $\gamma^{i,3}$ indicate the conditional influence coefficient of the state variable on the tail risk of the broker's yield, and the last column $\beta^{system/i}$ indicates the conditional coefficient of broker *i*'s tail risk infection on the capital market.

Table 6: The parameter estimation results of 19 securities company

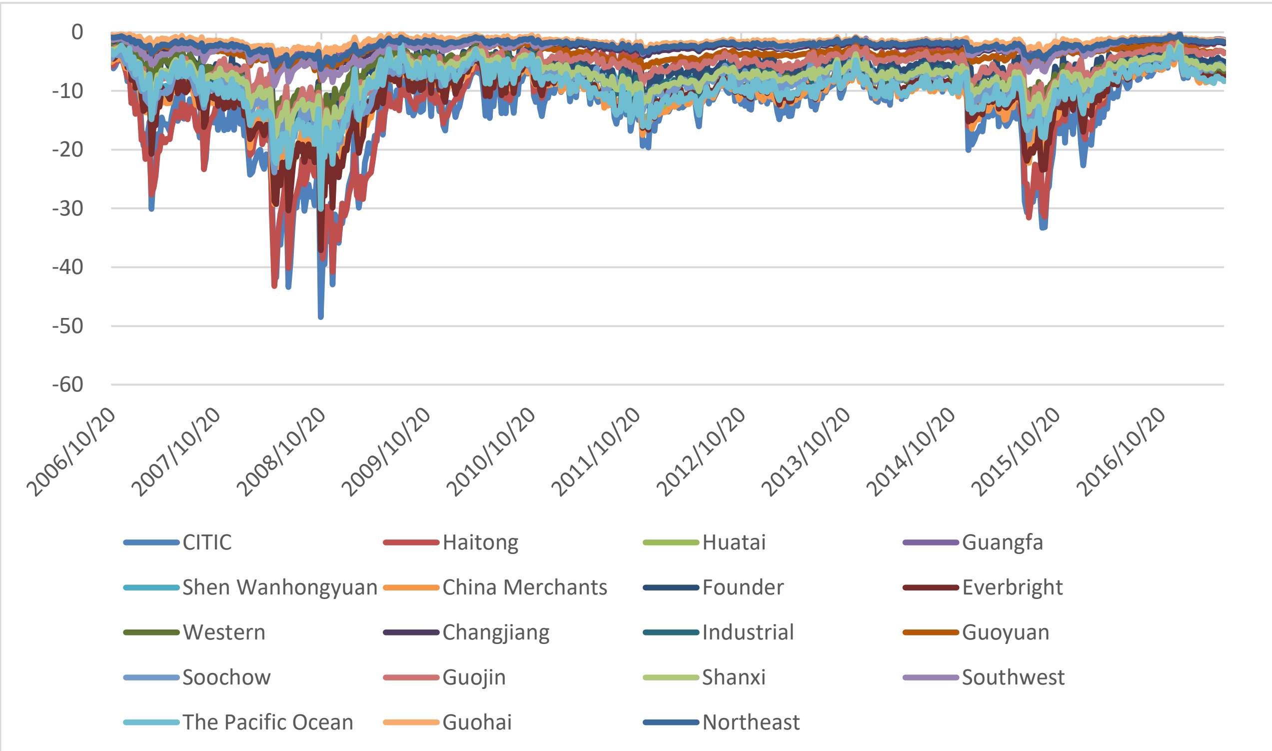
Securities	$\gamma_q^{i,1}$	$\gamma_q^{i,2}$	$\gamma_q^{i,3}$	$\beta_q^{system/i}$
CITIC	-2.09 （-4.25）	-2.57 （-5.42）	-1.17 （-4.60）	0.75 （29.52）
Haitong	0.20 （0.41）	-2.20 （-8.11）	-1.28 （-7.28）	0.49 （5.96）
Huatai	-2.40 （-3.53）	-1.79 （-11.87）	-1.74 （-8.79）	0.75 （28.30）
Guangfa	-3.47 （-2.17）	-2.32 （-5.18）	-1.95 （-2.98）	0.12 （9.69）
Shen Wanhongyuan	-2.95 （-2.19）	-2.44 （-5.92）	-2.38 （-3.53）	0.39 （4.45）
China Merchants	-2.50 （-2.78）	-1.81 （-7.28）	-1.80 （-5.63）	0.77 （20.76）
Founder	-2.35 （-6.66）	-2.07 （-5.46）	-0.77 （-4.33）	0.51 （6.64）
Everbright	-2.46 （-4.23）	-2.25 （-6.37）	-1.23 （-4.45）	0.69 （18.27）
Western	-3.48 （-5.63）	-2.13 （-10.18）	-1.73 （-6.15）	0.48 （11.37）
Changjiang	-2.62 （-3.71）	-2.14 （-9.12）	-1.80 （-5.81）	0.17 （15.53）
Industrial	-2.41 （-4.59）	-1.98 （-9.67）	-1.28 （-8.01）	0.58 （13.22）
Guoyuan	-4.75 （-2.93）	-2.78 （-4.96）	-2.48 (-4.05)	0.18 (15.04)
Soochow	-2.34 (-3.88)	-1.65 (-11.52)	-1.99 (-8.50)	0.61 (12.90)
Guojin	-2.90 (-3.13)	-2.69 (-9.83)	-2.66 (-5.14)	0.26 (11.39)
Shanxi	-2.72 (-4.60)	-1.91 (-9.88)	-1.56 (-7.46)	0.54 (8.48)
Southwest	-1.67 (-2.39)	-2.16 (-10.30)	-1.75 (-6.06)	0.15 (3.12)
The Pacific Ocean	-3.48 (-2.30)	-2.44 (-5.30)	-1.63 (-2.20)	0.61 (5.25)
Guohai	-3.69 (-4.67)	-2.64 (-6.02)	-1.55 (-7.78)	0.10 (5.32)
Northeast	-3.15 (-3.69)	-2.49 (-8.40)	-1.85 (-5.00)	0.12 (5.73)

Data source: Organized according to Wind database

The empirical results show that Z_1 (market liquidity), Z_2 (bond market income) and Z_3 (market overall income) have a negative influence on brokers' tail risk, which indicate that state variables such as overall market liquidity, bond market returns and overall market returns have a significant lag effect on the yield loss of securities firms during crisis and the direction is negative, that is, the better the overall liquidity of the current market, the higher the overall yield of the bond market and the higher the overall rate of return of the whole market, the greater risk brokers will face loss of income in the future. This is consistent with the "volatility paradox" mentioned in Adrian and Brunnermeier (2016) (risks always accumulate when fluctuations are small and are exposed during crises). The current market environment of China is good with abundant liquidity, high level of return and low volatility, indicating that the current market is relatively stable, but this is a process of risk accumulation, which increases the risk of future loss of return. Judged from the impact of brokers on the tail risk of the capital market, the conditional influence coefficient is positive, indicating that the tail risk of brokerage is positively correlated with the tail risk of the capital market. Among them, the largest value of the conditional influence coefficient is China Merchants Securities, which reaches 0.77 and is highly positively correlated. CITIC Securities and Huatai Securities rank the second, both at 0.75, also at a relatively high level. The lowest three are Guangfa Securities, Northeast Securities and Guohai Securities, which are 0.12, 0.12 and 0.1 respectively.

5.3 Time series changes of risk spillover intensity

Based on the parameter estimation results in Table 6, the time-series risk contributions of the 19 listed brokers to the capital market are calculated (excluding the suspension data). As shown in Figure 1, the empirical results portray the temporal changes in the risk contributions of individual brokers in crisis to the capital market.



Data source: Organized according to Wind database

Figure 1: Change in the contribution of brokers to the systemic risk of capital market

The empirical results show that since 2006, the risk contributions of individual brokers to the capital market have been at a low level for most of the time, but there have been extreme fluctuations during the two stock market crashes (2007 to 2008, and 2015 to 2016). Observing the overall market, under normal circumstances, the fluctuation of individual brokerages $\Delta^{\$}CoVaR_t$ is insufficient to trigger systemic risk exposure, but when all brokers are in crisis, it is easy to form resonance and strengthen the contributions of individual brokers to the systemic risk of capital market. Before the two stock market crashes, $\Delta^{\$}CoVaR_t$ of all brokers showed a significant increase, indicating that market risks are accumulating. During stock market crashes, $\Delta^{\$}CoVaR_t$ began to increase rapidly and substantially, indicating that systemic risk exposure events occurred. After stock market crashes, $\Delta^{\$}CoVaR_t$ began to fall sharply, indicating that market risk is released. By comparing individual brokers, we can see that the larger the size of a single broker, the greater its contribution to the systemic risk of the capital market, so the size of a broker has an important impact on the risk contribution. Among brokers, CITIC Securities and Haitong Securities, the two largest securities firms, have long been at the forefront of risk contributions to the capital market, which are consistent with the static analysis results. It can also be seen that the time series changes of all brokers $\Delta^{\$}CoVaR_t$ are basically synchronized, which may reflect the similarity of business types and structures of the securities firms in China. The brokers' contributions to systemic risk in the event of crisis are also relatively synchronized, further strengthening and amplifying the risks.

5.4 Analysis of the influencing factors

Based on the macro-state variable data, considering the impact of the brokerage size, the previous parts use the principal component analysis method and the quantile regression method to measure the dynamic change of the risk contributions of individual brokers to the capital market. In order to further study the influencing factors of individual brokerage risk contribution, we still select six securities firms including CITIC Securities, Haitong Securities, Changjiang Securities, Guojin Securities, Southwest Securities and Northeast Securities as research samples, as they represent large-, medium- and small-scale brokerages respectively. After eliminating the scale, we recalculate the risk contributions of individual brokers to the capital market, and analyze the main factors affecting the changes of brokerages' risk contribution to the capital market from the micro-features of brokers such as leverage ratio, maturity mismatch, scale and price-to-book ratio. Considering the availability of data, we select the monthly data from January 2014 to June 2017 and the monthly average of dynamic $\Delta CoVaR_t$ for calculation. Since the calculated $\Delta CoVaR_t$ values are all negative, for the convenience of calculation, the absolute values of $\Delta CoVaR_t$ are taken for regression analysis.

1. Leverage ratio (LE): Calculated by dividing the total assets of a broker by the shareholder's equity, indicating the leverage level of the broker.

2. Maturity mismatch (DM): Current assets minus short-term debt, divided by

shareholder equity, indicates the level of mismatched funds of listed brokers.

3. Market size (EQ): Calculated by dividing the market value of a single broker by the average of the total market capitalization of all brokers, indicating the size of the broker.

4. Price-to-book ratio (BM): Dividing the stock price per share by the net assets per share, indicating whether the market is overheated and reflecting investor enthusiasm for individual stocks.

Regression model settings:

$$\left|\Delta CoVaR_t\right| = \alpha + \beta_1 LE_{t-1} + \beta_2 DM_{t-1} + \beta_3 EQ_{t-1} + \beta_4 BM_{t-1} + \varepsilon \tag{22}$$

Table 7: Parameter estimation result of influencing factors

Securities	LE（β_1）	DM（β_2）	EQ（β_3）	BM（β_4）
CITIC	4.37 (2.17)	1.86 (3.31)	23.58 (4.66)	-3.63 (-2.66)
Haitong	7.56 (9.54)	0.26 (1.61)	-24.25 (-4.44)	-6.12 (-5.52)
Changjiang	0.29 (4.23)	0.01 (2.86)	-5.36 (-4.50)	0.11 (1.11)
Guojin	2.24 (5.95)	0.01 (0.73)	11.16 (1.62)	0.34 (1.82)
Southwest	0.73 (2.89)	0.00 (-0.95)	5.25 (1.81)	0.31 (1.00)
Northeast	0.18 (2.65)	0.01 (2.16)	-13.02 (-3.51)	0.24 (2.70)

Data source: Organized according to Wind database

As shown in Table 7, the coefficients of the leverage ratio of the six brokers to the risk contributions are positive, and the statistical results are all significant. These indicate that the increase in the leverage ratio of individual brokers will lead to an increase in their risk contribution to the capital market in the future. The coefficients of the maturity mismatch of the brokers are also positive, but the coefficients of Changjiang Securities and Northeast Securities are small, and the statistical results of Guojin Securities and Southwest Securities are not significant. These show that the more serious the maturity mismatch, the greater the risk contribution of brokers to the capital market in the future. But maturity mismatch is not the dominant factor; sometimes it may need to be combined with scale to analyze a broker's influence. The coefficients of the market size of the brokers have both positive and negative values, but the absolute values are large and the statistical results are significant, which indicates that market size has an important influence on the risk contributions of securities firms to the capital market, though it is not always positive influence. Sometimes the relatively conservative securities firms with larger size will become a cushion for the capital market and reduce the systemic risk of capital market. The coefficients of the price-to-book ratio of the brokers to the risk contributions are quite different. The coefficients of the price-to-book ratio of large-size brokers are negative, and the statistical results are significant; the coefficients of the price-to-book ratio of medium-size brokers are positive, but the values are small, and the statistical results are not significant; the coefficients of the price-to-book ratio of small-size brokers are positive, the values are small, and only the statistical result of Northeast Securities is significant. These show that the more optimistic investors are for a large-size broker with high price-to-book ratio, the lower its future risk contribution will be; the more optimistic investors are for a small- and medium-size broker with high price-to-book ratio, the higher its future risk contribution will be.

6 Conclusions

Based on the $\Delta CoVaR$ method proposed by Adrian and Brunnermeier (2016), from the static and dynamic dimensions, we use the quantile regression and principal component analysis method to measure the risk spillover effects between 19 listed brokers in China and their risk contributions of to the capital market, and to analyze the influencing factors of the risk contribution. The conclusions of this paper are as follows:

Firstly, there is a risk spillover when a single broker is in crisis, but the spillover effects are different depending on brokers. The correlation between Chinese brokers is very strong, and the risk they bear can be transmitted through various channels such as asset price linkage and business linkage. At present, brokerage firms are financial institutions with relatively high degree of marketization in China, but the shareholding structures are mostly state-owned or state-shared. The various interest incentives are superimposed on the government's rescue route, which gives managers a greater risk preference. In addition, the assets involved in securities companies are large in scale, but their core capital is relatively small compared to the risks they bear, and they cannot be completely endorsed by the government like banks, and thus are more prone to crisis. When brokers with very large spillover effects are in crisis, the supervisory authorities should promptly rescue them to prevent the spread of risks and avoid systemic risk exposure. In daily supervision, institutions with large spillover effects should implement stricter regulatory standards, restrain their excessive risk-taking tendency and prevent systemic risk accumulation.

Secondly, the high risk of a single broker does not indicate a large risk contribution to the capital market. The supervisory authority should not only pay attention to the operational risks of individual brokers, but also focus on their contribution to the systemic risk of the capital market. It is not enough to prevent and control the operating risks faced by individual brokers in order to ensure the overall stability of the capital market. Brokers which contribute more to the systemic risk should be required to have higher risk coverage, their leverage should be strictly restrained, their ability to absorb the risk of unanticipated losses caused by specific businesses should be increased, their capability to resist liquidity risks should be enhanced, and their participation in high-risk businesses should be limited. A countercyclical adjustment mechanism can also be adopted.

Thirdly, market size is an important factor to be considered for regulation, but not the only factor. As can be seen from the empirical data, in general, the larger the size of a brokerage is, the greater its risk contribution is, but other factors such as relevance also have an important impact on the risk contribution. Therefore, when identifying systemically important institutions, the supervisory authority must consider not only the size of individual brokerages and their market relevance, but also other factors that affect the risk contribution of brokerages. Judged from the characteristics of brokers themselves, factors such as excessive leverage of brokerage firms, serious mismatches in maturity and high price-to-book ratio of small- and medium-sized brokerage firms need special attention from regulatory authorities.

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