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The ESG Impact on Financial Stability: Evidence from China

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Abstract

Systemic risk management is always of vital importance for financial stability, meanwhile Environmental (E), Social (S) and Governance (G) are a popular framework on a global scale which is used to assess business risks and opportunities. However, there is relatively little research about the relationship between ESG and systemic risk, especially in developing markets. Therefore, this study aims to analyze the joint and separate pillar effects of ESG on financial stability measured by Yuan ΔCoVaR in developing markets and selects the Chinese market as a case study. Publicly available stock price is used to estimate the value at risk (VaR) using the basic historical simulation method. After calculating the VaR, a quantile regression is applied between the systemic loss and individual loss to obtain the CoVaR and ΔCoVaR. We then obtain theYuan ΔCoVaR by making ΔCoVaR in Yuan terms. The regression of Yuan ΔCoVaR on ESG is then built by a fixed effects model. Using a sample of 20 Chinese publicly traded commercial banks over 2017-2021, we find that a higher level of ESG indicates higher systemic risk. Furthermore, the separate pillars of ESG have a significantly positive relationship with systemic risk.

Key words: systemic risk; ESG; ΔCoVaR; quantile regression; fixed effects

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1. Introduction

The 2008 financial crisis sounded an alarm for risk management of the financial system. The recent breakdown of Silicon Valley Bank again highlights the importance of systemic risk. On March 10th, 2023, Silicon Valley Bank, after 40 years of establishment, announced bankruptcy and sent science and technology start-up companies into chaos (Sanderson, 2023). One possible reason is that Silicon Valley bank failed to effectively reduce asset durations and hedge risks in response to significant and fast monetary policy changes. This illustrates that, under the condition of unstable financial markets, the need of managing market risk is of great importance, since any financial institution with poor risk management can easily replicate the contagion effect of Silicon Valley banks which may result in a financial crisis.

In recent years, sustainability is a new research trend in China, especially climate-related topics, like temperature shocks and low carbon transition. To prompt sustainable development, China commits to achieving carbon peak by 2030 and carbon neutrality by 2060 (Zhao et al. 2022), which could affect the ESG components of the firm. Also, some Chinese recent policies regarding promoting green finance and ESG information closure, further highlight the significance of ESG, may motivate more firms and investors to take the environmental and social benefits into account. These policies include the green finance pilot zones policy in 2017 (Sun, Zhou & Gan, 2023) and the proposal in 2021 by the Ministry of Ecology and Environment about forming a system of mandatory environmental information disclosure by 2025 (Luo, Wei & He, 2023). According to Caldecott & Robins (2014), such environment-related policies and strategies could affect the values of existing assets and future assets investments, which addresses the issues of stranded assets. They relate the stranded assets to the financial system in a way where the values of the assets affected by environmental risk could result in financial instability.

In addition, there is some research beginning to investigate if environmental factors, especially climate related factors, may have an impact on the systemic risk. Brunetti et al. (2021) find that climate related risk could raise the vulnerability of the financial system. They illustrated that, through the impact on financial intermediaries, market function and large assets repricing, climate risk could eventually affect financial stability. Sometimes such risk impact could be predicted and avoided. Battiston et al. (2017) find the timing and expectation of climate policies could affect systemic risk. They point out that if climate policies are implemented early in a stable framework, it is possible for market participants to predict the effects, however, if climate policies are uncertain, sudden, and delayed, the market may fail to fully predict the impact of policies and climate-policy-related sectors will be put into the exposure of systemic risk. Therefore, these relationships encourage us to take risk management into account when analyzing the ESG factors and CoVaR serves as a specific measurement of systemic risk in our case to look further into the impact of ESG components.

As for the Chinese financial market, the large banking sector plays a dominant role (Allen et al., 2012). These banks could enhance the financial stability through their efforts such as reducing the non-performing loans and boosting efficiency (Allen et al., 2012), while their characteristics, such as being highly leveraged and cyclical, could be the factor to trigger systemic risk. On the other hand, banks play an important intermediary role in the process of sustainable development (Dorasamy, 2013; Yip & Bocken, 2018). Therefore, the Chinese commercial banks act as a perfect link for us to investigate the impact of ESG on systemic risks.

We found that the previous studies on ESG mainly concentrate on its relationship with financial performance (Cerqueti et al., 2022), and tend to neglect the impact in the risk dimension (Scholtens & van't Klooster, 2019). In addition, the existent research considering the impact of ESG on the firm mainly focuses on the developed market (Bahadori, Kaymak & Seraj, 2021), with few relevant studies based on the Chinese market. The research on sustainability and financial systemic risk in China has just started and is not yet perfect and in-depth. Due to the research gap, we consider focusing on the emerging market since it faces a lot of challenges from different aspects, thus calling for more attention to sustainability standards (Bahadori, Kaymak & Seraj, 2021).

Our purpose is to explore the relationship between sustainability and financial stability in a developing market, where we use systemic risk to represent the financial stability and ESG scores to represent ESG performance. Generally, we have two specific research questions:

Q1: Do banks with higher ESG scores have a relatively low contribution to systemic risk?

Q2: How do separate ESG pillars influence systemic risk?

Given the increasingly rapid development trend in China and the importance of sustainability, we study the impact of sustainability on systemic risk. The contribution of this article is mainly in two aspects: First, the use of the CoVaR method to measure the impact of ESG on financial systemic risk is of innovative significance. Specifically, there is no research that studies the ESG impact on systemic risk of the Chinese financial market based on the CoVaR method. We are the first to do this. Second, we make up for the lack of systemic risk research in developing markets. Additionally, studying the relationship between ESG and systemic risk will influence systemic risk management and the development of sustainability in the banking sector.

The remaining parts of this paper are structured as follows. Section 2 is the theoretical framework, basically introducing the concept development of ESG and its separate pillars and giving some context of systemic risk background and measurements. Section 3 is the literature review, describing the current research situation of systemic risk, sustainability as well as the relationship between these two. Section 4 introduces the methodology we employ in this paper, mainly including the method of estimating VaR, the quantile regression method of estimating CoVaR and ΔCoVaR, and fixed effects model built for panel regression. Section 5 explains the sample data selection, control variables setting, descriptive statistics of data and correlation matrix while section 6 talks about empirical results and analysis as well as robustness check. The final section is the conclusion drawing, stating our findings, research delimitations and future research capabilities.

2. Theoretical Framework

In this section, we firstly give the background and development about the concept of ESG and its separate pillars as well as the definition of risk and systemic risk. In addition, we introduce different methods of measuring risk and systemic risk, such as MES, SRISK and ΔCoVaR.

2.1 Defining ESG and ESG Pillars

An important concept in society is ESG, which is defined as how firms and investors incorporate issues concerning the environment, society, and governance in their business model (Gillan, Koch & Starks, 2021). The environmental pillar focuses on the environmental impact of corporate activities, concerning climate change, natural resources, and pollution (pwc, 2023). As we know, climate change is difficult to predict, and could easily catch people unprepared with a wide range of impact. According to Brunetti et al. (2021), adverse effects caused by climate change can create risks to economic activity and therefore amplify financial risks. For example, they further conclude that weather related changes damage property, causing bank losses and thus reducing bank investment. Therefore, climate change is a global concern and an important factor that affects the stability of the financial system. A range of potential physical outcomes coming from climate change could be seen as climate risks (Brunetti et al. 2021). These risks capture more and more attention from firms and investors, as they are attempting to take such risks into consideration on their decisions regarding investment portfolios, pricing, and risk management (Brunetti et al. 2021).

For the social pillar, it is about social concerns that are related to corporate activities, including social opportunity, healthcare, and labor management (pwc, 2023). These increasingly concerned social issues could encourage firms and investors to involve in activities that bring social benefits. As for the governance pillar, it is associated with the governance matters of the company, where corporate governance, corporate behavior and ownership are included (pwc, 2023). The governance pillar brings benefits to the company as it can be regarded as a credible commitment of the firm to corporate social responsibilities, which encourages the investors while poor governance acts as the key factor for the financial crisis (Nollet, Filis & Mitrokostas, 2016).

2.2 Defining Systemic Risk

As for systemic risk, economic globalization, war, pandemic, financial technology innovation, and sustainability are all its key drivers. This paper defines systemic risk as:

> Systemic risk refers to the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by comovements (correlation) among most or all the parts. (Kaufman & Scott, 2003, p.371)

Smaga（2014） defines systemic risk as the risk of a shock that could lead to imbalances to an extent that would disrupt the financial system and affect the economy negatively. By comparing the systemic risk defined by different literature, he gets four conclusions. Firstly, systemic risk affects a substantial proportion of the financial system and institutions and impairs the functioning of the financial system. Secondly, the transmission of shocks among the linked parts of the system is the critical aspect of the systemic risks, which could have a negative impact on the economy. Thirdly, the definitions of systemic risks began to increase largely after the financial crisis. Fourthly, due to the outbreak of the financial crisis, studies begin to focus more on their effects on the impairments of financial system functioning and the negative consequences for the economy.

As for the concept of systemic risk, it could be endogenous when it is caused by aggregated conduct of the financial entities or one of them, or it could be exogenous when it comes from causes outside the financial system like the instability of the economy (Smaga, 2014). Allen and Carletti (2013) divide systemic risk into four types: panics (the bank crisis caused by multiple equilibria); bank crisis caused by the price falls of assets; contagion effects; and mismatches in the foreign currency in the financial system. If systemic risk continues to accumulate, it may cause financial crises and widespread destructive effects, threaten the stability of the financial system, and even impede the development of the global economy. Therefore, it is necessary and essential to measure systemic risk.

2.3 The Measurement of Risk

A lot of methods could be applied to measure the risk level of financial institutions. VaR is the most common one. As proposed by Hull (2018), VaR at α confidence level means the probability of the portfolio losing more than VaR is 1-α. Many ways could be applied to estimate VaR, and generally there are two kinds of approaches: non-parametric and parametric approaches.

For non-parametric approaches, basic historical simulation (BHS) and volatility-weighted historical simulation (VWHS) are the most commonly used ones. According to Hull (2018), BHS gives each day an equal weight of 1/n, and ranks all of the observations from the worst to the best. He concludes that VaR is calculated by summing the weights of observations until the significance level is exceeded. On the basis of BHS, VWHS scales the original losses L by volatility σ and employs BHS to the rescaled losses (Goorbergh & Vlaar, 1999). It means that if volatility is high, VWHS will then scale up the original losses L by a multiplier $L_t^* = \frac{\sigma_{T+1}}{\sigma_T} * L_t$. Generally, the EWMA model (The Exponentially Weighted Moving Average Model) (Hull, 2018) is used to find the volatility:

$$\sigma_{T+1}^2 = (1-\lambda)\varepsilon_T^2 + \lambda\sigma_T^2 \quad (1)$$

where λ is the decay factor, ε is time zero innovation and σ squared is the unconditional variance of the loss sample.

Parametric methods usually assume parametric loss distribution. For the normal distribution method, provided by Jorion (2001), we assume that the losses follow a normal distribution, with a mean μ and a standard deviation σ as two parameters, also known as location and scale separately. In this way, VaR calculated like Hull (2018) stated is as follows:

$$VaR_\alpha = \mu + \sigma Z_\sigma \quad (2)$$

Unlike BHS, normal distribution is usually used on a large sample of data. Another method similar to normal distribution method is student-t distribution method. According to Cont (2001), the t-distribution method assumes that losses follow a student t-distribution and introduces two new parameters: the scale σ^* (similar but not identical to normal distribution) and degrees of freedom ν (controls the behavior of the tail, for normal distribution ν=∞):

$$VaR_\alpha = \mu + \sqrt{\frac{\nu-2}{\nu}}\sigma t_{\alpha,\nu} \quad (3)$$

$$\sqrt{\frac{\nu-2}{\nu}}\sigma = \sigma^* \quad (4)$$

When the confidence level is higher, the difference of VaR estimate between normal distribution and t-distribution is higher, since the difference in α-quantiles between these two distributions is larger. Putting it into application, when estimating the systemic risk in the field of insurance in China, Wu (2019) calculates the average and median VaR loss value under the assumption of 5% and 1% of normal distribution and uses the average VaR as the measurement.

Besides VaR, some other researchers choose distance to default as a risk measurement. Distance to Default (Jessen & Lando, 2015) is calculated as the inverse standard normal cumulative distribution function of the PD:

$$PD = Pr\ (lnA_T < lnK)\ = N(-DD)\ \ (5)$$

$$DD = \frac{lnA_0+\left(\mu_A+\frac{\sigma_A^2}{2}\right)T-lnK}{\sigma_A\sqrt{T}}\ \ (6)$$

where A_0 is the market value of assets and K is the nominal value of bond. The firm defaults if and only if $A_T < K$(Jessen & Lando, 2015). When considering the stability of the European banking sector, Chiaramonte et al (2022) use a market-based measure of default risk. They estimate the distance to default according to probability of default.

Besides methods mentioned above, expected shortfall is also an efficient risk assessment method, which is defined as the expected loss given a VaR violation (Acerbi and Tasche, 2002):

$$ES_\alpha = E[X > VaR_\alpha] = \frac{1}{1-\alpha}\int_{x=\alpha}^{x=1} VaR_x dx\ \ (7)$$

According to Lupu et al (2020), VaR and ES are both used as risk measures as well as the indicators to capture the extent that investors perceive the risk and find the robustness checking results are very similar by taking means of historical simulation. In this paper, we employ VaR as our risk measures since it is expressed in price units and can be easily interpreted as the extent of risk. In addition, VaR can be applied and compared to different stocks or bonds, and thus being widely used by financial industry professionals.

2.4 The Measurement of Systemic Risk

VaR and ES measure the individual risk faced by the institution. However, when it comes to measuring systemic risks, there are some other effective ways like marginal expected shortfall (MES), SRISK, and ΔCoVaR. Acharya et al (2016) defines systemic expected shortfall as the expected amount of the bank's undercapitalization in the case of the undercapitalization of the whole financial system. Being related to SES, he also proposes MES, which can be used to measure systemic risk by estimating how each bank's risk can increase overall system risks and is defined as:

$$\frac{\partial ES_\alpha}{\partial y_i} = -E[r_i | R \leq -VaR_\alpha] = MES_\alpha^i \quad (8)$$

where R is regarded as the return of the whole banking sector and MES_α^i is the individual bank's marginal expected shortfall.

According to Brownlees and Engle (2016), another way to measure systemic risk by taking the capital shortfall into account is SRISK. They say that SRISK is a function of a firm's size, expected equity loss, and leverage, and is defined as the expected capital shortfall of the institution conditional on the market performing poorly:

$$SRISK_{it} = E_t \ (CS_{i\,t+h} | R_{m\,t+1:\,t+h} < C) \quad (9)$$

where $R_{m\ t+1:t+h}$ is the multiperiod arithmetic market return during time t+1 and t+h, and $R_{m\ t+1:t+h} < C$ is the systemic event.

Unlike the MES and SRISK conditional on the poor market, CoVaR considers the case when the specific institution is in distress (Adrian & Brunnermeier, 2016) and focuses the systemic risk on the VaR aspect. In their paper, $CoVaR_q^{j|C(X^i)}$ is the VaR of the financial system given that this entity i is under a specific state, and it is given as:

$$Pr(X^j | C(X^i) \leq CoVaR_q^{j|C(X^i)}) = q\% \quad (10)$$

Based on the CoVaR, ΔCoVaR (Adrian & Brunnermeier, 2016) measures how the VaR of the financial system would change when a company is in disruption compared to its normal state. They define delta VaR as the contribution of the institution to the systemic risk, which is the difference between the VaR of the financial system under distress condition ($X^i = VaR_q^i$) and under median condition ($X^i = VaR_{50}^i$):

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50}^i} \quad (11)$$

Besides the methods above, there is other literature on measuring systemic risk. DIP (Huang, Zhou & Zhu, 2011) is the risk-neutral expected loss exceeding a specific loss threshold. Also, Billio et al. (2012) estimate the systemic risk based on the Granger-causality networks.

In our paper, we use the method of ΔCoVaR as it is easily applicable. Also, it highlights the tail dependency between the financial system and the individual institution and helps to offer regulators a macroprudential viewpoint cross-sectionally (Adrian & Brunnermeier, 2016).

3. Literature Review

When studying ESG or systemic risk, financial performance is always one of the most important aspects to pay attention to. There is some previous literature focusing on the impact of ESG on financial performance where generally they find a positive link between these two (Cornett, Erhemjamts & Tehranian, 2016; Forcadell & Aracil, 2017; Lins, Servaes & Tamayo, 2017; Nollet, Filis & Mitrokostas, 2016) As for studies about systemic risk and financial performance, some characteristics of the financial assets or institutions are proven to be the factors to influence systemic risk (Brunnermeier et al., 2020; Elyasiani & Jia, 2019; Ivanov & Jiang, 2020).

Moreover, some existing literature about the relationship between systemic risk generally shows that a higher level of sustainability represents a lower contribution to systemic risk (Scholtens & van't Klooster, 2019; Tóth et al., 2021). Specifically, certain ESG components have a positive impact on reducing systemic risk based on different markets (Bashir et al., 2021; Chiaramonte et al., 2022; Lisin et al., 2022) and it is possible to affect the vulnerability of the system by taking specific ESG pillars into account (An et al., 2022; Zhang & Wang, 2023).

3.1 ESG and Financial Performance

Nollet, Filis and Mitrokostas（2016）investigate the relationship between corporate social performance (CSP) measured by ESG disclosure score and accounting-based corporate financial performance (CFP) in both the linear model and non-linear model: the linear model suggests CSP relates to return on capital negatively; the non-linear model indicates a long-run positive relationship (u-shaped) between the CSP and CFP, which means that CSR will pay off only after arriving at certain criteria. They also discover that government is the main factor affecting the relationship, which should be put more focus on in corporate investment strategies. Cornett, Erhemjamts and Tehranian (2016) find that there is a positive relationship between corporate social responsibility measured by ESG rating and the financial performance measured by return on equity around the financial crisis. Similarly, another study shows that when there is a low level of trust caused by the negative shocks in society, firms with high CSR are more likely to have better stock performance (Lins, Servaes & Tamayo, 2017), and sustainability could also be seen as a method to rebuild their reputation (Park, Lee & Kim, 2014; Forcadell & Aracil, 2017). Therefore, ESG may have a positive impact on the firm performance, and this could be the reason why more and more firms are actively involving themselves in ESG practices even though these efforts could be costly and paid back over a long time.

3.2 Systemic Risk and Financial Performance

The relationship between systemic risk and financial performance is linked in multiple ways. Brunnermeier et al (2020) conclude that asset price bubbles are strongly related to higher systemic risk. Moreover, they further state that higher loan growth and maturity mismatch tend to increase systemic risk, making the financial system more vulnerable to asset price bubbles. Asset securitization is also empirically tested to influence systemic risk. Residential mortgage and other forms of securitization activities increase the exposure to systemic risk (Ivanov & Jiang, 2020). By applying CoVaR as the measure of risk to market distress and using the panel regression with random effects to estimate the impact of asset securitization on systemic risk, Ivanov and Jiang (2020) find that the cross effects of both securitized loans and securitized products play an essential role in determining risks of financial institution. In addition, there is some research about whether the size and structure of banks will have an impact on systemic risk. Large banks seem to suffer greater systemic risk than small banks (Pais & Stork, 2013). However, according to Elyasiani and Jia (2019), organizational complexity is the most relevant factor related to the systemic risk of banks (SRISK). Therefore, we can conclude that bank regulators should focus more on the impact of bank structure on bank performance and systemic risk rather than just limiting the bank sizes and acquisitions.

3.3 ESG and Systemic Risk

Based on the current sustainability and financial systemic risk situation, there has been some empirical research from previous studies. For European markets, bank stability, especially during financial turmoil, attracted people's attention. The ESG has positive joint and separate effects on bank fragility and the benefits are expected to be larger with a longer time period of ESG disclosures (Chiaramonte et al., 2022). For North American markets, ESG is found to improve financial stability by reducing the likelihood of companies going bankrupt using Ohlson O-Score (Lisin et al., 2022). In recent years, scholars have also conducted research in related fields based on the Chinese market. Chinese banking transparency is regarded as a significant determinant of changes in financial stability (Bashir et al., 2021). They use multiple variations of a two-step system generalized method of moments approach and get the results that transparency with market power lessens the insolvency risk of banks as well as credit market risk.

In addition, there are some researchers going deeply into studying the impact of sustainability factors on systemic risk. For the environmental level, An et al (2022) analyzes the impact of transition risks caused by climate change on Chinese financial market stability by using the TVP-VaR model, they find in the short or medium terms, an increasing climate change, measured by the climate change index (CCI), will cause more financial market pressure while the impact is uncertain in the long run (An et al, 2022). For the governance level, Zhang and Wang (2023) study the impact of economic policy uncertainty on bank stability at the governance level. Using the Stimulus–Organism–Response (SOR) theory to explain the transmission path of opacity between economic policy uncertainty and bank stability, they find that the economic policy uncertainty has a negative impact on bank stability through the mediating role of opacity. Researchers also find that there are spillover effects from the banks' sustainability to the whole financial system: a higher level of sustainability of the banks measured by their attributes in environmental, social, and governance could lead to lower default risk and a reduction in their contribution to systemic risk (Scholtens & van't Klooster, 2019; Tóth et al., 2021). These foundations could bring more feasibility for our intention to investigate their relationship but adopt different measures.

To conclude, the previous literature generally shows that the ESG may have a positive impact on the financial performance and financial stability. Therefore, in our paper, we would expect higher ESG scores as well as ESG pillar scores could lead to lower systemic risk.

4. Methodology

We proceed to research the relationship between ESG scores and systemic risk. In this part we talk about methodology applied to estimate VaR and CoVaR and build the model for panel regression. For methodology in detail, the first step is to estimate the VaR. Taking our data feature into consideration, we intend to use a rolling window sample to estimate VaR based on the basic historical simulation method. For the next step, we analyze the systemic risk using the CoVaR approach, and a quantile regression method is used to catch CoVaR and ΔCoVaR. Finally, we examine the relationship between ESG scores and Yuan ΔCoVaR by applying the panel regression method based on a fixed effects model built on balanced panel data. This is to run the regression of Yuan ΔCoVaR on the ESG index and its separate ESG pillar scores, which solves research questions one and two respectively.

4.1 Estimating the VaR

Taking our data limitations into consideration, we intend to use the BHS method to estimate VaR on a rolling window of 200 days. According to the definition, VaR at α confidence level means we are α % certain that the loss during a time period of length T will not be exceeded (Hull, 2018). Before we get access to VaR, we need to define the losses. Losses are calculated as:

$$L_t^i = - \ln\left(\frac{Price_t^i}{Price_{t-1}^i}\right) \quad (12)$$

As mentioned above, VaR at the α confidence level is defined as the α quantile of the loss distribution. In the basic historical simulation (BHS), there is a sample of T losses, and the number of losses L that are larger than VaR is by definition (1- α)T. Therefore, based on Hull (2018), VaR is calculated as follows:

$$Pr\ (L^i \leq\ VaR_\alpha^i) \quad (13)$$

$$VaR_\alpha = l^s_{(1-\alpha)T+1} \quad (14)$$

4.2 Estimating the CoVaR, ΔCoVaR and Δ¥CoVaR

We choose quantile regression as our main method to estimate CoVaR and ΔCoVaR since it can provide some complementary information for the data features hidden from the method of least squares and become increasingly important as it can capture the heterogeneity and consider the additional covariates (Koenker, 2017).

The quantile regression was originally proposed by Koenker and Bassett (1978). According to the stylized version of the quantile regression model by Adrian and Brunnermeier (2016), the expected value of the quantile regression of the α-quantile losses of the financial system on institutional losses is given by:

$$\hat{L}_\alpha^{system|L^i} = \hat{a}_\alpha^i + \hat{b}_\alpha^i L_i \quad (15)$$

As for the losses of the financial system, we weigh all the banks with their respective market capitalizations to get the capital weighted factors:

$$w_t^i = \frac{market\ capital_t^i}{\sum_{i=1}^{n}\quad market\ capital_t^i} \quad (16)$$

Summing the product of capital weighted factors and the losses of each bank at time t, we obtain the financial system losses at time t:

$$\hat{L}_{\alpha,t}^{system|L^i} = \sum_{i=1}^{n} \quad w_t^i * L_t^i \ \ (17)$$

After getting the values of $\hat{L}_{\alpha}^{system|L^i}$ and L_i , we can estimate the parameters of the quantile regression mentioned and apply these estimated parameters to the same quantile regression to calculate the conditional quantile $CoVaR_{\alpha}^{i}$(Adrian & Brunnermeier, 2016):

$$CoVaR_q^i = VaR_q^{system|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \ \ (18)$$

Therefore, by taking the difference, ΔCoVaR (Adrian & Brunnermeier, 2016) is calculated as:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{system|VaR_{50}^i} = \hat{\beta}_q^i (VaR_q^i - VaR_{50}^i) \ \ (19)$$

Based on Adrian and Brunnermeier (2016), the Dollar ΔCoVaR (Yuan CoVaR in our case) could be calculated by taking the market value of each bank and multiplying with the estimated ΔCoVaR. Therefore, extending their CoVaR method, the $\Delta^{¥}CoVaR_{\alpha}^{i}$ can be written as:

$$\Delta^{¥}CoVaR_{\alpha}^{i} \ = \ {}^{¥}Size^{i} * \Delta CoVaR_{\alpha}^{i} \ \ (20)$$

4.3 Fixed Effects Model

After we get the Yuan ΔCoVaR of these banks over 5 years, we choose to use the panel regression method to investigate the impact of ESG on the systemic risk. Panel regression could capture variation both in the cross-section and the time-series. Since our sample data is panel data, the estimated results from pooled OLS which assumes no entity or time specific heterogeneity will be biased and inconsistent. Furthermore, the significance value for the F-test for poolability, which is shown in Table 5, suggests that we should reject the null hypothesis that fixed effects are jointly zero. Therefore, a fixed effects model is better to adopt in order to eliminate the heterogeneity. According to the fixed effects model by Allison (2009), it can be written as:

$$y_{it} = \mu_t + \beta x_{it} + \gamma z_i + \alpha_i + \varepsilon_{it} \quad (21)$$

where μ_t is the incept, and x_{it} are the variables that vary over time while z_{it} are the ones that do not change across time; αi and εit are the two error terms, one is different between individuals and the other one is different over time (Allison, 2009).

Drawing on the experience of Zelenyuk and Faff (2022) using dollar ΔCoVaR to measure the relationship between systemic risk and CEO pay, we use Yuan ΔCoVaR in our case. Since our sample data is balanced panel data, we intend to apply the fixed effects model to run the regression of the $\Delta^{¥}CoVaR_{\alpha}^{i}$ on the ESG total scores as well as the sub-pillar scores while controlling for the time specific effects to consider the shocks among banks (Chen & Chen, 2018; Aevoae et al. 2023).

Therefore, we construct the contribution to systemic risk as a function of the ESG data and other control variables defined in Table 1. As for the regression of separate ESG pillars, we simply replace the independent variable 'ESG' with environment pillar scores, social pillar scores and governance pillar scores respectively:

$$\Delta^{¥}CoVaR_{it} = \beta_1 ESG_{i,t} + \beta_2 LEV_{i,t} + \beta_3 NPL_{i,t} + \beta_4 ID_{i,t} + \delta_t + \varepsilon_{i,t} \quad (22)$$

5. Data

After describing the main methodology, we use in this paper, in this section, we introduce our data selection, data source, variables selection and some preliminary empirical results. Specifically, in the first part we explain the reason why we select the data as our sample, how we get access to the data and some preliminary results used for panel regression. In the second part we introduce how we select the control variables for regression with some brief explanations. Finally, we present a summary of the descriptive statistics for bank losses as well as the regression variables.

5.1 Sample Selection

So far, there are a total of 59 publicly traded commercial banks in China, among them 48 have public ESG data. Considering the need for banks to have both complete ESG scores and stock data, we ultimately select 20 listed commercial banks as samples, which include state-owned commercial banks, joint-stock commercial banks and city commercial banks. The assets of the selected sample banks account for the vast majority of the total assets of the Chinese banking system, therefore, the samples could well represent the entire Chinese financial system. The time horizon of this paper covers the period from 2017 to 2021, a total of 5 years.

The 20 publicly traded Chinese banks are listed in Appendix 1. The data of selected banks consists of their daily stock returns, daily market capitalization, yearly ESG total scores and yearly separate pillar scores (shown in Appendix 2). The daily stock close price of selected banks and ESG related data as well as the daily market capitalization are obtained from Refinitiv Eikon database. The estimated 5% and 50% VaR of 20 banks for 2017-2021, using the BHS method on a rolling window of 200 days, could be found in Appendix 3. The quantile regression results of 5 years are shown in the Appendix 4, while CoVaR, ΔCoVaR and Yuan ΔCoVaR results for 5 years could be seen in the Appendix 6. For robustness check, the 10 years quantile regression parameters could be found in Appendix 5 while the results of 10-year ΔCoVaR and Yuan CoVaR are in the Appendix 7.

5.2 Control Variables Selection

The control variables for our fixed effects model are chosen according to the literature (Aevoae et al., 2023; Sassen, Hinze & Hardeck, 2016). These control variables explained in Table 1 are selected for bank-specific characteristics such as leverage, default risk and income diversification. The degree of leverage is captured by total loans over total assets. The default risk is measured by the non-performing ratio which is calculated by non-performing loans over total loans. The diversification of income measured by the proportion of non-interest income in revenue. As for the financial data of our control variables, leverage and non-performing ratios are obtained from Bloomberg, and the non-interest income rates are obtained through the annual reports of banks which could be accessed through the official website links provided in the Appendix 1.

Table 1 Variables Explanation

Table 1 reports the type of variables in all of the regressions and gives a brief explanation and measurement of different variables.

Variables	**Type**	**Description**
Yuan CoVaR	Dependent variable	Yuan CoVaR takes bank size into consideration and is calculated by multiplying ΔCoVaR with corresponding market capitalization.
ESG	Independent variable	ESG represents the total scores of ESG.
E	Independent variable	Environmental pillar
S	Independent variable	Social pillar
G	Independent variable	Governance pillar
LEV	Control variable	Leverage ratio (LEV) is calculated by total loans over total assets.
NPL	Control variable	Default risk (NPL) is measured by non-performing loans over total loans.
ID	Control variable	Income diversification (ID) is non-interest income over revenue.
δ	Time fixed effects	Time fixed effects (δ) account for the time shocks
ε	Error term	ε is the error term.

5.3 Descriptive Statistics

As mentioned before, daily stock close price of 20 listed banks covering the time period from 2017 to 2021 is used in the paper. And related bank losses are defined as the negative log returns. The table below shows a summary of descriptive data statistics of 20 bank losses according to their log returns.

Table 2 Descriptive statistics of 20 bank losses

Table 2 presents the data statistics of 20 bank losses covering the time period from 2017.01-2021.12, mainly including the mean, standard deviation, the minimum losses and maximum losses. The bank names corresponding to the ticker symbol are listed in Appendix 1.

Ticker symbol	Mean	Std.Error	Std.Deviation	Min	Max
601988.SH	0.0099%	0.0277%	0.9651%	-6.4022%	6.7631%
601328.SH	0.0184%	0.0294%	1.0265%	-5.8093%	7.8359%
600036.SH	-0.0836%	0.0524%	1.8268%	-9.5211%	6.8975%
600016.SH	0.0545%	0.0295%	1.0286%	-8.0819%	6.9335%
000001.SZ	-0.0488%	0.0600%	2.0949%	-9.5629%	10.5075%
601009.SH	-0.0120%	0.0481%	1.6765%	-9.5621%	8.3171%
601398.SH	-0.0040%	0.0339%	1.1824%	-8.1830%	5.9882%
601939.SH	-0.0061%	0.0403%	1.4068%	-8.1883%	9.0441%
601288.SH	0.0044%	0.0302%	1.0552%	-6.8803%	8.0043%
601166.SH	-0.0136%	0.0463%	1.6163%	-9.3326%	8.2961%
600000.SH	0.0312%	0.0365%	1.2720%	-8.6415%	8.0704%
601169.SH	0.0497%	0.0295%	1.0277%	-8.7498%	7.5252%
601229.SH	0.0265%	0.0360%	1.2554%	-7.9870%	10.5231%
002142.SZ	-0.0937%	0.0583%	2.0326%	-9.5356%	6.7279%
601998.SH	0.0269%	0.0385%	1.3441%	-9.3845%	7.7526%
601818.SH	0.0134%	0.0397%	1.3860%	-9.4858%	7.4874%
600015.SH	0.0394%	0.0316%	1.1014%	-9.2373%	5.5152%
600919.SH	0.0371%	0.0405%	1.4119%	-9.5910%	6.6939%
600926.SH	-0.0149%	0.0540%	1.8850%	-9.5310%	8.0588%

601997.SH	0.0451%	0.0432%	1.5071%	-9.5547%	8.7114%
Systemic Loss	-0.0069%	0.0317%	1.1042%	-8.1056%	6.2013%

From the table above we could see that China Minsheng Banking Corporation (L4) has the largest daily average loss of 0.055% while Bank of Ningbo (L14) has the smallest daily loss of -0.094%, which is a return of 0.094%. As for the volatility, measured by standard deviation, it is obvious that Ping An Bank (L5) and Bank of Ningbo (L14) present the highest volatility of 2.09% and 2.03% respectively. Besides, we observe that the maximum loss is largest for Bank of Shanghai (L13) with 10.52% and smallest for Bank of Jiangsu (L18).

As mentioned in the data section, we choose eight variables for regression, one dependent variable Yuan ΔCoVaR (in million), four independent variables ESG, E, S, G, and three control variables to explain bank-specific characteristics, with descriptive statistics in Table 3.

Table 3 Descriptive statistics of regression variables (2017.01-2021.12)

Table 3 presents the data statistics of the main variables used in the fixed effects regression model covering the time period from 2017.01-2021.12, mainly including the mean, standard deviation, the minimum losses and maximum losses.

	Mean	**Std.Error**	**Std.Dev**	**Min**	**Max**
Yuan ΔCoVaR	6033.832	790.306	7903.059	252.666	37668.215
ESG	43.741	1.110	11.099	25.019	62.576
E	37.572	1.992	19.924	1.449	79.184
S	44.278	1.200	12.001	22.685	68.311
G	45.468	1.779	17.793	15.154	85.192
LEV	0.504	0.008	0.076	0.270	0.620
NPL	0.013	0.001	0.005	0.000	0.022
ID	0.271	0.009	0.095	0.044	0.511

Table 4 reports the correlation coefficients between the systemic risk, ESG, separate pillar and control variables for the selected data. From the table we could see that ESG and its separate pillar are positively correlated with Yuan ΔCoVaR, which may indicate that banks with higher ESG, especially higher Environment pillar tend to cause higher systemic risk. The specific relationship between ESG, different pillars and ΔCoVaR will be tested in separate regressions and described in the next section.

The correlation between each ESG pillar is naturally positive and high. Besides, the leverage control variable has a strongly positive correlation with Yuan ΔCoVaR which is within our expectations. Moreover, the correlation within the three control variables is relatively weak and no multicollinearity concerns are found.

Table 4 Correlation matrix

Table 4 presents the correlation between the main variables used in the fixed effects regression model covering the time period from 2017.01-2021.12.

	Yuan ΔCoVaR	ESG	E	S	G	LEV	NPL	ID
Yuan ΔCoVaR	1.00							
ESG	0.59	1.00						
E	0.48	0.77	1.00					
S	0.50	0.73	0.58	1.00				
G	0.35	0.71	0.35	0.08	1.00			
LEV	0.44	0.52	0.58	0.34	0.33	1.00		
NPL	0.07	-0.07	-0.14	-0.08	0.01	0.11	1.00	
ID	0.08	0.25	0.25	0.39	-0.04	0.15	-0.18	1.00

6.Empirical Results

This chapter mainly analyzes the regression results respective to our two research questions, tests the poolability and multicollinearity issues as well as check the robustness of our main results. This part is structured as follows, first, we will give a discussion regarding the empirical results on statistical aspects. Then, we analyze the robustness of our model using data from different time periods and end up with making a short comparison and explanation of these results.

6.1 Regression Results

Table 5 5-year fixed effects model between Yuan CoVaR and ESG as well as its separate pillars

This table presents the estimates of the fixed effects model specified in equation 22. Variables are defined in Table 1. In the parentheses are the p-values. *, **, and *** represent the significance level of 10%, 5%, and 1% respectively. Errors are adjusted for clustering, in this case, to allow for heteroskedasticity and serial correlation, so there are no relevant tests for these two problems.

Dependent Variable: YuanΔCoVaR	(1)	(2)	(3)	(4)
ESG	406.90***			
	(0.0000)			
E		196.16***		
		(0.0020)		
S			332.73***	
			(0.0000)	
G				100.08***
				(0.0007)
LEV	22,140***	24,930***	38,480***	42,330***
	(0.0002)	(0.0005)	(0.0000)	(0.0000)
NPL	24,290	35,020	-56,230	-27,170
	(0.7923)	(0.7162)	(0.4595)	(0.7747)
ID	-10,820***	-9860.4	-18,560***	-151.79

	(0.0081)	(0.1659)	(0.0041)	(0.9783)
F-statistic for Poolability	2.7256**	3.2295**	2.9773**	1.0736
	(0.0341)	(0.0159)	(0.0233)	(0.3743)
VIF	1.78	1.55	1.69	1.36
Time FE	YES	YES	YES	YES
observations	100	100	100	100
banks	20	20	20	20

According to the results, the coefficient of ESG is significantly positive at 1% significance level, which indicates that a higher ESG score would lead to higher Yuan ΔCoVaR. When it comes to analyzing the effect of separate pillars on systemic risk, we regress the Yuan ΔCoVaR on each ESG pillar scores in place of ESG combined scores. The results suggest that the coefficients of the environmental, social, and governance pillars all show statistical significance with positive signs at 1% level. This represents that all separate pillars are positively associated with Yuan ΔCoVaR.

As for the control variables, within our expectation, leverage is positively correlated to Yuan ΔCoVaR which shows that a bank with higher leverage level would have a larger contribution to the systemic risk. In addition, in the regression (1) and (3) with the ESG and social pillar as the independent variable respectively, the relationship between ID and Yuan ΔCoVaR are negative, indicating the systemic risk could be reduced with a more diversified income structure.

Almost all of the F-statistics for poolability suggest that we should reject the null hypothesis and choose a fixed effects model rather than pooled OLS model. In addition, Variance Inflation Factor (VIF) value greater than 10 indicates multicollinearity. Since each VIF value is obviously below 10 for different regression, there are no multicollinearity issues in this model.

6.2 Robustness Analysis

To check the robustness of our model, we replace the 5 years sample data with 10 years unbalanced panel data, which adds two banks and covers a longer period from 2012-2021. This is to test if our model could generate the same results as before, and results are shown in Table 6 below.

Table 6 Robustness results with data from 10 years time period

This table presents the robustness test regarding Table 5. Variables are defined in Table 1. In the parentheses are the p-values. *, **, and *** represent the significance level of 10%, 5%, and 1% respectively. Errors are adjusted for clustering, in this case, to allow for heteroskedasticity and serial correlation, so there are no relevant tests for these two problems.

Dependent Variable: Yuan ΔCoVaR	(1)	(2)	(3)	(4)
ESG	267.08***			
	(0.0000)			
E		138.13***		
		(0.0004)		
S			247.43***	
			(0.0000)	
G				72.194***
				(0.0016)
LEV	32,390***	38,540***	43,840***	48,960***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)
NPL	28,670	-488.39	17,300	-14,860
	(0.7586)	(0.9951)	(0.8564)	(0.8742)
ID	-4,576.9	-4,795.0	-13,000	-372.66
	(0.4188)	(0.4843)	(0.1169)	(0.9495)
F-statistic	5.9058***	3.6622***	6.6056***	4.5017***

for Poolability	(0.0000)	(0.0004)	(0.0000)	(0.0000)
VIF	1.50	1.42	1.51	1.32
Time FE	YES	YES	YES	YES
observations	153	153	153	153
banks	22	22	22	22

From Table 6 we could clearly see that the coefficient of ESG and its separate pillars are still significantly positive at 1% significance level with a different time period. The leverage control variable remains a strongly positive association with Yuan ΔCoVaR as before, which is within our expectation. Therefore, the signs and significance of variables generally keep unchanged compared with Table 5.

To conclude, to solve the heteroskedasticity, standard errors are adjusted for clustering. Besides, the poolability test and VIF value in Table 5 indicates that we should choose the fixed effects model rather than pooled OLS model and there is no evidence for multicollinearity. All above results and test analysis show that our model could be robust to model selection, heteroskedasticity and multicollinearity concerns.

7. Conclusions

This study sets out to assess the impact of ESG and the separate pillars on financial stability which is measured by Yuan ΔCoVaR. We evaluate this impact by answering two research questions mentioned in the introduction section. For the first question “Do banks with higher ESG scores have a relatively low contribution to systemic risk?”, the results suggest that banks with higher ESG scores have a larger contribution to systemic risk. For our second research question “How do separate ESG pillars influence systemic risk?”, we find that separate ESG pillars relate positively to systemic risk. These results are different with the studies based on the developed market where they generally find a positive link between ESG and financial stability (Chiaramonte et al., 2022; Lisin et al., 2022). In addition, our results differ from other studies focusing on the level of sustainability of banks and systemic risk where they find that a higher level of sustainability may contribute to system stability (Scholtens & van't Klooster, 2019; Tóth et al., 2021). Furthermore, like some research (An et al, 2022; Zhang & Wang, 2023) shows that ESG factors could affect bank stability, our paper partly supports that separate pillars could be the factors that affect financial stability, though in a negative way.

One possible reason is that in a developing market, ESG is an emerging concept with an imperfect information closure system and incomplete regulation framework. In this situation, banks with incomplete disclosure of ESG information and insufficient attention to ESG activities tend to be small and medium-sized banks, while banks with higher ESG scores tend to have higher corporate social responsibility with a more formal operating structure and a larger size. Such nationally important banks could play a key role in the whole financial system and have a larger contribution to the financial system thus may lead to a higher systemic risk. In addition, ESG activities sometimes could be seen as costly which require funds and other resource investments, and they tend to pay off in the long run. Therefore, its benefits on financial stability may not be reflected so quickly.

The first limitation in our study is the insufficient sample, which only covers 20 banks in a 5-year period, since ESG disclosure is a relatively new trend in China and its data from previous years is not available for some banks. Besides, due to the insufficient development of ESG in developing markets, it is possible that we may get an unexpected relationship between ESG and systemic risk, since it is still in a developing stage. Therefore, with more ESG scores, stock prices coming out as well as with the popularization and development of ESG in China, the results for ESG studies may be more convincing.

To some extent, our paper fills the gap of ESG research on systemic risk for developing markets in Asia. For regulators, we stress the importance of enhancing ESG information disclosure and forming a well-established ESG regulation system. For banks, we suggest they focus more on ESG development activities and income diversification meanwhile pay attention to leverage level. For future research, our study could give some guidelines for studies on the relationship between ESG and systemic risk based on one specific developing market. Furthermore, it is recommended to conduct research on a combination of several developing markets to see if the results have some similarities. Future studies with a comparative analysis on the ESG impact in risk dimension based on the Chinese market and other developing markets would also be of interest.

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Appendix:

Appendix 1 List of firms included in the data

Ticker symbol	Bank name	Currency	Bank type	Official website
601988.SH	Bank of China	CNY	State-owned commercial bank	BANK OF CHINA GLOBAL WEB SITE (boc.cn)
601328.SH	Bank of Communications	CNY	State-owned commercial bank	www.bankcomm.com/BankCommSite/default.shtml
600036.SH	China Merchants bank	CNY	Joint-stock commercial bank	China Merchants Bank -- Home (cmbchina.com)
600016.SH	China Minsheng Banking Corporation	CNY	Joint-stock commercial bank	CHINA MINSHENG BANK (cmbc.com.cn)
000001.SZ	Ping An Bank	CNY	Joint-stock commercial bank	https://bank.pingan.com/
601009.SH	Bank of Nanjing	CNY	City commercial bank	https://www.njcb.com.cn/
601077.SH	Chongqing Rural Commercial Bank	CNY	Rural commercial bank	ChongQing Rural Commercial Bank (cqrcb.com)
601398.SH	Industrial and Commercial Bank of China	CNY	State-owned commercial bank	Home-ICBC China
601939.SH	China Construction Bank	CNY	State-owned commercial bank	http://www.ccb.com/en/home/indexv3.html
601288.SH	Agricultural Bank of China	CNY	State-owned commercial bank	Agricultural Bank of China (abchina.com)
601166.SH	Industrial Bank	CNY	Joint-stock commercial bank	Welcome to CIB

600000.SH	Shanghai Pudong Development Bank	CNY	Joint-stock commercial bank	https://www.spdb.com.cn/
601169.SH	Bank of Beijing	CNY	City commercial bank	https://www.bankofbeijing.com.cn/
601229.SH	Bank of Shanghai	CNY	City commercial bank	https://www.bosc.cn/en/
002142.SZ	Bank of Ningbo	CNY	City commercial bank	https://www.nbcb.com.cn/english/
601658.SH	Post Savings Bank of China	CNY	State-owned commercial bank	PSBC
601998.SH	China CITIC Bank	CNY	Joint-stock commercial bank	https://www.citicbank.com/
601818.SH	China Everbright Bank	CNY	Joint-stock commercial bank	http://www.cebbank.com/site/gdywwz/CEB_Homepage/Bank%20profile/index.html
600015.SH	Huaxia Bank	CNY	Joint-stock commercial bank	https://www.hxb.com.cn/en/
600919.SH	Bank of Jiangsu	CNY	City commercial bank	http://www.jsbchina.cn/EN/index.html
600926.SH	Bank of Hangzhou	CNY	City commercial bank	http://www.hzbank.com.cn/
601997.SH	Bank of Guiyang	CNY	City commercial bank	https://www.bankgy.cn/portal/zh_CN/home/index.html

Appendix 2 ESG and separate pillar scores for ten years

		ESG Score	Environmental Pillar Score	Social Pillar Score	Governance Pillar Score
601988.SH	2012	41.08	61.47	35.43	46.10
601328.SH	2012	43.87	50.65	29.94	65.77
600036.SH	2012	54.38	71.42	49.65	59.48

600016.SH	2012	40.76	59.40	50.03	29.01
601077.SH	2012	22.41	36.15	26.04	22.29
601398.SH	2012	67.95	75.05	56.27	86.61
601939.SH	2012	59.90	58.29	53.82	74.34
601288.SH	2012	31.94	61.73	18.79	43.56
002142.SZ	2012	6.77	15.26	6.21	10.25
601998.SH	2012	47.53	19.75	38.33	77.41
601988.SH	2013	42.77	62.28	33.69	52.77
601328.SH	2013	47.71	51.00	27.18	79.95
600036.SH	2013	48.75	72.49	49.87	42.97
600016.SH	2013	38.73	59.83	46.70	27.82
601077.SH	2013	23.48	32.70	19.77	36.43
601398.SH	2013	55.44	75.09	55.46	52.85
601939.SH	2013	45.48	58.42	45.57	45.48
601288.SH	2013	31.22	62.24	18.65	41.43
002142.SZ	2013	7.43	15.25	7.05	10.92
601998.SH	2013	43.96	16.71	37.84	69.38
601988.SH	2014	34.27	59.00	33.21	31.22
601328.SH	2014	44.36	51.12	29.05	68.13
600036.SH	2014	47.36	71.49	43.85	47.92
600016.SH	2014	42.17	62.35	48.21	34.21
601077.SH	2014	24.30	33.13	19.55	38.97
601398.SH	2014	59.46	70.83	55.22	66.14
601939.SH	2014	50.75	63.06	45.42	58.53
601288.SH	2014	29.98	56.62	16.44	43.35
002142.SZ	2014	22.03	15.45	16.40	38.61
601998.SH	2014	43.66	15.45	38.80	67.83

601818.SH	2014	6.72	15.45	9.71	5.30
601988.SH	2015	35.41	70.55	36.22	26.77
601328.SH	2015	46.35	59.06	33.02	66.19
600036.SH	2015	49.60	71.72	42.96	56.46
600016.SH	2015	36.82	63.56	42.73	29.01
601077.SH	2015	30.57	40.23	36.35	32.87
601398.SH	2015	68.16	73.17	65.07	76.96
601939.SH	2015	49.59	76.45	51.44	42.85
601288.SH	2015	39.69	64.25	26.73	54.25
002142.SZ	2015	13.78	18.28	11.76	22.08
601998.SH	2015	52.39	45.18	44.09	77.73
601818.SH	2015	10.42	43.97	10.63	7.75
601988.SH	2016	43.21	70.09	50.96	29.42
601328.SH	2016	45.35	60.67	40.89	53.01
600036.SH	2016	50.10	74.24	54.39	42.15
600016.SH	2016	42.51	66.52	53.65	30.99
601077.SH	2016	33.38	46.14	45.36	28.37
601398.SH	2016	66.93	75.84	67.48	70.25
601939.SH	2016	56.85	79.52	54.99	57.98
601288.SH	2016	46.32	70.09	31.28	65.17
002142.SZ	2016	26.56	21.15	41.86	16.11
601998.SH	2016	49.92	47.30	44.73	71.58
601818.SH	2016	16.55	47.30	21.74	10.54
601988.SH	2017	54.41	57.22	55.63	51.60
601328.SH	2017	58.93	49.42	56.27	66.41
600036.SH	2017	58.11	55.94	65.06	49.41
600016.SH	2017	40.42	34.85	50.97	28.11

000001.SZ	2017	27.24	13.01	28.22	31.58
601009.SH	2017	29.27	12.03	26.90	39.42
601077.SH	2017	50.73	37.02	57.27	47.22
601398.SH	2017	59.72	47.22	66.00	56.07
601939.SH	2017	60.37	61.47	56.13	65.77
601288.SH	2017	53.17	51.59	38.80	73.58
601166.SH	2017	30.35	17.09	43.41	17.66
600000.SH	2017	38.40	12.03	30.03	60.48
601169.SH	2017	25.94	16.36	25.72	30.08
601229.SH	2017	36.08	6.65	39.04	43.76
002142.SZ	2017	34.97	38.76	43.29	22.00
601658.SH	2017	51.00	34.81	58.50	47.13
601998.SH	2017	58.78	55.04	53.43	67.66
601818.SH	2017	28.11	20.38	32.08	25.74
600015.SH	2017	34.04	21.68	29.78	44.85
600019.SH	2017	45.09	60.98	38.17	33.63
600926.SH	2017	29.88	12.95	27.47	39.96
601997.SH	2017	28.80	3.08	38.42	25.83
601988.SH	2018	51.75	58.93	48.61	53.20
601328.SH	2018	57.13	49.78	57.56	59.46
600036.SH	2018	59.19	53.46	61.73	57.98
600016.SH	2018	37.35	36.11	44.97	27.35
000001.SZ	2018	31.23	17.56	34.39	32.34
601009.SH	2018	35.15	12.09	24.28	59.35
601077.SH	2018	46.43	35.62	50.88	44.62
601398.SH	2018	57.24	46.98	60.69	56.60
601939.SH	2018	60.91	58.92	57.36	66.61

601288.SH	2018	43.79	48.97	32.76	56.92
601166.SH	2018	32.62	22.67	45.01	19.54
600000.SH	2018	49.99	16.03	34.31	85.19
601169.SH	2018	32.26	17.28	33.80	36.12
601229.SH	2018	38.89	10.38	42.95	44.69
002142.SZ	2018	33.63	37.78	43.02	19.02
601658.SH	2018	50.28	38.11	56.13	47.09
601998.SH	2018	62.34	56.82	51.74	79.15
601818.SH	2018	39.36	30.19	45.49	34.58
600015.SH	2018	32.31	22.88	25.50	45.46
600019.SH	2018	42.04	57.62	34.44	32.15
600926.SH	2018	38.69	13.17	43.84	41.79
601997.SH	2018	30.67	10.78	38.10	28.39
601988.SH	2019	49.54	56.64	45.43	52.35
601328.SH	2019	55.56	56.42	56.36	54.12
600036.SH	2019	53.30	51.65	59.15	45.91
600016.SH	2019	46.68	36.86	61.77	29.82
000001.SZ	2019	29.11	24.20	32.08	26.98
601009.SH	2019	38.98	13.60	26.94	65.73
601077.SH	2019	46.95	36.07	48.48	49.18
601398.SH	2019	56.68	48.23	60.83	54.33
601939.SH	2019	60.47	57.51	55.75	68.16
601288.SH	2019	50.81	52.87	33.52	73.81
601166.SH	2019	36.38	24.92	49.45	22.96
600000.SH	2019	32.03	28.90	32.24	32.99
601169.SH	2019	25.02	17.96	31.04	19.55
601229.SH	2019	36.52	11.05	47.03	32.23

002142.SZ	2019	32.64	46.17	41.41	15.15
601658.SH	2019	47.48	37.14	54.39	42.10
601998.SH	2019	60.93	57.54	50.59	76.52
601818.SH	2019	41.14	53.29	45.39	30.42
600015.SH	2019	32.46	26.33	23.64	47.06
600019.SH	2019	50.38	70.44	40.05	38.55
600926.SH	2019	38.71	19.56	42.91	40.59
601997.SH	2019	26.63	13.19	34.24	21.51
601988.SH	2020	61.20	56.61	58.54	66.69
601328.SH	2020	51.16	58.07	56.20	41.45
600036.SH	2020	52.83	56.64	68.31	29.98
600016.SH	2020	43.02	33.78	60.80	22.21
000001.SZ	2020	38.56	29.62	52.34	23.13
601009.SH	2020	38.85	13.80	29.46	61.81
601077.SH	2020	44.17	54.84	45.99	37.39
601398.SH	2020	56.21	45.66	60.65	54.31
601939.SH	2020	60.97	59.37	54.68	70.28
601288.SH	2020	41.84	49.96	35.51	47.32
601166.SH	2020	33.81	27.00	44.57	21.70
600000.SH	2020	40.35	71.55	34.44	36.01
601169.SH	2020	33.55	18.36	27.05	48.59
601229.SH	2020	41.51	11.69	44.15	49.79
002142.SZ	2020	46.77	46.64	40.82	55.01
601658.SH	2020	45.17	36.98	57.51	31.44
601998.SH	2020	61.30	56.21	49.16	80.06
601818.SH	2020	42.51	74.98	42.46	29.59
600015.SH	2020	36.81	27.19	26.99	54.18

600019.SH	2020	54.43	73.34	46.67	40.03
600926.SH	2020	39.08	20.35	43.10	41.03
601997.SH	2020	38.73	22.48	39.69	43.90
601988.SH	2021	62.58	63.38	60.19	65.54
601328.SH	2021	44.98	45.70	53.02	33.60
600036.SH	2021	53.64	63.85	63.70	35.71
600016.SH	2021	41.25	34.72	60.79	16.95
000001.SZ	2021	48.90	39.12	66.12	29.10
601009.SH	2021	56.90	54.24	39.39	82.09
601077.SH	2021	45.73	55.54	51.21	34.27
601398.SH	2021	59.78	52.44	62.49	58.99
601939.SH	2021	60.10	66.91	50.57	70.50
601288.SH	2021	50.88	56.11	39.09	65.04
601166.SH	2021	46.36	54.30	64.84	17.73
600000.SH	2021	43.24	78.24	40.58	32.90
601169.SH	2021	29.18	22.57	22.68	40.78
601229.SH	2021	55.28	73.08	46.43	60.35
002142.SZ	2021	45.85	51.44	38.47	53.77
601658.SH	2021	43.86	42.98	57.30	25.70
601998.SH	2021	61.82	61.88	49.37	78.95
601818.SH	2021	46.84	79.18	47.69	32.72
600015.SH	2021	42.46	37.40	36.95	52.08
600019.SH	2021	69.46	76.57	61.02	73.10
600926.SH	2021	41.32	24.49	40.46	49.25
601997.SH	2021	37.10	29.56	42.81	32.23

Appendix 3 5% and 50%-var of banks

Bank Name	**Time**	**5%VaR**	**50%VaR**
Bank of China	2017	0.012750	0.000000
	2018	0.018466	0.000000
	2019	0.015414	0.000000
	2020	0.011933	0.000000
	2021	0.008677	0.000000
Bank of Communications	2017	0.011694	0.000000
	2018	0.015861	0.000281
	2019	0.018567	-0.000148
	2020	0.012686	0.000079
	2021	0.010414	0.000596
China Merchants bank	2017	0.020271	-0.000270
	2018	0.026957	-0.000256
	2019	0.029664	-0.000285
	2020	0.025546	0.000801
	2021	0.028728	0.000709
China Minsheng Banking Corporation	2017	0.013135	0.000878
	2018	0.019442	0.000153
	2019	0.015655	0.000359
	2020	0.014547	0.000053
	2021	0.013507	0.000163
Ping An Bank	2017	0.019023	0.000000
	2018	0.032548	0.000600
	2019	0.029299	0.000360
	2020	0.031560	0.000040

	2021	0.034452	0.001015
Bank of Nanjing	2017	0.018078	0.000134
	2018	0.023693	0.000121
	2019	0.026931	-0.000734
	2020	0.025071	0.000292
	2021	0.024976	0.000908
Industrial and Commercial Bank of China	2017	0.017994	-0.000964
	2018	0.022853	0.000101
	2019	0.018352	-0.000226
	2020	0.013930	0.000091
	2021	0.013019	0.001042
China Construction Bank	2017	0.014206	0.000000
	2018	0.026202	0.000823
	2019	0.023619	-0.000034
	2020	0.016172	-0.000044
	2021	0.020299	0.000796
Agricultural Bank of China	2017	0.013033	0.000000
	2018	0.022054	0.000000
	2019	0.018509	-0.000117
	2020	0.012307	0.000000
	2021	0.009613	0.000000
Industrial Bank	2017	0.012684	0.000166
	2018	0.016835	0.000849
	2019	0.023110	0.000108
	2020	0.023746	0.000503
	2021	0.032594	0.000183

Shanghai Pudong Development Bank	2017	0.013434	0.000775
	2018	0.019423	0.000412
	2019	0.021256	0.000015
	2020	0.021736	-0.000397
	2021	0.017616	0.001013
Bank of Beijing	2017	0.012958	0.000000
	2018	0.016933	0.000648
	2019	0.016960	0.000048
	2020	0.016187	0.000380
	2021	0.011807	0.000041
Bank of Shanghai	2017	0.019442	0.001159
	2018	0.021497	0.000400
	2019	0.020753	-0.000135
	2020	0.016681	0.000122
	2021	0.015436	0.000343
Bank of Ningbo	2017	0.019965	0.000669
	2018	0.028350	0.000815
	2019	0.026805	-0.000391
	2020	0.029612	0.002163
	2021	0.037895	0.000105
China CITIC Bank	2017	0.016976	0.001553
	2018	0.023218	0.000044
	2019	0.020108	0.000034
	2020	0.016961	0.000556
	2021	0.015005	0.000016
China Everbright Bank	2017	0.012134	0.000000

	2018	0.017653	0.000000
	2019	0.021384	0.000000
	2020	0.021986	0.001627
	2021	0.023610	0.002188
Huaxia Bank	2017	0.012978	0.000967
	2018	0.017517	0.001176
	2019	0.017739	0.000739
	2020	0.015838	0.000713
	2021	0.014817	0.000880
Bank of Jiangsu	2017	0.018995	0.001478
	2018	0.020342	0.001286
	2019	0.017952	0.000427
	2020	0.017769	0.000171
	2021	0.025544	0.000033
Bank of Hangzhou	2017	0.025273	0.002048
	2018	0.023935	0.000643
	2019	0.020986	-0.000042
	2020	0.023647	-0.000084
	2021	0.034514	0.001048
Bank of Guiyang	2017	0.022903	0.001074
	2018	0.023074	0.000410
	2019	0.024292	0.000908
	2020	0.025424	0.000349
	2021	0.019567	0.000933

Appendix 4 Estimated parameters of the 5 years quantile regression

Bank Name	Parameter	Value
Bank of China	α	-0.000170
	β	0.943714
Bank of Communications	α	-0.000236
	β	0.850374
China Merchants bank	α	0.000335
	β	0.501506
China Minsheng Banking Corporation	α	-0.000531
	β	0.834405
Ping An Bank	α	0.000127
	β	0.404722
Bank of Nanjing	α	-0.000021
	β	0.487915
Industrial and Commercial Bank of China	α	-0.000039
	β	0.825137
China Construction Bank	α	-0.000032
	β	0.708634
Agricultural Bank of China	α	-0.000115
	β	0.884999
Industrial Bank	α	-0.000005
	β	0.544327
Shanghai Pudong Development Bank	α	-0.000284
	β	0.668329
Bank of Beijing	α	-0.000466

	β	0.788682
Bank of Shanghai	α	-0.000232
	β	0.591867
Bank of Ningbo	α	0.000279
	β	0.386251
China CITIC Bank	α	-0.000247
	β	0.638914
China Everbright Bank	α	-0.000162
	β	0.634015
Huaxia Bank	α	-0.000391
	β	0.797337
Bank of Jiangsu	α	-0.000268
	β	0.512438
Bank of Hangzhou	α	-0.000022
	β	0.358857
Bank of Guiyang	α	-0.000316
	β	0.527401

Appendix 5 Estimated parameters of 10 years quantile regression

Bank Name	**Parameter**	**Value**
Bank of China	α	-0.000125
	β	0.834621
Bank of Communications	α	-0.000138
	β	0.733539

China Merchants bank	α	0.000206
	β	0.585139
China Minsheng Banking Corporation	α	-0.000143
	β	0.645775
Ping An Bank	α	0.000078
	β	0.480757
Bank of Nanjing	α	0.000080
	β	0.518808
Chongqing Rural Commercial Bank	α	-0.000542
	β	0.470649
Industrial and Commercial Bank of China	α	-0.000100
	β	0.881138
China Construction Bank	α	-0.000048
	β	0.753869
Agricultural Bank of China	α	-0.000089
	β	0.884921
Industrial Bank	α	0.000083
	β	0.583429
Shanghai Pudong Development Bank	α	0.000011
	β	0.626174
Bank of Beijing	α	-0.000070
	β	0.654845
Bank of Shanghai	α	-0.000227
	β	0.513117
Bank of Ningbo	α	0.000254

	β	0.458204
Postal Savings Bank of China	α	0.000116
	β	0.473181
China CITIC Bank	α	-0.000077
	β	0.551532
China Everbright Bank	α	-0.000093
	β	0.658294
Huaxia Bank	α	-0.000144
	β	0.672428
Bank of Jiangsu	α	-0.000199
	β	0.416680
Bank of Hangzhou	α	-0.000015
	β	0.323150
Bank of Guiyang	α	-0.000137
	β	0.413755

Appendix 6 Estimated results of 5%, 50%-CoVaR, ΔCoVaR and YuanΔCoVaR

Bank name	**Time**	**5% CoVaR**	**50%CoVaR**	**ΔCoVaR**	**YuanΔCoVaR**
Bank of China	2017	0.011860	-0.000172	0.012032	13177.95
	2018	0.017254	-0.000172	0.017426	18521.10
	2019	0.014374	-0.000172	0.014546	14957.74
	2020	0.011089	-0.000172	0.011262	10408.37
	2021	0.008016	-0.000172	0.008188	7030.56
Bank of Communications	2017	0.009709	-0.000236	0.009944	4144.40

	2018	0.013251	0.000003	0.013249	5437.21
	2019	0.015553	-0.000362	0.015914	6604.71
	2020	0.010552	-0.000169	0.010720	3602.97
	2021	0.008620	0.000271	0.008348	2651.17
China Merchants bank	2017	0.010506	0.000205	0.010301	7322.11
	2018	0.013859	0.000212	0.013647	9829.27
	2019	0.015217	0.000197	0.015020	12793.75
	2020	0.013152	0.000742	0.012410	11600.46
	2021	0.014748	0.000696	0.014052	18412.79
China Minsheng Banking Corporation	2017	0.010426	0.000199	0.010228	3057.45
	2018	0.015689	-0.000405	0.016094	4300.10
	2019	0.012529	-0.000234	0.012763	3312.76
	2020	0.011605	-0.000490	0.012094	2848.53
	2021	0.010737	-0.000398	0.011135	2049.10
Ping An Bank	2017	0.007817	0.000118	0.007699	1732.69
	2018	0.013291	0.000361	0.012930	2372.54
	2019	0.011976	0.000264	0.011712	2902.83
	2020	0.012891	0.000134	0.012757	3797.32
	2021	0.014062	0.000529	0.013533	5415.60
Bank of Nanjing	2017	0.008802	0.000047	0.008755	591.74
	2018	0.011542	0.000040	0.011501	757.18
	2019	0.013122	-0.000377	0.013498	941.05
	2020	0.012214	0.000124	0.012090	926.80
	2021	0.012168	0.000425	0.011743	1109.64
Industrial and Commercial Bank of China	2017	0.014802	-0.000842	0.015643	32342.98
	2018	0.018810	0.000037	0.018773	37668.21

	2019	0.015097	-0.000233	0.015329	29931.41
	2020	0.011448	0.000029	0.011419	20232.45
	2021	0.010696	0.000814	0.009882	16681.92
China Construction Bank	2017	0.010031	-0.000036	0.010067	14770.81
	2018	0.018532	0.000548	0.017984	27599.99
	2019	0.016701	-0.000060	0.016761	24024.95
	2020	0.011424	-0.000067	0.011491	15406.54
	2021	0.014349	0.000528	0.013821	17156.01
Agricultural Bank of China	2017	0.011417	-0.000118	0.011534	13716.10
	2018	0.019400	-0.000118	0.019517	24550.99
	2019	0.016263	-0.000221	0.016484	20688.91
	2020	0.010774	-0.000118	0.010892	12484.71
	2021	0.008390	-0.000118	0.008508	9035.49
Industrial Bank	2017	0.006899	0.000085	0.006814	2446.63
	2018	0.009159	0.000457	0.008702	2880.38
	2019	0.012574	0.000054	0.012521	4760.53
	2020	0.012920	0.000269	0.012652	4538.04
	2021	0.017736	0.000094	0.017642	7565.58
Shanghai Pudong Development Bank	2017	0.008691	0.000230	0.008460	3167.71
	2018	0.012693	-0.000012	0.012706	4055.97
	2019	0.013919	-0.000278	0.014196	4830.99
	2020	0.014239	-0.000553	0.014793	4516.98
	2021	0.011485	0.000389	0.011096	3142.34
Bank of Beijing	2017	0.009776	-0.000444	0.010220	1378.00
	2018	0.012910	0.000067	0.012843	1722.56
	2019	0.012932	-0.000407	0.013338	1637.23

	2020	0.012322	-0.000145	0.012467	1306.43
	2021	0.008867	-0.000412	0.009279	910.59
Bank of Shanghai	2017	0.011271	0.000450	0.010821	1309.22
	2018	0.012488	0.000001	0.012487	1534.27
	2019	0.012048	-0.000316	0.012363	1610.05
	2020	0.009637	-0.000164	0.009801	1163.00
	2021	0.008900	-0.000033	0.008933	997.37
Bank of Ningbo	2017	0.007999	0.000546	0.007453	665.63
	2018	0.011238	0.000602	0.010636	955.12
	2019	0.010641	0.000136	0.010505	1306.99
	2020	0.011725	0.001123	0.010602	1904.25
	2021	0.014925	0.000328	0.014596	3391.06
China CITIC Bank	2017	0.010595	0.000741	0.009854	2709.24
	2018	0.014583	-0.000223	0.014806	4065.10
	2019	0.012597	-0.000229	0.012826	3384.27
	2020	0.010586	0.000104	0.010482	2389.68
	2021	0.009336	-0.000241	0.009577	2061.97
China Everbright Bank	2017	0.007529	-0.000164	0.007693	1436.74
	2018	0.011028	-0.000164	0.011192	2178.69
	2019	0.013393	-0.000164	0.013558	2737.49
	2020	0.013775	0.000867	0.012908	2448.59
	2021	0.014804	0.001223	0.013582	2540.69
Huaxia Bank	2017	0.009955	0.000378	0.009577	1123.10
	2018	0.013574	0.000544	0.013030	1360.09
	2019	0.013751	0.000197	0.013554	1600.90
	2020	0.012235	0.000176	0.012060	1212.25

	2021	0.011421	0.000309	0.011112	1028.71
Bank of Jiangsu	2017	0.009468	0.000492	0.008976	808.94
	2018	0.010158	0.000393	0.009765	761.69
	2019	0.008933	-0.000047	0.008980	722.41
	2020	0.008840	-0.000178	0.009018	653.01
	2021	0.012824	-0.000249	0.013073	1221.03
Bank of Hangzhou	2017	0.009044	0.000709	0.008334	369.05
	2018	0.008564	0.000205	0.008358	345.54
	2019	0.007506	-0.000041	0.007546	327.23
	2020	0.008460	-0.000056	0.008516	545.28
	2021	0.012360	0.000350	0.012010	1071.49
Bank of Guiyang	2017	0.011762	0.000249	0.011513	378.54
	2018	0.011852	-0.000101	0.011953	353.93
	2019	0.012495	0.000162	0.012333	354.91
	2020	0.013092	-0.000133	0.013224	341.71
	2021	0.010002	0.000175	0.009827	252.67

Appendix 7 Estimated results of ΔCoVaR and Yuan CoVaR for ten years

Bank name	**Time**	**ΔCoVaR**	**YuanΔCoVaR(*million)**
Bank of China	2012	0.008359	6451.1
	2013	0.011205	8763.9
	2014	0.011638	9039.4
	2015	0.032412	38694.9
	2016	0.021859	20518.0
	2017	0.008899	9621.3

	2018	0.015412	16380.1
	2019	0.012865	13228.6
	2020	0.009960	9205.2
	2021	0.007242	6217.8
Bank of Communications	2012	0.010556	3493.7
	2013	0.015184	4963.8
	2014	0.012945	4099.1
	2015	0.029426	13210.7
	2016	0.023816	8774.2
	2017	0.008898	3746.2
	2018	0.011428	4690.2
	2019	0.013728	5697.3
	2020	0.009248	3107.9
	2021	0.007201	2286.9
China Merchants bank	2012	0.011259	2696.5
	2013	0.014941	4052.8
	2014	0.012120	3302.2
	2015	0.018123	7863.3
	2016	0.016062	6684.7
	2017	0.009928	5889.1
	2018	0.015923	11468.4
	2019	0.017525	14927.3
	2020	0.014479	13535.0
	2021	0.016395	21483.3
China Minsheng Banking Corporation	2012	0.012581	2350.6
	2013	0.022767	5721.9
	2014	0.015169	3292.2

	2015	0.021771	6900.1
	2016	0.019429	6051.7
	2017	0.007719	2297.4
	2018	0.012456	3328.0
	2019	0.009878	2563.9
	2020	0.009360	2204.6
	2021	0.008618	1585.9
Ping An Bank	2017	0.006597	1218.1
	2018	0.015359	2818.3
	2019	0.013913	3448.2
	2020	0.015154	4510.7
	2021	0.016075	6433.0
Bank of Nanjing	2017	0.010150	691.9
	2018	0.012230	805.1
	2019	0.014353	1000.6
	2020	0.012855	985.5
	2021	0.012487	1179.9
Chongqing Rural Commercial bank	2019	0.005115	349.1
	2020	0.011564	616.4
	2021	0.007820	333.4
Industrial and Commercial Bank of China	2012	0.009964	13970.7
	2013	0.013309	18845.0
	2014	0.011043	14291.8
	2015	0.027850	46685.0
	2016	0.017700	26215.6
	2017	0.011028	20936.9
	2018	0.020047	40235.3

	2019	0.016370	31964.9
	2020	0.012195	21605.6
	2021	0.010553	17814.1
China Construction Bank	2012	0.009313	11182.9
	2013	0.014373	17125.6
	2014	0.010076	11234.5
	2015	0.029480	37269.7
	2016	0.020063	21872.9
	2017	0.009499	13389.0
	2018	0.019132	29364.6
	2019	0.017831	25558.1
	2020	0.012225	16390.0
	2021	0.014703	18251.1
Agricultural Bank of China	2012	0.010733	9265.9
	2013	0.015302	13208.5
	2014	0.012504	10380.5
	2015	0.030734	33680.8
	2016	0.020039	19890.3
	2017	0.009178	10450.9
	2018	0.019516	24548.2
	2019	0.016482	20689.2
	2020	0.010891	12483.6
	2021	0.008507	9034.7
Industrial Bank	2017	0.006573	2270.6
	2018	0.009327	3088.8
	2019	0.013420	5097.5
	2020	0.013561	4862.2

	2021	0.018909	8106.8
Shanghai Pudong Development Bank	2017	0.007732	2788.5
	2018	0.011904	3803.5
	2019	0.013301	4522.3
	2020	0.013860	4236.5
	2021	0.010396	2945.6
Bank of Beijing	2017	0.007764	1090.2
	2018	0.010646	1428.7
	2019	0.011075	1359.3
	2020	0.010351	1085.5
	2021	0.007704	756.3
Bank of Shanghai	2017	0.009610	1343.2
	2018	0.010825	1329.6
	2019	0.010718	1395.3
	2020	0.008497	1009.2
	2021	0.007745	864.9
Bank of Ningbo	2012	0.010945	292.5
	2013	0.012304	343.0
	2014	0.009697	283.0
	2015	0.019078	1057.2
	2016	0.020084	1122.9
	2017	0.008793	675.8
	2018	0.012617	1133.4
	2019	0.012462	1546.7
	2020	0.012578	2256.1
	2021	0.017323	4022.0
Postal Savings Bank of China	2020	0.006518	2626.1

	2021	0.010990	5171.3
China CITIC Bank	2012	0.012193	2082.2
	2013	0.014388	2605.1
	2014	0.014427	3001.3
	2015	0.024823	7485.2
	2016	0.022052	5777.3
	2017	0.009323	2650.1
	2018	0.012781	3509.1
	2019	0.011072	2921.4
	2020	0.009048	2062.9
	2021	0.008267	1780.0
China Everbright Bank	2014	0.012536	1612.4
	2015	0.027733	5733.1
	2016	0.022308	3775.0
	2017	0.008948	1650.4
	2018	0.011621	2262.1
	2019	0.014077	2842.3
	2020	0.013402	2542.4
	2021	0.014102	2638.0
Huaxia Bank	2017	0.009177	1096.1
	2018	0.010989	1147.0
	2019	0.011431	1350.1
	2020	0.010170	1022.3
	2021	0.009371	867.6
Bank of Jiangsu	2017	0.008875	933.2
	2018	0.007940	619.4
	2019	0.007302	587.4

	2020	0.007341	531.7
	2021	0.010630	992.9
Bank of Hangzhou	2017	0.007954	424.2
	2018	0.007527	311.2
	2019	0.006795	294.7
	2020	0.007668	491.0
	2021	0.010815	964.9
Bank of Guiyang	2017	0.011872	429.3
	2018	0.009377	277.7
	2019	0.009675	278.4
	2020	0.010375	268.1
	2021	0.007710	198.2