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RESEARCH ARTICLE

Bank tail risk in China

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Abstract

In this study, we investigate the tail dependency between bank stocks in China and 35 common risk factors. We measure univariate and multivariate conditional tail risk probabilities. The evidence indicates that tail events from risk factors in the banking, security trading, real estate, and energy industries have the largest effects on the realization of extreme returns from Chinese bank stocks. The univariate conditional tail risk is considerably higher than the unconditional tail risk. The impact of multiple tail events from several risk factors occurring simultaneously is much stronger than tail events from one single risk factor. In general, there is a stronger cross-market tail linkage between emerging market risk factors and bank stocks in China when compared with developed market risk factors. However, the cross-market tail linkage between developed market risk factors and bank stocks in China rose sharply during the 2008 financial crisis.

KEYWORDS

bank stocks, loan loss provisions, risk factors, tail risk

JEL CLASSIFICATION

G21, G12

1 | INTRODUCTION

Tail risk, especially tail risk in the banking sector, has increasingly caught the attention of risk managers, investors, and regulators since the financial crisis of 2008. Earlier studies measure tail risk at the bank level. However, these measures cannot capture the bank's risk connection to other banks or to macro-economic conditions. A few papers have started to investigate tail risk measures, aiming to capture the tail dependency between a particular institution and the entire financial system (Acharya et al., 2012, 2017; Adrian & Brunnermeier, 2016; Brownlees & Engle, 2017).

Acharya et al. (2012) and Brownlees and Engle (2017) developed the SRISK measure which calculates the expected capital shortfall of individual institutions conditional on the entire financial market being in a crisis. When SRISK is equal to zero, the institution will not need to raise capital in a severe crisis. Adrian and Brunnermeier (2016) propose to employ quantile regressions to measure the change in conditional VaR, that is, $\Delta CoVaR$. This can be used to measure the change in a particular institution's risk given the whole financial system is in distress. Alternatively, it can be used to capture the change in $CoVaR$ of the whole financial system conditional on the distress of a particular institution. Acharya et al. (2017) calculate the marginal expected shortfall (*MES*). *MES* aims to measure the firm's expected capital losses during a crisis. *MES* is easy to compute: one can simply calculate each bank's average return during the 5% worst days for the market. Acharya et al. (2017) show that *MES* does a good job in explaining realized stock returns during a financial crisis.[1]

In this paper, we investigate the tail dependency between bank stocks in China and risk factors in China, risk factors in emerging markets, and risk factors in developed markets. Our approach is simple and flexible and builds on the work from the financial market contagion literature (Bae et al., 2003; Chiu et al., 2015; Dungey et al., 2005). Our approach provides a more general analysis of tail risk in the cross-section and over time for bank stocks. Our approach also addresses tail risk issues during a financial crisis, which has been the focus of earlier studies using SRISK, $\Delta CoVaR$, or *MES* measures.

The methodology is different from that used in other studies. First, we construct a probability-based measure of tail risk, including both unconditional and conditional probabilities. The univariate conditional probability examines the probability of tail events from individual bank stocks conditional on tail events from one particular risk factor. We can identify the most influential risk factor via univariate conditional probability. Second, we examine multivariate conditional probability conditional on tail events from several risk factors occurring simultaneously. We expect the multivariate conditional probabilities to increase sharply as tail events from more risk factors take place simultaneously. Third, we construct a probability-based measure of tail risk using daily returns from within a fiscal year. We obtain pooled time-series and cross-sectional tail risk probabilities that can be used to examine which bank characteristics determine bank tail risk. Finally, our approach allows us to examine the cross-market tail linkage. We can easily collect risk factors from emerging markets and developed markets and assess the impact of tail events from these markets on tail events of individual bank stocks in China.

We conduct our analysis in the Chinese financial market. China, as the largest emerging economy, has garnered increasing attention both in academic research and in practice. The banking sector plays an important role in China's financial system. Financing through the banking sector accounts for more than 80% of all financing channels in China.[2] Chinese commercial banks mainly include five large state-owned banks, some nationwide joint-stock banks, many small and medium city and rural banks, and some foreign banks. For our analysis, we select 31 banks listed in the Chinese stock market, including five large state-owned banks (*SOB*), eight nationwide joint-stock commercial banks (*JOB*), and 18 small and medium city commercial banks (*CCB*). Yang et al. (2021) adopt this same method to study bank tail risk in the United States.

We summarize our main results here. If we use the 95th percentile and 5th percentile values as our cut-off values, then, by definition, the unconditional upper and lower tail risk is 0.05 in both cases. When we consider univariate conditional tail risk probabilities, the univariate upper conditional probabilities increase by more than 10 times to 0.520, and the univariate lower

[1]See tab. 4 of Acharya et al. (2017).
[2]*Source*: Wind Database, http://www.wind.com.cn.

conditional probabilities increase by more than 10 times to 0.547 when the risk factor from the entire banking sector enters its extreme territories. The impact of entire banking sector tails far exceeds the impact of broad stock market tails. The corresponding univariate upper and lower conditional probabilities are 0.283 and 0.387, respectively, when the risk factor under consideration is the broad stock market index. The other two industries with large tail event impacts are the securities trading sector and the insurance sector. The strong tail dependence between individual bank stock returns and financial sector index returns suggests that one might use financial sector index returns to compute *MES* as Acharya et al. (2017) did for the US market.

Then we look into the multivariate conditional tail risk probabilities when tail events from several risk factors occur simultaneously. Multiple risk factors' tail events are much more influential on individual bank stocks' tail events than tail events from a single risk factor. The chance of a bank stock's return realizing an extremely large positive return given one risk factor also realizing a large value (positive or negative) that is favorable to stock movement is only 0.016. When five risk factors simultaneously fall into their respective favorable tails, the probability increases more than seven times to 0.119. When 10 risk factors simultaneously fall into their respective favorable tails, the probability increases more than 18 times to 0.294. Similar patterns can be observed for the lower tail situation. Our evidence suggests that measures such as $\Delta CoVAR$ and *MES* can also be revised to be conditional on several risk factors. We can examine whether adding additional risk factors in *MES* will further improve their predictability for bank performance during financial crises.

We move on to examine cross-country tail linkage. We collect risk factors in the banking and security trading sectors from both emerging and developed markets. Broadly speaking, the impact of tail events from the emerging market financial sector on tail events of individual banks in China is roughly twice that of tail events from the developed market financial sector, based on our measures of univariate conditional probabilities. This is consistent with evidence from the cross-country financial contagion literature. For example, Hu (2010) finds that the tail dependence between the Chinese and US financial markets is generally low and that downturns in the US financial market have a weaker effect on the Chinese stock market compared to their effect on other countries. Hu (2010) adopts the time-varying conditional copula model to study dependence structure and employs stock market indices rather than individual stocks.

We further investigate the time paths of tail dependence between Chinese listed bank stocks and developed market risk factors for each year from 2007 to 2019. Conditional on unfavorable tail outcomes of developed market risk factors, the lower exceedance probability of Chinese banks in 2008 rises above 20%. The conditional tail risk probabilities in 2008 differ remarkably from the conditional tail risk probabilities in noncrisis years. The greater tail dependencies during bear markets imply that bank regulators should be alert to the increasing probability of bank stocks' crashing after a shock from developed countries.

Finally, we explore determiners of unconditional and conditional bank tail risks. Since we use daily bank stock returns to construct firm-level multivariate conditional probabilities, there will be cross-sectional and time-series variation in these probabilities that can be linked to bank characteristics. We consider a number of important bank characteristics. The empirical results show that loan loss provisions, the dominant bank accrual, is the most important determinant of bank tail risks. This is consistent with earlier studies that show banks have incentives to smooth reported earnings.[3] This can make the banks' financial conditions less transparent to stock market investors and lead to large positive or negative tail events on individual banks' returns.

[3]See Greenawalt and Sinkey (1988), Wahlen (1994), and Ahmed et al. (1999).

We organize the rest of the paper as follows. Section 2 introduces the tail risk measures. Section 3 provides a description of data sources and summary statistics. Section 4 carries out detailed empirical analysis of tail risk probabilities. Section 5 investigates bank characteristics that are related to bank tail risks. Section 6 concludes the study.

2 | TAIL RISK MEASURES

This section describes the tail risk measures in detail. We construct an unconditional exceedance model to describe the case of extreme bank returns and a conditional exceedance model to capture the tail linkage between risk factors and bank stocks. For conditional exceedance, we further investigate both univariate and multivariate cases. The univariate case measures the impact of a single risk factor, while the multivariate case examines the joint effect of several risk factors. We begin with unconditional exceedance.

2.1 | Unconditional tail risk probability

We first construct indicators to capture the incidence of large positive and negative daily returns of bank stocks. The indicator variable $I\_UP_{i,t}$ in Equation (1) represents the case when the daily return of bank stock i exceeds its upper tail threshold $High\_Tail_{type,year}$:

$$I\_UP_{i,t} = \begin{cases} 1, \text{ if } RET_{i.t} \geq High\_Tail_{type,year} \\ 0 \text{ if } RET_{i.t} < High\_Tail_{type,year} \end{cases}, \tag{1}$$

where i refers to bank stock, t refers to trading day, $type$ refers to bank type, and $year$ refers to fiscal year. $I\_UP_{i,t}$ equals 1 if daily return $RET_{i,t}$ is greater than the upper tail threshold $High\_Tail_{type,year}$, and 0 otherwise. Symmetrically, we define the indicator variable $I\_DOWN_{i,t}$ to capture the extremely low exceedance in the below equation:

$$I\_DOWN_{i,t} = \begin{cases} 1, \text{ if } RET_{i.t} \leq Low\_Tail_{type,year} \\ 0 \text{ if } RET_{i.t} > Low\_Tail_{type,year} \end{cases}. \tag{2}$$

The observed probability of extremely high returns for bank stock i in a given fiscal year can be calculated as follows:

$$PB\_UP_{i,year} = \frac{N_{1,year}}{N_{1,year} + N_{0,year}}, \tag{3}$$

where i and $year$ represent bank stock and fiscal year, respectively. $N_{1,year}$ is the count of ones and $N_{0,year}$ is the count of zeros in $I\_UP_{i,t}$. The sum of $N_{1,year} + N_{0,year}$ is the count of total trading days in a year. We can calculate $PB\_DOWN_{i,year}$, the probability of extremely low returns for bank stock i in a given fiscal year in a similar way.

2.2 | Conditional tail risk probability

Our goal is to examine the tail linkage between risk factors and individual bank stocks. Here, we construct a probability-based measure of conditional tail risk. The tail risk probabilities capture the possibility of daily bank stock returns realizing extreme returns, conditional on one or more risk factors realizing extreme values. The calculation of univariate conditional tail risk probability is relatively obvious. The calculation of multivariate conditional tail risk probability is less straightforward because the influence of risk factors on bank stocks may move them in opposite directions. For example, a broad stock market index will move individual bank stocks in a favorable direction. A broad bond market index will move individual bank stocks in an unfavorable direction.

2.2.1 | Favorable and unfavorable tails of risk factors

To distinguish between the good or bad news brought by different tail outcomes of the risk factors, we need to measure the typical direction in which a risk factor moves bank stocks. If the typical impact is positive, we define a risk factor's upper 5th percentile tail as a favorable tail. Similarly, we define its lower 5th percentile tail as an unfavorable tail. On the other hand, if the typical impact is negative, we label its lower 5th percentile tail as favorable and label its upper 5th percentile tail as unfavorable. To identify the typical direction in which a risk factor moves individual bank stocks, we run a univariate regression as in Equation (4) for each bank stock using each risk factor as the independent variable. Each risk factor will have 31 estimated slope coefficients from 31 banks. We use the medium value of 31 beta coefficients to define the usual influence from a risk factor. The regressions take the following form:

$$RET_{i,t} = \alpha_i + \beta_{i,X} X_t + \varepsilon_{i,t}, \tag{4}$$

where $RET_{i,t}$ denotes bank stocks' daily returns and X_t is the particular risk factor being considered, from the group of 35 risk factors.

2.2.2 | Univariate conditional risk probability

Given the favorable and unfavorable tail events from risk factors, we can now construct conditional exceedance probabilities. The indicator variable $CE\_UP/POS_{i,j,t}$ in Equation (5) captures the exceedance of bank stocks given a particular risk factor falls into its favorable tail:

$$CE\_UP/POS_{i,j,t} = I\_UP_{i,t} \times FACTOR\_POS_{j,t}, \tag{5}$$

where i, j, and t represent bank stock, risk factor, and trading day, respectively. Similarly, we construct an indicator variable $CE\_DOWN/NEG_{i,j,t}$ given a particular risk factor falls into its unfavorable tail:

$$CE\_DOWN/NEG_{i,j,t} = I\_DOWN_{i,t} \times FACTOR\_NEG_{j,t}. \tag{6}$$

Equations (5) and (6) describe the typical direction of co-movements between bank stocks and risk factors. However, there are occasions when a risk factor brings favorable news but individual bank stocks, nonetheless, realize extremely low returns, or vice versa. To characterize these situations, we construct the next two indicator variables:

$$CE\_UP/NEG_{i,j,t} = I\_UP_{i,t} \times FACTOR\_NEG_{j,t}, \tag{7}$$

and

$$CE\_DOWN/POS_{i,j,t} = I\_DOWN_{i,t} \times FACTOR\_POS_{j,t}. \tag{8}$$

With the four indicator variables from Equations (5) to (8), we calculate the univariate conditional exceedance probability $PB\_UP/POS_{i,j,year}$ as the fraction of days with extremely high returns for bank stock i given the j-th risk factor realizing a favorable tail outcome. We calculate $PB\_DOWN/NEG_{i,j,year}$, $PB\_UP/NEG_{i,j,year}$, and $PB\_DOWN/POS_{i,j,year}$ in a similar way.

2.2.3 | Multivariate conditional probability

Now we define risk factor co-exceedance as in Bae et al. (2003). Co-exceedance means the incidence of several risk factors moving into extreme territories on the same day. In a favorable scenario, several risk factors simultaneously fall into their respective favorable tails, which drives bank stocks to exceed their 95th percentile tail thresholds. In an unfavorable scenario, several risk factors simultaneously fall into their respective unfavorable tails, which drives bank stocks to fall below their 5th percentile tail thresholds. Thus, the multivariate conditional exceedance probability is calculated as:

$$PB\_UP/POS_{i,year} = \frac{N_{i,year,pos}}{N_{year,pos}}, \tag{9}$$

where i and $year$ represent bank stock and fiscal year. $N_{year,pos}$ is the count of trading days when several risk factors simultaneously fall into their favorable tails. $N_{i,year,pos}$ is the count of trading days when bank stock i achieves extremely high returns and several risk factors fall into their respective favorable tails simultaneously. Therefore, $PB\_UP/POS_{i,year}$ measures the probability of bank stocks realizing extreme returns conditional on a favorable co-exceedance of several risk factors. We calculate $PB\_DOWN/NEG_{i,year}$ in a similar way.

3 | DATA SOURCES AND SUMMARY STATISTICS

3.1 | Data and sample

We select 31 Chinese-listed banks and 35 risk factors in the period from January 2007 to December 2019. The listed banks included five large state-owned banks, eight nationwide joint-stock commercial banks, and 18 small and medium city commercial banks.

The measure of tail risk relies on daily returns on bank stocks and risk factors. Daily return data are from the China Stock Market and Accounting Research (CSMAR) database. For risk factors, Aggregate Bond Index data and AAA-, and A-rated bond daily yields are from the China Securities Index webpage.[4] Data for constructing other risk factors are from CSMAR and WIND databases. Bank accounting information mainly comes from WIND and BANKSCOPE, with missing data supplemented by annual reports.

[4]http://www.csindex.com.cn/

3.1.1 | Risk factors

We select the 35 most popular risk factors from the literature. Since the Chinese economy is classified as an emerging market, we also need to consider the factors that affect emerging markets' performance. In total, we consider 35 risk factors that potentially impact Chinese bank stocks' performance.

For stock market risk factors, we construct *EXMRET, SMB, HML, RMW, CMA, MOM*, and *ST_REV, LT_REV* using all industrial firms from CSMAR, as in Kenneth French's webpage. We also construct a liquidity factor (*LIQ*),[5] a dividend factor (*DIV*), a bank total size factor (*B_SMB*), a bank profitability factor (*B_ROE*), and a real estate leverage factor (*REAL_LEV*). In addition, we consider value-weighted returns from the following industries: banking (*BANK*), security-trading (*SECUR*), insurance (*INSUR*), and real estate (*REAL*).

For bond market risk factors, we use the percentage change in the bond market index (*BONDDRET*). We also construct *TERM* as the daily spread between 10- and 1-year treasury bonds yields. *CREDIT* is the daily spread between AAA and A-rated bond yields.

For commodity risk factors, we use percentage change in the China Commodity Index (*COMMDRET*). The source is the Commodity Research Bureau. *GOLDDRET* and *OILDRET* are returns on COMEX gold futures contracts and NYMEX light crude oil futures contracts, respectively. *GOLD* and *OIL* are the industrial portfolio returns from the gold-mining and oil industries.

For emerging market and developed market risk factors, we consider the following industries: banking (*DEV_BANK* and *EMG_BANK*), security-trading (*DEV_SECUR* and *EMG_SECUR*), insurance (*DEV_INSUR* and *EMG_INSUR*), real estate (*DEV_REAL* and *EMG_REAL*), and oil (*DEV_OIL* and *EMG_OIL*). MSCI provides data on all of these industries. We obtain the data from the WIND database.

3.1.2 | Bank accounting information

We also include a wide variety of bank financial statement information to explore what determines bank tail risk. Market value (*ME*) is equal to the share price multiplied by the number of common shares outstanding. We take into account the possibility of nonsynchronous trading, as in Dimson (1979). We impose the restriction that a minimum of 30 nonmissing daily return observations is available when estimating beta. Following Roll (1988), we use the fitted value and residual from the market regression model to measure price synchronicity ($R2$) and idiosyncratic volatility (*IVOL*), respectively. Other bank accounting items include loan loss provision (*LLP*), capital ratio (*CAPR*), allowance for loan losses (*ALLOW*), net interest margin (*NIM*), growth rate of earnings per share (*EPSG*), interest income to total income ratio (*ININC*), nonperforming assets scaled by total assets (*NPA*), growth rate of earnings per share (*EPSG*), and leverage (*LEV*). Appendix (Panel B) provides more details about the construction of the financial ratios.

3.2 | Summary statistics

Table 1 reports summary statistics for Chinese listed bank stocks and risk factors. Our sample consists of 31 Chinese-listed banks from January 2007 to December 2019. The total number of trading days is 3156. There are a total of 55,789 bank daily observations in the pooled sample.

[5]Liquidity is defined as in Amihud (2002).

TABLE 1 Summary statistics for risk factors and bank stocks.

Panel A: Basic statistics

	Obs	Mean	5%	Median	95%	Std Dev.
35 risk factors						
Stock market risk factors						
EXMRET (excess market return)	3156	0.045	−3.208	0.140	2.799	1.917
SMB (size factor)	3156	0.052	−1.236	0.118	1.063	0.747
HML (book-to-market factor)	3156	0.004	−0.998	−0.023	1.074	0.663
RMW (profitability factor)	3156	−0.015	−1.270	−0.084	1.407	0.901
CMA (investment factor)	3156	0.005	−0.967	0.013	0.942	0.601
MOM (momentum factor)	3156	−0.010	−2.003	0.018	2.000	1.295
ST_REV (short-term reversal factor)	3156	0.061	−1.140	0.052	1.335	0.757
LT_REV (long-term reversal factor)	3156	0.018	−0.907	0.008	1.021	0.615
LIQ (liquidity risk factor)	3156	0.006	−0.734	0.038	0.683	0.464
DIV (dividend yield risk factor)	3156	0.004	−0.552	−0.006	0.591	0.354
B_SMB (bank total assets factor)	3148	0.005	−0.750	0.004	0.815	0.523
B_ROE (financial sector profitability factor)	3148	0.002	−1.192	−0.008	1.224	0.792
BANK (banking sector index return)	3145	0.004	−1.221	−0.010	1.295	0.863
SECUR (security trading sector index return)	3132	0.013	−1.107	−0.007	1.147	0.725
INSUR (insurance sector index return)	3156	0.049	−2.601	−0.018	3.054	1.828
REAL (real estate sector index return)	3156	0.054	−3.487	0.080	3.443	2.140
REAL_LEV (real estate sector leverage factor)	3156	0.024	−1.051	0.011	1.157	0.685
Bond market risk factors						
BONDDRET (bond index return)	3156	0.016	−0.092	0.015	0.118	0.075
TERM (term premium)	3156	0.863	0.225	0.706	2.092	0.532
CREDIT (default premium)	2680	5.470	3.543	5.755	7.050	1.244
Commodity market risk factors						
COMMDRET (commodity index return)	2957	0.004	−0.692	0.014	0.693	0.464
GOLDDRET (% change in gold futures contract prices)	2999	−4.734	−4.769	−0.006	1.700	21.349
OILDRET (% change in oil futures contract prices)	3065	−2.933	−5.039	0.024	3.426	17.128
GOLD (gold-mining sector index return)	3156	0.050	−3.884	0.059	4.036	2.432
OIL (oil sector index return)	3156	0.012	−2.927	−0.003	2.986	1.941
Developed market industry risk factors						

(Continues)

TABLE 1 (Continued)

Panel A: Basic statistics

	Obs	Mean	5%	Median	95%	Std Dev.
DEV_BANK (banking sector index return)	3156	−0.002	−2.113	0.017	2.027	1.496
DEV_SECUR (security trading sector index return)	3156	0.004	−2.055	0.028	1.902	1.442
DEV_REAL (real estate sector index return)	3156	0.010	−1.743	0.055	1.574	1.209
DEV_INSU (insurance sector index return)	3156	0.014	−2.023	0.048	1.877	1.391
DEV_OIL (oil sector index return)	3156	0.009	−2.413	0.021	2.189	1.593
Emerging market industry risk factors						
EMG_BANK (banking sector index return)	3156	0.007	−2.030	0.037	1.904	1.420
EMG_SECUR (security trading sector index return)	3156	0.008	−2.044	0.046	1.915	1.409
EMG_INSU (insurance sector index return)	3156	0.027	−2.596	0.051	2.566	1.656
EMG_REAL (real estate sector index return)	3156	−0.003	−2.659	−0.010	2.619	1.687
EMG_OIL (oil sector index return)	3156	0.003	−2.444	0.041	2.296	1.738
Bank-specific variables						
ME (market capitalization, in million Yuan)	238	2224.598	45.463	1003.607	10,850.640	3234.691
AT (total assets, in million Yuan)	238	52,828.595	1230.000	24,650.000	213,000.000	65,258.990
BETA (beta)	238	0.557	0.065	0.542	1.152	0.334
IVOL (idiosyncratic volatility)	238	165.275	76.631	147.779	304.923	71.696
R2 (price synchronicity)	238	0.313	0.032	0.342	0.564	0.152
CAPR (capital ratio)	238	0.129	0.102	0.127	0.159	0.021
LLP (annual loan loss provisions)	238	0.005	0.002	0.004	0.010	0.003
ALLOW (total allowance for loan losses)	238	0.013	0.007	0.013	0.021	0.004
NIM (net interest margin)	238	0.024	0.017	0.024	0.032	0.004
EPSG (earnings per share growth rate)	221	−0.031	−0.772	0.043	0.388	0.330
ININC (interest income ratio)	238	0.041	0.032	0.040	0.051	0.006
LEV (leverage)	238	0.933	0.912	0.934	0.955	0.014
NPA (nonperforming assets/total assets)	238	0.006	0.003	0.006	0.011	0.003
VOLUME (trading volume in million Yuan)	238	20,820.053	3460.641	12,001.812	6905.621	27,646.992
DLLP1 (discretionary LLP)	199	0.000	−0.003	0.000	0.003	0.002

TABLE 1 (Continued)

Panel A: Basic statistics	Obs	Mean	5%	Median	95%	Std Dev.
NDLLP1 (nondiscretionary LLP)	199	0.005	0.002	0.005	0.010	0.002
DLLP2 (discretionary LLP)	144	0.000	−0.006	0.000	0.007	0.004
NDLLP2 (nondiscretionary LLP)	144	0.011	0.004	0.010	0.019	0.005
RET (daily return of bank stocks)	55,789	0.001	−0.031	0.000	0.035	0.024

Panel B: Pairwise correlations							
	SMB	***HML***	***RMW***	***CMA***	***MOM***	***ST_REV***	***LT_REV***
EXMRET	0.234**	0.042**	−0.338**	−0.082**	0.014	0.086**	0.057**
SMB		−0.255**	−0.857**	0.339**	−0.061**	0.040**	0.202**
HML			0.214**	0.429**	−0.204**	−0.039**	0.521**
RMW				−0.304**	0.055**	−0.112**	−0.210**
CMA					−0.173**	−0.097**	0.490**
MOM						−0.033*	0.014
ST_REV							−0.131**
	LIQ	*DIV*					
EXMRET	0.119**	0.005					
LIQ		−0.078**					
	B_SMB	*B_ROE*	*BANK*	*SECUR*	*INSUR*	*REAL*	*REAL_LEV*
EXMRET	0.185**	0.030*	0.606**	0.716**	0.637**	0.890**	−0.040**
B_SMB		−0.117**	−0.009	0.059**	0.083**	0.157**	0.028
B_ROE			0.177**	0.136**	0.067**	0.067**	−0.026
BANK				0.962**	0.746**	0.658**	0.087**
SECUR					0.852**	0.747**	0.074**
INSUR						0.650**	0.107**
REAL							0.043**
	BONDDRET	*TERM*	*CREDIT*				
EXMRET	−0.015	0.022	−0.001				
BONDDRET		−0.078**	0.074**				
TERM			−0.579**				
	COMMDRET	*GOLDDRET*	*GOLD*	*OILDRET*	*OIL*		
EXMRET	0.138**	0.004	0.818**	0.012	0.668**		
COMMDRET		0.017	0.142**	0.166**	0.097**		
GOLDDRET			−0.004	0.760**	0.010		
GOLD				0.010	0.552**		

(Continues)

TABLE 1 (Continued)

Panel B: Pairwise correlations

	SMB	*HML*	*RMW*	*CMA*	*MOM*	*ST_REV*	*LT_REV*
OILDRET					0.021		
	BETA	*IVOL*	*R2*				
ME	−0.376**	−0.277**	−0.273**				
BETA		0.417**	0.331**				
IVOL			−0.111*				
	CAPR	*LLP*	*ALLOW*	*NIM*	*EPSG*	*ININC*	*LEV*
ME	0.141**	−0.057	0.112*	−0.149**	0.051	−0.371**	−0.176**
CAPR		0.081	0.195**	−0.002	−0.151**	−0.223**	−0.778**
LLP			0.368**	−0.131**	−0.138**	0.146**	−0.296**
ALLOW				−0.087	−0.130*	−0.077	−0.324**
NIM					0.119*	0.480**	0.083
EPSG						0.073	0.132**
ININC							0.180**
	*DLLP*1	*NDLLP*1	*DLLP*2	*NDLLP*2			
ME	−0.062	−0.055	−0.128	−0.094			
*DLLP*1		0.064	0.816**	0.132			
*NDLLP*1			0.327**	0.626**			
*DLLP*2				0.046			

Panel C: 95th percentile and 5th percentile tail thresholds for each bank group in each fiscal year

	Large state-owned banks (*SOB*)		**Joint-stock banks (*JOB*)**		**Small-and-medium city commercial banks (*CCB*)**	
	95th percentile	**5th percentile**	**95th percentile**	**5th percentile**	**95th percentile**	**5th percentile**
2007	0.046	−0.040	0.066	−0.049	0.058	−0.043
2008	0.042	−0.049	0.069	−0.071	0.064	−0.062
2009	0.038	−0.030	0.049	−0.042	0.050	−0.038
2010	0.022	−0.024	0.032	−0.034	0.033	−0.038
2011	0.017	−0.017	0.027	−0.027	0.027	−0.027
2012	0.015	−0.012	0.024	−0.019	0.028	−0.021
2013	0.020	−0.019	0.042	−0.033	0.032	−0.029
2014	0.033	−0.017	0.041	−0.023	0.034	−0.023
2015	0.046	−0.043	0.051	−0.043	0.061	−0.050
2016	0.016	−0.016	0.019	−0.020	0.038	−0.031
2017	0.018	−0.013	0.020	−0.015	0.038	−0.031

TABLE 1 (Continued)

Panel C: 95th percentile and 5th percentile tail thresholds for each bank group in each fiscal year

	Large state-owned banks (*SOB*)		Joint-stock banks (*JOB*)		Small-and-medium city commercial banks (*CCB*)	
	95th percentile	5th percentile	95th percentile	5th percentile	95th percentile	5th percentile
2018	0.023	−0.024	0.025	−0.026	0.030	−0.030
2019	0.014	−0.014	0.025	−0.020	0.031	−0.027
Analysis of variance test		By fiscal year			By bank groups	
		95th percentile	5th percentile		95th percentile	5th percentile
F-test		7.06**	11.18**		3.22**	2.09
(*p*-value)		(0.00)	(0.00)		(0.05)	(0.14)

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. Panel A reports summary statistics, including the number of observations, mean, median, the 5th percentile value, the 95th percentile value, and the standard deviation. All variables are categorized into the following three groups: (i) risk-factors; (ii) market and bank accounting variables; and (iii) daily returns of individual bank stocks. Summary statistics for risk factors are constructed using time-series data. Summary statistics for market and bank accounting variables are constructed from pooled firm-year observations. Summary statistics for daily returns of individual stocks (RET) are constructed from pooled firm-year daily observations. The details of the construction of the variables are provided in Appendix (Panel A). Panel B reports the pair-wise correlation coefficients for selected variables. * and ** indicate significance at the 10% and 5% levels, respectively.

Over the full sample period, the 95th percentile value of bank stock daily returns is 3.5%. The 5th percentile value of bank stock daily returns is −3.1%. There are a total of 238 pooled bank-year observations for bank accounting ratios. The mean market capitalization is 2.225 billion RMB. The mean value of capital ratio (*CAPR*) is 12.9%. The mean value of loan loss provision (*LLP*) is 0.5%. The mean value of allowance for loan losses (*ALLOW*) is 1.3%.

Panel B shows that the market excess return factor (*EXMRET*) is highly correlated with the banking sector index return (*BANK*), with a highly significant correlation of 0.606. The correlations of *EXMRET* with *SECUR* and *INSUR* are also highly significant at 0.716 and 0.637, respectively. Among these bank characteristics, *LLP* and *ALLOW* have a highly significant correlation of 0.368. The correlation between bank size (*ME*) and interest income (*ININC*) is significantly negative at −0.371. This indicates that large banks' incomes are more diversified.

Panel C reports the varying tail thresholds for individual bank stocks across bank categories and fiscal years ($High\_Tail_{type,year}$ and $Low\_Tail_{type,year}$), where *type* refers to *SOB, JOB*, and *CCB*, respectively. We notice that during the 2008 global financial crisis, the tail thresholds are much higher in absolute value when compared to the thresholds using the entire sample. The tail thresholds for joint-stock banks (*JOB*) are 6.9% and –7.1%, respectively, in the 2008 fiscal year. This suggests considerable variation of tail thresholds over time. The ANOVA test confirms this result, with corresponding *F*-statistics of 7.06 and 11.18, respectively. Both *p*-values are zero. On the other hand, the difference in tails among different bank groups is much smaller. The test statistics drop to 3.22 and 2.09, respectively. The corresponding *p*-values are 0.05 and 0.14, respectively.

We also investigate whether tail critical values for the 35 risk factors vary in the time-series. We conduct a proportional test for the sample with each fiscal year versus the full sample. Panel A in Table 1 shows that the 95th percentile of excess market daily returns over the entire sample is 2.799%. In other words, excess daily returns exceed 2.799% in 5% of the days in the full sample. For each fiscal year, we calculate the proportion of days when excess market daily returns exceed 2.799% and then test the difference with the full sample proportion. We find that in more than 70% of the fiscal years, the proportion of trading days with *EXMRET* exceeding 2.799% is significantly different from the proportion using the full sample. Our conclusions are

TABLE 2 Unconditional exceedance of bank stock returns.

	A Number of trading days in a fiscal year	B Number of trading days when *RET* ≥ 95th percentile	C Number of trading days when *RET* ≤ 5th percentile	D *PB_UP* Mean across years	E *PB_DOWN* Mean across years
	3% and −3% high and low tail thresholds				
Mean	234	15	13	0.067	0.055
Minimum	66	0	0	0.000	0.000
Median	243	12	8	0.051	0.033
Maximum	245	56	63	0.269	0.258
	95th percentile and 5th percentile tail thresholds by fiscal year and bank groups				
Mean	234	12	12	0.052	0.051
Minimum	66	0	0	0.000	0.000
Median	243	11	11	0.049	0.049
Maximum	245	33	37	0.197	0.152
				PB_UP	*PB_DOWN*
	Wilcoxon rank sum test statistic for the difference in median values			0.992	−2.818**
	(*p*-value)			(0.36)	(0.00)

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. The table summarizes statistics for unconditional exceedance probabilities of bank stock returns. In Panel A, the high and low tail thresholds for daily bank stock returns are 3% and −3%, respectively. In Panel B, the high and low tail thresholds are the 95th percentile and 5th percentile critical values of daily bank stock returns in each fiscal year for each bank group. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*). Column A reports the mean number of trading days in a fiscal year. Column B reports the mean value of the number of trading days when a bank's stock return (*RET*) is above the high tail threshold. Column C reports the mean value of the number of trading days when a bank's stock return (*RET*) is below the low tail threshold. Column D reports the mean value of observed likelihood *PB_UP*. Column E reports the mean value of observed likelihood *PB_DOWN*. The table also reports the Wilcoxon rank-sum test for the difference in median values of unconditional exceedance probabilities *PB_UP* and *PB_DOWN*, respectively, when we use constant and varying tail thresholds. ** indicates significance at the 5% level.

similar when we carry out the tests for other risk factors. Therefore, tail critical values of risk factors also vary in the time series.

4 | EMPIRICAL ANALYSIS

4.1 | Unconditional tail risk

Table 2 reports the unconditional tail risk probabilities of bank stocks. Panel A uses constant tail thresholds. We use 3% as the high tail threshold and −3% as the low tail threshold.[6] During our sample period, there are, on average, 234 trading days each year. The average number of days with daily returns exceeding 3% is 15. The average number of days with daily returns

[6]For bank stock daily returns in our sample period, the 95th and 5th percentile cut-off values are 3.5% and −3.1%, respectively. For symmetry of the extreme up and down stock price movement, we choose 3% and −3% as constant tail thresholds.

falling below −3% is 13. The average unconditional tail risk probability (*PB_UP*) is 0.067. The average unconditional tail risk probability (*PB_DOWN*) is 0.055. There is considerable evidence of variation in the pooled sample of unconditional tail risk probabilities. The upper tail exceedance probabilities (*PB_UP*) range from 0.000 to 0.269, and the lower tail exceedance probabilities (*PB_DOWN*) range from 0.000 to 0.258.

Panel B uses the varying thresholds $High\_Tail_{type,year}$ and $Low\_Tail_{type,year}$. Now the variation in unconditional tail risk probability is largely reduced, ranging from 0.000 to 0.197 for *PB_UP* and 0.000 to 0.152 for *PB_DOWN*. We implement the Wilcoxon rank sum tests to see if there are differences in the median values of unconditional tail risk probabilities when we use two types of tail thresholds. For *PB_UP*, the *Z*-statistic is 0.992 with a *p*-value of 0.36. For *PB_DOWN*, the *Z*-statistic is –2.818 with a *p*-value of 0.00. For all our subsequent empirical analyses, we report the results using varying thresholds.

4.2 | The influence of risk factors

In this section, we examine the direction in which risk factors move individual bank stocks via regression betas. If the median value of a risk factor's betas is positive, the 95th percentile tail of the risk factor will be assigned as a favorable tail. If the median value of a risk factor's beta is negative, the 5th percentile tail of the risk factor will be assigned as a favorable tail. The definition of each risk factor's unfavorable tail is similar.

Table 3 summarizes the OLS regression results from Equation (4). All banks have positive betas with respect to the market excess return factor (*EXMRET*) and 93.5% of them are significant. In addition, the factors of *BANK, SECUR, INSU, REAL*, and *OIL* industries have large positive regression slope coefficients.

There are other risk factors that have positive effects on bank stocks, including the *HML* risk factor and several risk factors from emerging market industries. These risk factors typically move in the same direction as bank stocks, so their upper tail outcomes are classified as favorable and their lower tail outcomes are classified as unfavorable.

In contrast, the momentum factor (*MOM*), liquidity factor (*LIQ*), and dividend factor (*DIV*) tend to move bank stocks in the opposite direction. For example, 90.3% of all banks' betas with respect to the *MOM* factor are negative. Therefore, for *MOM, LIQ*, and *DIV*, their upper 5th percentile tails are classified as unfavorable tails for bank stocks, while their lower 5th percentile tails are classified as favorable tails for bank stocks.

4.3 | Univariate conditional tail risk probability

Given the favorable and unfavorable tail outcomes of each risk factor, we construct univariate conditional tail risk probabilities. Again we employ varying tails $High\_Tail_{type,year}$ and $Low\_Tail_{type,year}$, where subscript *type* equals *SOB, JOB*, and *CCB*, respectively, and subscript *year* refers to fiscal year.

Table 4 summarizes the results for Chinese bank stocks. In Column A, *PB_UP*/*POS* represents the upper exceedance probability in relation to one risk factor's favorable tail outcome. In Column B, *PB_UP*/*NEG* represents the upper exceedance probability of bank stocks in relation to one risk factor's unfavorable tail outcome. Taking the market excess return factor (*EXMRET*) as an example, when *EXMRET* falls into its 95th percentile tail, Column A shows that bank stocks exceed $High\_Tail_{type,year}$ with a probability of 0.283. When the market excess return factor falls into its 5th percentile tail, Column B shows that bank stocks exceed $High\_Tail_{type,year}$ with a probability of only 0.025. Column C reports that the median difference

TABLE 3 The impact of individual risk factors on bank stock returns.

Risk factor	Mean $\hat{\beta}_{i,X}$	Median $\hat{\beta}_{i,X}$	Percentage (%) $\hat{\beta}_{i,X} >= 0$	Percentage (%) $\hat{\beta}_{i,X} < 0$	Percentage (%) $t(\hat{\beta}_{i,X}) > 1.96$	Percentage (%) $t(\hat{\beta}_{i,X}) < -1.96$	Mean R^2
EXMRET	0.750	0.725	100.0	0.0	93.5	0.0	0.219
SMB	0.009	−0.223	41.9	58.1	22.6	51.6	0.027
HML	0.488	0.674	80.6	19.4	54.8	0.0	0.034
RMW	−0.113	0.010	54.8	45.2	41.9	32.3	0.022
CMA	−0.223	−0.204	12.9	87.1	0.0	25.8	0.004
MOM	−0.183	−0.137	9.7	90.3	0.0	61.3	0.012
ST_REV	0.129	0.142	74.2	25.8	25.8	6.5	0.006
LT_REV	0.212	0.063	58.1	41.9	25.8	9.7	0.007
LIQ	−1.041	−1.402	16.1	83.9	0.0	64.5	0.081
DIV	−0.686	−0.458	19.4	80.6	6.5	48.4	0.012
B_SMB	1.533	1.360	90.3	9.7	80.6	3.2	0.069
B_ROE	−0.256	−0.047	48.4	51.6	22.6	35.5	0.018
BANK	1.025	1.011	100.0	0.0	96.8	0.0	0.426
SECUR	1.017	1.023	100.0	0.0	96.8	0.0	0.433
INSUR	0.587	0.608	100.0	0.0	96.8	0.0	0.275
REAL	0.698	0.693	100.0	0.0	93.5	0.0	0.242
REAL_LEV	0.264	0.282	80.6	19.4	51.6	0.0	0.014
BONDDRET	−0.727	−0.486	38.7	61.3	0.0	6.5	0.004
TERM	0.716	0.134	87.1	12.9	22.6	0.0	0.003
CREDIT	−8.142	0.013	74.2	25.8	6.5	3.2	0.005
COMMDRET	0.587	0.579	96.8	3.2	83.9	0.0	0.010
GOLDDRET	0.002	0.002	87.1	12.9	0.0	0.0	0.001
OILDRET	0.001	0.003	64.5	35.5	0.0	0.0	0.001
GOLD	0.437	0.430	100.0	0.0	93.5	0.0	0.129
OIL	0.707	0.677	96.8	3.2	93.5	0.0	0.212
DEV_BANK	0.296	0.293	96.8	3.2	83.9	0.0	0.021
DEV_SECUR	0.322	0.293	96.8	3.2	87.1	0.0	0.022
DEV_INSUR	0.379	0.295	96.8	3.2	90.3	0.0	0.024
DEV_REAL	0.390	0.387	96.8	3.2	71.0	0.0	0.026
DEV_OIL	0.202	0.210	96.8	3.2	80.6	0.0	0.015
EMG_BANK	0.623	0.604	96.8	3.2	96.8	0.0	0.083
EMG_SECUR	0.693	0.650	96.8	3.2	96.8	0.0	0.102

TABLE 3 (Continued)

Risk factor	Mean $\hat{\beta}_{i,X}$	Median $\hat{\beta}_{i,X}$	Percentage (%) $\hat{\beta}_{i,X} >= 0$	Percentage (%) $\hat{\beta}_{i,X} < 0$	Percentage (%) $t(\hat{\beta}_{i,X}) > 1.96$	Percentage (%) $t(\hat{\beta}_{i,X}) < -1.96$	Mean R^2
EMG_INSUR	0.643	0.632	96.8	3.2	96.8	0.0	0.137
EMG_REAL	0.532	0.526	96.8	3.2	96.8	0.0	0.109
EMG_OIL	0.411	0.420	96.8	3.2	93.5	0.0	0.056

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. The table summarizes the slope coefficients and t-statistics for regressions of individual daily bank stock returns (*RET*) on each of the risk factors (*X*).

between the two conditional probabilities is 0.257 with a Z-statistic of 17.32 that is highly significant.

The right columns of Panel A compare the conditional exceedance probabilities of bank stocks falling below $Low\_Tail_{type,year}$ given a risk factor's unfavorable or favorable tail outcome. The risk factors are similarly successful in predicting the lower tail probabilities for bank stocks. The liquidity factor (*LIQ*) has a significantly negative impact on bank stock returns. Column E shows when *LIQ* falls into its upper 95th percentile tail, which is an unfavorable tail for bank stocks, bank stock daily return falls below $Low\_Tail_{type,year}$ with a probability of 0.183. Column F shows when *LIQ* falls into its lower 5th percentile tail, which is a favorable tail for bank stocks, bank stock daily return falls below $Low\_Tail_{type,year}$ with a much smaller probability of 0.049. Column G shows that the difference between *PB_DOWN/NEG* and *PB_DOWN/POS* is 0.133 with a Z-statistic of 12.70 that is highly significant.

Overall, the univariate results from Panel A suggest that the tail linkage between Chinese bank stocks *BANK, SECUR*, and *INSUR* are strong. When these three risk factors fall into their respective favorable tails, the upper tail conditional exceedance probabilities of bank stocks are 0.520, 0.507, and 0.374, respectively. The corresponding lower tail conditional exceedance probabilities are 0.547, 0.526, and 0.407, respectively. Other influential risk factors include *HML, B_SMB, REAL, GOLD, OIL*, and industry risk factors in emerging markets *EMG_BANK, EMG_SECUR, EMG_INSUR, EMG_REAL*, and *EMG_OIL*. For these risk factors, all values of *PB_UP/POS* minus *PB_UP/NEG* exceed 0.100. All values of *PB_DOWN/NEG* minus *PB_DOWN/POS* also exceed 0.100. This indicates a high probability of tail dependence between individual bank stocks and risk factors.

4.4 | The cross-country tail linkage

The results in Panel A of Table 4 also reveal a strong tail linkage between emerging market risk factors and individual bank stocks. These emerging market risk factors include *EMG_BANK, EMG_SECUR, EMG_INSUR, EMG_REAL*, and *EMG_OIL*. They can bring significant shocks to the returns of individual bank stocks in China. Conditional on their favorable tail outcome, the difference between upper tail risk probabilities *PB_UP/POS* and *PB_UP/NEG* could reach 0.161, 0.185, 0.201, 0.171, and 0.109, respectively. Conditional on their unfavorable tail outcome, the difference between lower tail risk probabilities *PB_DOWN/NEG* and *PB_DOWN/POS* could reach 0.177, 0.203, 0.277, 0.255, and 0.165, respectively.

In contrast, the tail linkage between developed market risk factors and individual bank stocks is much weaker. For the same set of five industries (*BANK, SECUR, INSUR, REAL*, and *OIL*), the difference between *PB_UP/POS* and *PB_UP/DOWN* is less than 0.100 for all

TABLE 4 Univariate conditional exceedances of bank stock returns.

	Panel A: Univariate conditional exceedance probabilities							
	Upper tail conditional risk				Lower tail conditional risk			
	A	B	C	D	E	F	G	H
	PB_UP|POS	*PB_UP|NEG*	Col A minus Col B	*Z*-statistic for Col C	*PB_DOWN|NEG*	*PB_DOWN|POS*	Col E minus Col F	*Z*-statistic for Col G
EXMRET	0.283	0.025	0.257	17.32**	0.387	0.007	0.380	18.70**
SMB	0.106	0.030	0.076	9.31**	0.108	0.100	0.007	1.54
HML	0.140	0.031	0.108	12.54**	0.134	0.044	0.090	11.81**
RMW	0.091	0.037	0.054	6.84**	0.095	0.136	−0.041	−4.73**
CMA	0.084	0.060	0.024	3.11**	0.100	0.099	0.001	−0.91
MOM	0.105	0.056	0.050	6.53**	0.127	0.074	0.053	6.09**
ST_REV	0.103	0.110	−0.007	1.44	0.096	0.102	−0.006	0.08
LT_REV	0.107	0.072	0.034	2.13**	0.109	0.072	0.037	2.96**
LIQ	0.236	0.019	0.217	17.07**	0.183	0.049	0.133	12.70**
DIV	0.093	0.052	0.041	6.02**	0.122	0.080	0.042	3.83**
B_SMB	0.239	0.071	0.167	10.90**	0.214	0.056	0.158	11.75**
B_ROE	0.186	0.096	0.090	5.97**	0.143	0.083	0.060	5.37**
BANK	0.520	0.011	0.509	19.06**	0.547	0.004	0.543	19.36**
SECUR	0.507	0.008	0.499	19.49**	0.526	0.003	0.523	19.41**
INSUR	0.374	0.013	0.361	18.79**	0.407	0.006	0.402	18.77**
REAL	0.297	0.022	0.276	18.07**	0.393	0.006	0.387	18.54**
REAL_LEV	0.122	0.039	0.083	8.31**	0.091	0.086	0.005	1.21
BONDDRET	0.079	0.054	0.025	2.63**	0.078	0.070	0.007	0.01
TERM	0.055	0.044	0.010	0.24	0.056	0.061	−0.005	−0.53

TABLE 4 (Continued)

Panel A: Univariate conditional exceedance probabilities								
	Upper tail conditional risk				Lower tail conditional risk			
	A	B	C	D	E	F	G	H
	PB_UP/POS	*PB_UP/NEG*	Col A minus Col B	*Z*-statistic for Col C	*PB_DOWN/NEG*	*PB_DOWN/POS*	Col E minus Col F	*Z*-statistic for Col G
CREDIT	0.050	0.058	−0.009	−2.41**	0.061	0.045	0.017	2.84**
COMMDRET	0.064	0.045	0.020	3.46**	0.124	0.039	0.086	8.71**
GOLDDRET	0.055	0.042	0.012	1.74*	0.054	0.059	−0.005	−1.66
OILDRET	0.071	0.048	0.023	3.60**	0.063	0.035	0.028	3.57**
GOLD	0.171	0.030	0.142	13.93**	0.320	0.021	0.299	17.89**
OIL	0.269	0.007	0.261	18.41**	0.397	0.010	0.387	18.59**
DEV_BANK	0.075	0.033	0.042	6.05**	0.124	0.035	0.088	9.94**
DEV_SECUR	0.075	0.038	0.037	6.08**	0.128	0.034	0.094	10.56**
DEV_INSUR	0.100	0.039	0.061	7.71**	0.137	0.038	0.099	9.87**
DEV_REAL	0.107	0.041	0.066	8.74**	0.148	0.026	0.122	12.93**
DEV_OIL	0.099	0.053	0.046	5.42**	0.120	0.040	0.080	8.87**
EMG_BANK	0.184	0.024	0.161	15.47**	0.198	0.021	0.177	16.72**
EMG_SECUR	0.208	0.023	0.185	16.63**	0.220	0.017	0.203	17.53 **
EMG_INSUR	0.225	0.024	0.201	16.35**	0.280	0.004	0.277	18.98**
EMG_REAL	0.195	0.023	0.171	14.70**	0.266	0.012	0.255	18.13**
EMG_OIL	0.148	0.039	0.109	10.79**	0.189	0.025	0.165	15.75**

Panel B: Time-varying univariate conditional probabilities for developed market risk factors

	DEV_BANK		*DEV_SECUR*		*DEV_INSUR*		*DEV_REAL*		*DEV_OIL*	
	PB_UP/POS	*PB_DOWN/NEG*	*PB_UP/POS*	*PB_DOWN/NEG*	*PB_UP/POS*	*PB_DOWN/NEG*	*PB_UP/POS*	*PB_DOWN/NEG*	*PB_UP/POS*	*PB_DOWN/NEG*
2007	0.034	0.021	0.005	0.051	0.030	0.022	0.121	0.103	−0.034	0.046
2008	0.120	0.250	0.114	0.235	0.131	0.247	0.213	0.257	0.175	0.230
2009	−0.017	−0.005	−0.012	0.061	0.016	−0.005	0.062	0.077	0.096	0.011
2010	0.077	0.144	0.080	0.161	0.077	0.149	0.041	0.242	0.060	0.259
2011	0.024	0.016	0.024	0.026	0.004	−0.013	0.101	0.050	0.087	0.089
2012	0.029	0.074	0.029	0.044	0.038	0.049	0.087	0.107	0.052	0.024
2013	0.005	0.172	0.094	0.193	0.182	0.109	0.182	0.104	0.094	0.098
2014	0.019	−0.019	−0.005	−0.043	0.014	−0.024	0.135	0.082	0.146	−0.049
2015	0.060	0.067	0.120	0.082	0.084	0.053	0.024	0.204	0.011	0.073
2016	0.151	0.228	0.031	0.203	0.108	0.328	0.082	0.116	−0.024	−0.041
2017	0.033	0.029	0.020	0.038	0.038	0.053	−0.012	0.008	−0.010	−0.003
2018	−0.002	0.153	−0.018	0.157	−0.050	0.198	0.021	0.272	−0.050	0.148
2019	0.036	0.042	0.037	0.041	0.123	0.056	−0.020	0.028	0.077	0.139

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. The table summarizes the univariate conditional co-exceedance probabilities of bank stock returns. The high and low tail thresholds are the 95th percentile and 5th percentile critical values of daily bank stock returns in each fiscal year for each bank group. The tail thresholds for risk factors also vary across fiscal years. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*). *PB_UP/POS* is the probability that the bank stock return is above the high tail threshold conditional on the risk factor being in its favorable 5% tail. *PB_UP/NEG* is the probability that the bank stock return is above the high tail threshold conditional on the risk factor being in its unfavorable 5% tail. Columns A and B report the mean values *PB_UP/POS* and *PB_UP/NEG*, respectively. Columns C and D report the mean value of *PB_UP/POS* − *PB_UP/NEG* and the corresponding *Z*-statistic. *PB_DOWN/NEG* is the probability that the bank stock return is below the low tail threshold conditional on the risk factor being in its unfavorable 5% tail. *PB_DOWN/POS* is the probability that the bank stock return is below the low tail threshold conditional on the risk factor being in its favorable 5% tail. Columns E and F report the mean values of *PB_DOWN/NEG* and *PB_DOWN/POS*, respectively. Columns G and H report the mean value of *PB_DOWN/NEG* − *PB_DOWN/POS* and the corresponding *Z*-statistic. * and ** indicate significance at the 10% and 5% levels, respectively.

five industries.[7] The difference between *PB_DOWN/NEG* and *PB_DOWN/POS* is also less than 0.100, with the exception of the developed market real estate sector. This is consistent with findings in the cross-country financial contagion literature. For example, Hu (2010) finds that the tail dependence between the Chinese and US financial markets is generally low, and downturns in the US financial market have a weaker effect on the Chinese stock market compared to their effects on other countries. Thus, the Chinese stock market is viewed as the most insulated from extreme global negative shocks (Liu, 2014).

So far, we have reported the average value of univariate conditional exceedance probability using data pooled from all years. However, there is an extensive literature that studies time-varying tail dependence during crises. Ye et al. (2012) and Dimitriou et al. (2013) present strong evidence of changing tail dependence under extreme conditions. Chen et al. (2014) show that dynamic lower tail dependence is much higher in crisis periods than in noncrisis periods. To show that this is also true in our analysis, we investigate the patterns of tail dependence between developed market risk factors and individual bank stocks in China for each year from 2007 to 2019 in Panel B. Conditional on favorable tail outcomes of developed market risk factors, the upper exceedance probability of Chinese banks in 2008 rises above 10%. Conditional on unfavorable tail outcomes of developed market risk factors, the lower exceedance probability of Chinese banks in 2008 rises above 20%. The conditional tail risk probabilities in 2008 differ remarkably from the conditional tail risk probabilities in noncrisis years. This indicates a significant increase in cross-market linkage during bear markets, consistent with the correlation breakdown hypothesis (King & Wadhwani, 1990). The greater tail dependencies seen during bear markets imply that bank regulators should be alert to the increasing probability of bank stock crashes after a shock from developed countries.

4.5 | Multivariate conditional tail risk probability

In the previous section, we study tail dependence between individual risk factors and bank stocks. However, risk factors also tend to move together and can simultaneously affect the tail outcomes of bank stocks. In this section, we attempt to investigate the joint impact of several risk factors simultaneously entering their respective extreme territories. As mentioned earlier, we report the results for the varying tail thresholds $High\_Tail_{type,year}$ and $Low\_Tail_{type,year}$.

The left panel in Table 5 reports the likelihood of bank returns exceeding $High\_Tail_{type,year}$ when there are exactly n co-exceedances among 35 risk factors. The first column presents the number of risk factors that fall into their respective favorable tails simultaneously. Notice it stops when n reaches 22 because there is not a single day in our sample period on which more than 22 risk factors simultaneously enter their respective favorable tails. The second column shows that there are, on average, 64.4 days in a fiscal year when one risk factor falls into its favorable tail, and the average number of trading days decreases to 36.2 when two risk factors simultaneously enter their respective favorable tails. The third column counts the average number of individual bank stocks' daily exceedances given exactly n risk factor co-exceedances occurring. The fourth column reports the corresponding multivariate conditional probability. For example, when there is only one risk factor co-exceedance, the probability of individual bank stock returns exceeding $High\_Tail_{type,year}$ is 0.016. When five risk factors fall into their respective favorable tails simultaneously, this probability increases to 0.119. When 15 risk factors fall into their respective favorable tails simultaneously, this probability increases to 0.605.

[7] When we calculate the univariate conditional exceedance probabilities based on risk factors from U.S. market industries, the conclusions remain robust.

TABLE 5 Multivariate conditional exceedances of bank stock returns.

***RET* ≥ *High_Tail*$_{type,year}$**				***RET* ≤ *Low_Tail*$_{type,year}$**			
Risk factor co-exceedances		**Bank stock conditional exceedances**		**Risk factor co-exceedances**		**Bank stock conditional exceedances**	
Number of co-exceedances	**Mean number of trading days**	**Mean number of trading days**	**Mean value of conditional probability**	**Number of co-exceedances**	**Mean number of trading days**	**Mean number of trading days**	**Mean value of conditional probability**
1	64.400	0.910	0.016	1	53.871	1.014	0.019
2	36.233	1.086	0.030	2	37.757	1.024	0.029
3	22.038	0.995	0.052	3	18.981	0.848	0.048
4	14.105	0.700	0.050	4	10.943	0.929	0.079
5	11.595	1.329	0.119	5	8.271	0.776	0.097
6	5.538	0.833	0.169	6	4.476	0.595	0.134
7	4.676	0.633	0.138	7	4.090	0.695	0.176
8	2.981	0.786	0.276	8	3.895	1.076	0.310
9	2.210	0.538	0.271	9	2.252	0.671	0.275
10	2.181	0.762	0.294	10	1.652	0.395	0.223
11	1.176	0.367	0.355	11	0.986	0.300	0.300
12	1.624	0.729	0.405	12	0.376	0.248	0.658
13	0.633	0.386	0.647	13	0.638	0.243	0.294
14	0.810	0.238	0.258	14	0.538	0.238	0.464
15	0.514	0.329	0.605	15	0.862	0.524	0.611
16	0.210	0.210	1.000	16	0.390	0.233	0.607
17	0.219	0.081	0.422	17	0.557	0.300	0.527
18	0.000	0.000		18	0.352	0.262	0.725
19	0.000	0.000		19	0.271	0.224	0.825
20	0.076	0.076	1.000	20	0.000	0.000	
21	0.000	0.000		21	0.276	0.267	0.952
22	0.148	0.110	0.742	22	0.076	0.076	1.000
23				23	0.000	0.000	
24				24	0.076	0.052	0.688

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. The table summarizes multivariate conditional exceedances of bank stocks. The table shows the mean probability of a positive bank return exceedance conditional on exactly n co-exceedances of risk factors, $n = 1, 2, \ldots, 35$. The table also shows the mean probability of a negative bank return exceedance conditional on exactly n co-exceedances of risk factors, $n = 1, 2, \ldots, 35$. The left panel ends at 22 because there were no trading days on which more than 22 co-exceedances of risk factors occur. The right panel ends at 24 because there were no trading days on which more than 24 co-exceedances of risk factors occur. The high and low tail thresholds are the 95th percentile and 5th percentile values of daily bank stock returns in each fiscal year for each bank group. The tail thresholds of risk factors vary across fiscal years. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*).

Similar to the upper exceedance probability, the columns in the right panel of Table 5 also show that when there are more risk factor co-exceedances, the conditional probabilities of extremely low bank stock daily returns become much higher. Compared with the case of tail events from a single risk factor, tail events from several risk factors occurring simultaneously lead to much larger tail risk probabilities for individual bank stocks.

5 | FURTHER ANALYSIS

5.1 | The determinants of banks' unconditional tail risks

Now we investigate the determinants of individual banks' unconditional and conditional tail risks. Note that we count the frequency of exceedance events within each fiscal year using daily returns. For example, we count how many times each individual stock has exceeded the 3% critical value within a particular fiscal year. We divide this number by the total number of trading days within each year. This is our measure of upper tail risk probability for every bank in each year. The probabilities are firm-year observations, constructed using daily bank stocks' returns and daily values of risk factors. We do not directly link daily return data to annual accounting data.

Then we run the following regression to examine the determinants of unconditional tail risks, as in Equation (10). The variables on both the left- and right-hand sides use annual observations. Therefore, the regressions use pooled bank-year observations as follows:

$$\begin{aligned}\ln(1+Y_{i,t}\times 250) = {} & \gamma_0+\gamma_1\ln(AT_{i,t})+\gamma_2 BETA_{i,t}+\gamma_3 IVOL_{i,t}+\gamma_4 R2_{i,t}+\gamma_5 CAPR_{i,t}\\ & +\gamma_6 LLP_{i,t}+\gamma_7 ALLOW_{i,t}+\gamma_8 NIM_{i,t}+\gamma_9 EPSG_{i,t}+\gamma_{10} ININC_{i,t}\\ & +\gamma_{11} LEV_{i,t}+\gamma_{12} NPA_{i,t}+\gamma_{13} VOLUMN_{i,t}+\gamma_{14} A\_SHARE\_ONLY_{i,t}\\ & +\gamma_{15} LLP_{i,t}\times A\_SHARE\_ONLY_{i,t}+\mathrm{YEAR}_t+BANK_i+\varepsilon_{i,t},\end{aligned} \tag{10}$$

where i and t represent bank stock and fiscal year, respectively. $Y_{i,t}$ denotes the unconditional exceedance probability $PB\_UP_{i,t}$ or $PB\_DOWN_{i,t}$. $Y_{i,t}$ is multiplied by 250 to annualize the probabilities. We add a number of one to $Y_{i,t}\times 250$ because $Y_{i,t}$ could take the value of zero. $Y_{i,t}\times 250$ is actually the annual frequency count of extreme returns in a fiscal year. The explanatory variables include: the natural log of total assets ($\ln(AT)$), beta ($BETA$), idiosyncratic volatility ($IVOL$), price synchronicity ($R2$), loan loss provision (LLP), capital ratio ($CAPR$), allowance for loan losses ($ALLOW$), net interest margin (NIM), growth rate of earnings per share ($EPSG$), interest income ratio ($ININC$), leverage (LEV), and nonperforming asset ratio (NPA). $YEAR_t$ are year dummy variables used to control for macro shocks, and $BANK_i$ controls for bank fixed effects.

Our study selects 31 Chinese listed banks and includes five large state-owned banks, eight joint-stock banks, and 18 small and medium city commercial banks. Among them, nine banks either have shares traded in the Hong Kong Stock Exchange or have ADRs traded on New York Stock Exchange. There are no B-share banks in our sample. To address the issue that the developed markets are more efficient, we separate our sample stocks into two groups. Group One contains 22 bank stocks with A-shares traded in Shanghai or Shenzhen Stock Exchange only. Group Two contains nine bank stocks with either H-shares traded in Hong Kong Stock Exchange or N-shares traded in New York Stock Exchange. We create an indicator variable (A_SHARE_ONLY) to be included in the regressions.

Columns (1) and (2) in Table 6 control for fixed firm effects and fixed year effects and report bank-level clustered t-statistics. Columns (3) and (4) omit the fixed firm effects but include dummy variables for state-owned banks (*SOB*) and small and medium city commercial banks (*CCB*) and their interactions with size (*SOB_SIZE* and *CCB_SIZE*). Our goal is to examine whether ownership structure also affects tail risks.

The regression results show that *IVOL* has a positive impact on upper and lower tail risks. We also identify important bank-specific financial ratios that affect bank tail risks. *LLP* is significantly positive in all models, whereas *ALLOW* exhibits no explanatory power. Column (3) shows that nonperforming assets are detrimental to bank stocks' performance. Banks with more nonperforming assets have a significantly lower probability of extremely high returns even when the risk factors move into their respective positive tails.

We use the three indicator variables *SOB, JOB*, and *CCB* to investigate whether ownership structure also affects bank tail risk. Due to the higher costs of attracting consumers and the increasing pressure of market competition, smaller banks prefer risk-seeking activities (Tabak et al., 2013). Unsurprisingly, Column (4) supports a higher fragility for small and medium city commercial banks. *CCB* has an estimate of 3.313 with a t-statistic of 2.60 in the case of lower tail unconditional probabilities (*PB_DOWN*). The interaction term between *CCB* and bank size is significantly negative. *CCB_SIZE* has an estimate of −0.265 with a t-statistic of −3.14. This indicates that the size effect for smaller banks is even stronger. At the same time, both *PB_UP* and *PB_DOWN* of large state-owned banks are significantly higher than those of joint-stock banks, with estimated coefficients (t-statistics) for *SOB* being 4.437 (4.36) and 3.974 (2.28), respectively. This finding confirms the "too big to fail" hypothesis. Due to explicit or implicit government subsidies, large financial institutions tend to seek high-risk investments, such as short-term debt financing, which in turn leads to greater risks (Bakkar et al., 2020).

Table 6 also shows regression results when we include the dummy variable *A_SHARE_ONLY*. For upper tail unconditional tail risk, Column (3) shows that the estimated coefficient of *A_SHARE_ONLY* is 0.304 with a t-statistic of 3.50. For lower tail unconditional risk, Column (4) shows that the estimated coefficient of *A_SHARE_ONLY* is 0.374 with a t-statistic of 2.15. We find a significantly higher unconditional tail risk for bank stocks with shares traded in A-shares market only, consistent with the fact that the developed markets are more efficient.

5.2 | The determinants of banks' conditional tail risk

Unconditional tail risk focuses on the risk of an individual bank in isolation, while conditional exceedance probability measures the spillover effects from risk factors. To examine whether the conditional tail risk probabilities also depend on bank characteristics, we replace $Y_{i,t}$ in Equation (10) with $PB\_UP/MPOS_{i,t}$ or $PB\_DOWN/MNEG_{i,t}$. The two probabilities measure the frequency of extremely high or extremely low bank returns given at least one risk factor entering its favorable or unfavorable extreme territory, respectively. Note that in Table 5, we report $PB\_UP/POS_{i,t}$ or $PB\_DOWN/NEG_{i,t}$. These are the probabilities conditional on there being exactly n risk factor co-exceedances.

Table 7 consistently finds that the relationship between *LLP* and bank tail risk remains strong. *LLP* is highly significant in all models. Column (4) shows that the estimated coefficient of *CCB* is 3.441 with a t-statistic of 2.51, which indicates that when at least one risk factor falls into its extreme unfavorable territory, smaller banks will be more exposed to higher downside risk. However, when at least one risk factor falls into its extreme favorable territory, smaller banks will not be more exposed to higher upside risk. The estimated coefficient of *CCB_SIZE* on lower conditional tail risk is −0.275 with a t-statistic of −3.06. This implies that the adverse impact of risk factors will magnify the downside risk for small banks.

TABLE 6 Bank characteristics and unconditional tail risk.

	(1) $RET \geq High\_Tail_{type,year}$ (*PB_UP*)	(2) $RET \leq Low\_Tail_{type,year}$ (*PB_DOWN*)	(3) $RET \geq High\_Tail_{type,year}$ (*PB_UP*)	(4) $RET \leq Low\_Tail_{type,year}$ (*PB_DOWN*)
Intercept	−8.358*	−1.707	−6.265	0.481
	(−1.84)	(−0.37)	(−1.67)	(0.16)
ln(*AT*)	0.156***	0.156***	0.126	0.135
	(4.19)	(4.25)	(1.46)	(1.56)
BETA	−0.248	−0.387*	−0.274	−0.406
	(−1.28)	(−1.79)	(−1.12)	(−1.54)
IVOL	0.010***	0.011***	0.009***	0.010***
	(6.28)	(6.92)	(5.55)	(5.75)
*R*2	1.007	1.663***	0.934	1.600***
	(1.67)	(3.76)	(1.35)	(3.15)
CAPR	10.824***	6.116**	6.791***	1.178
	(3.57)	(2.08)	(3.22)	(0.56)
LLP	57.142**	59.653*	70.107***	74.924**
	(2.56)	(1.97)	(3.41)	(2.52)
ALLOW	−0.867	−3.438	−0.949	−3.745
	(−0.14)	(−0.59)	(−0.21)	(−0.66)
NIM	7.482	20.475*	4.343	14.996
	(0.76)	(1.74)	(0.43)	(1.52)
EPSG	0.254***	0.150*	0.271***	0.169**
	(3.07)	(1.80)	(3.80)	(2.24)
ININC	−2.473	−3.300	−4.006	−3.050
	(−0.29)	(−0.32)	(−0.80)	(−0.34)
LEV	4.235	−2.904	3.520	−3.710
	(0.94)	(−0.59)	(1.21)	(−1.24)
NPA	8.771	21.207*	−17.773***	−8.023
	(0.74)	(1.82)	(−3.21)	(−1.08)
VOLUME	0.005	0.003	−0.006	−0.017
	(0.17)	(0.07)	(−0.26)	(−0.46)
A_SHARE_ONLY	−0.014	0.038	0.304***	0.374**
	(−0.08)	(0.18)	(3.50)	(2.15)
A_SHARE_ONLY × *LLP*	4.405	−12.007	−27.901	−47.463
	(0.22)	(−0.42)	(−1.37)	(−1.50)

(Continues)

TABLE 6 (Continued)

	(1) $RET \geq High\_Tail_{type,year}$ (PB_UP)	(2) $RET \leq Low\_Tail_{type,year}$ (PB_DOWN)	(3) $RET \geq High\_Tail_{type,year}$ (PB_UP)	(4) $RET \leq Low\_Tail_{type,year}$ (PB_DOWN)
CCB			2.777	3.313**
			(1.63)	(2.60)
CCB_SIZE			−0.226*	−0.265***
			(−1.93)	(−3.14)
SOB			4.437***	3.974**
			(4.36)	(2.28)
SOB_SIZE			−0.254***	−0.224**
			(−3.84)	(−2.13)
Firm effect	Yes	Yes	No	No
Year effect	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
R^2	0.493	0.503	0.587	0.605
Observations	221	221	221	221

Note: The sample consists of 31 Chinese listed banks over the period from January 2007 to December 2019. The table reports pooled time-series and cross-sectional regressions of $\ln(1 + PB\_UP \times 250)$ and $\ln(1 + PB\_DOWN \times 250)$ on bank characteristics, respectively. The high and low tail thresholds are the 95th percentile and 5th percentile values of daily bank stock returns in each fiscal year for each bank group. The tail thresholds of risk factors vary across fiscal years. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 7 also shows regression results when we include the dummy variable *A_SHARE_-ONLY*. Column (3) shows that the estimated coefficient of *A_SHARE_ONLY* is 0.341 with a *t*-statistic of 3.44. Column (4) shows that the estimated coefficient of *A-SHARE_ONLY* is 0.375 with a *t*-statistic of 2.04. Consistent with Table 6 for unconditional tail risks, we find significantly higher conditional tail risks for bank stocks with A-shares traded in China only.

We include trading volume (*VOLUME)* in Tables 6 and 7 as well. We find no evidence of a reliable relation between trading volume and bank tail risk. We also standardize the volume data in the cross-section by adjusting for the mean and dividing by cross-sectional standard deviations. The conclusions remain the same.

5.3 | Discretionary and nondiscretionary loan loss provisions

Tables 6 and 7 show that loan loss provision is closely associated with tail risk. As the dominant accrual in bank accounting, loan loss provision is viewed as the most convenient tool for bank managers to smooth earnings. As in Beatty and Liao (2014), we separate dominant accrual (*LLP*) into discretionary and nondiscretionary parts. We follow the work of Collins et al. (1995) and Bushman and Williams (2012) to do the decomposition. Our aim is to assess which component is affiliated with bank stocks' tail risks. The predicted values in Equations (11) and (12) are nondiscretionary *LLP*s (*NDLLP1* and *NDLLP2*) and residuals are discretionary *LLP*s (*DLLP1* and *DLLP2*). The discretionary components are more subject

TABLE 7 Bank characteristics and conditional tail risk.

	(1)	**(2)**	**(3)**	**(4)**
	***RET* ≥ *High_Tail*$_{type,year}$ (*PB_UP|MPOS*)**	***RET* ≤ *Low_Tail*$_{type,year}$ (*PB_DOWN|MNEG*)**	***RET* ≥ *High_Tail*$_{type,year}$ (*PB_UP|MPOS*)**	***RET* ≤ *Low_Tail*$_{type,year}$ (*PB_DOWN|MNEG*)**
Intercept	−8.675*	−1.124	−6.579	0.685
	(−1.83)	(−0.23)	(−1.67)	(0.22)
ln(*AT*)	0.148***	0.158***	0.113	0.137
	(3.77)	(3.98)	(1.20)	(1.52)
BETA	−0.308	−0.421*	−0.335	−0.443
	(−1.33)	(−1.90)	(−1.18)	(−1.65)
IVOL	0.010***	0.011***	0.009***	0.010***
	(5.44)	(6.60)	(4.70)	(5.50)
*R*2	1.026	1.843***	0.939	1.751***
	(1.59)	(3.77)	(1.26)	(3.20)
CAPR	11.256***	6.334*	7.470***	2.130
	(3.48)	(2.03)	(3.31)	(0.89)
LLP	65.561**	58.283*	76.960***	67.819**
	(2.70)	(1.83)	(3.37)	(2.14)
ALLOW	−0.563	−4.828	−0.338	−4.317
	(−0.09)	(−0.78)	(−0.07)	(−0.69)
NIM	5.323	16.471	2.366	11.670
	(0.50)	(1.39)	(0.21)	(1.13)
EPSG	0.258***	0.166*	0.273***	0.179**
	(3.06)	(1.84)	(3.66)	(2.18)
ININC	−0.295	−1.659	−2.340	−2.774
	(−0.03)	(−0.15)	(−0.43)	(−0.29)
LEV	4.676	−3.584	4.056	−3.974
	(0.99)	(−0.70)	(1.35)	(−1.26)
NPA	8.748	22.046*	−18.078***	−6.912
	(0.74)	(1.92)	(−2.87)	(−0.82)
VOLUME	0.015	0.004	0.003	−0.013
	(0.48)	(0.13)	(0.13)	(−0.34)
A_SHARE_ONLY	0.021	0.046	0.341***	0.375**
	(0.12)	(0.21)	(3.44)	(2.04)
A_SHARE_ONLY × *LLP*	−1.180	−13.864	−32.844	−45.878

(Continues)

TABLE 7 (Continued)

	(1) RET ≥ $High\_Tail_{type,year}$ (PB_UP/MPOS)	(2) RET ≤ $Low\_Tail_{type,year}$ (PB_DOWN/MNEG)	(3) RET ≥ $High\_Tail_{type,year}$ (PB_UP/MPOS)	(4) RET ≤ $Low\_Tail_{type,year}$ (PB_DOWN/MNEG)
	(−0.06)	(−0.47)	(−1.48)	(−1.39)
CCB			2.766	3.411**
			(1.48)	(2.51)
CCB_SIZE			−0.227*	−0.275***
			(−1.77)	(−3.06)
SOB			4.502***	4.253**
			(3.97)	(2.29)
SOB_SIZE			−0.259***	−0.244**
			(−3.53)	(−2.19)
R^2	0.517	0.523	0.602	0.617
Observations	221	221	221	221
Firm effect	Yes	Yes	No	No
Year effect	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. The table reports the pooled time-series and cross-sectional regressions of ln (1 + *PB_UP/MPOS* × 250) and ln (1 + *PB_DOWN/MNEG* × 250) on bank characteristics where PB_UP/MPOS is the probability of individual bank daily returns exceeding their high tail threshold, conditional on at least one of the 35 individual risk factors falling into its favorable tail. *PB_DOWN/MNEG* is the probability of individual bank daily returns falling below their low tail threshold, conditional on at least one of the 35 individual risk factors falling into its unfavorable tail. The high and low tail thresholds are the 95th percentile and 5th percentile values of daily bank stock returns in each fiscal year for each bank group. The tail thresholds of risk factors vary across fiscal years. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

to manipulation by bank managers. Table 8 reports the decomposition results using the two models. The modified model from Collins et al. (1995) is as follows:

$$LLP_{i,t} = \alpha_0 + \alpha_1 ALLOW_{i,t-1} + \alpha_2 NPA_{i,t-1} + \alpha_3 \Delta NPA_{i,t} + \alpha_4 \ln(AT_{i,t-1}) + \alpha_5 CAP_{i,t-1} + \alpha_6 EBLLP_{i,t} + \alpha_7 CRISIS_{i,t} + \varepsilon_{i,t}. \quad (11)$$

All variables are standard and defined in Appendix (Panel B). $CRISIS_{i,t}$ is the crisis period dummy which equals 1 in the 2008 fiscal year. Total assets controls for the size effect. $CAP_{i,t-1}$ considers the possibility of capital management. The model of Bushman and Williams (2012) is as follows:

$$LLP_{i,t} = \alpha_0 + \alpha_1 \Delta NPA_{i,t+1} + \alpha_2 \Delta NPA_{i,t} + \alpha_3 \Delta NPA_{i,t-1} + \alpha_4 \Delta NPA_{i,t-2} + \alpha_5 \ln(AT_{i,t-1}) + \alpha_6 CAP_{i,t-1} + \alpha_7 EBLLP_{i,t} + \alpha_8 CRISIS_{i,t} + \varepsilon_{i,t}. \quad (12)$$

A major difference is that Bushman and Williams (2012) exclude $ALLOW_{i,t-1}$ and add ΔNPA_{t+1}.

TABLE 8 Estimation of discretionary and nondiscretionary loan loss provisions.

Collins et al. (1995) model		**Bushman and Williams (2012) model**	
Intercept	−0.000	Intercept	−0.008
	(−0.22)		(−1.33)
$ALLOW_{i,t-1}$	0.032	$\Delta NPA_{i,t+1}$	0.494**
	(1.12)		(8.61)
$NPA_{i,t-1}$	0.227**	$\Delta NPA_{i,t}$	−0.129
	(2.33)		(−0.48)
$\Delta NPA_{i,t}$	0.490**	$\Delta NPA_{i,t-1}$	0.139
	(4.05)		(0.41)
		ΔNPA_{t-2}	0.025
			(0.12)
$\ln(AT_{i,t-1})$	−0.001**	$\ln(AT_{i,t-1})$	0.976**
	(−5.55)		(4.69)
$CAP_{i,t-1}$	0.000	$CAP_{i,t-1}$	−0.113**
	(0.02)		(−2.66)
$EBLLP1_{i,t}$	0.742**	$EBLLP2_{i,t}$	0.000
	(12.05)		(1.17)
$CRISIS_{i,t}$	−0.000	$CRISIS_{i,t}$	0.003
	(−0.61)		(1.37)
R^2	0.680	R^2	0.625
Observations	199	Observations	144

Note: The table estimates two models of discretionary and nondiscretionary loan loss provision ($LLP_{i,t}$) using pooled time-series cross-sectional data. The first model is based on Collins et al. (1995). The independent variables include lagged loan loss allowances ($ALLOW_{i,t-1}$), lagged nonperforming assets ($NPA_{i,t-1}$), change in nonperforming assets ($\Delta NPA_{i,t}$), natural log of lagged total assets ($\ln(AT_{i,t-1})$), lagged shareholder capital ($CAP_{i,t-1}$), earnings before provisions and taxes ($EBLLP_{i,t}$), and an indicator variable that captures the financial crisis of 2008 ($CRISIS_{i,t}$). The scaling variable is total assets ($AT_{i,t}$). The second model is based on Bushman and Williams (2012). The independent variables include lead, current, lagged one, and lagged two changes in nonperforming assets (ΔNPA_{t+1}, ΔNPA_t, ΔNPA_{t-1}, and ΔNPA_{t-2}), natural log of lagged total assets ($\ln(AT_{i,t-1})$), lagged shareholder capital ($CAP_{i,t-1}$), earnings before provisions and taxes ($EBLLP_{i,t}$), and the period of financial crisis ($CRISIS_{i,t}$). The scaling variable is beginning of the fiscal year total loans ($LNTAL_{i,t-1}$). Bank level clustered t-statistics are reported in the OLS regressions. ** indicates significance at the 5% level.

The results from the Collins et al. (1995) model show that when NPA_{t-1} and ΔNPA_t increase, bank managers will set aside more LLP against future loan losses. The positive and significant estimated coefficient for $EBLLP$ supports the earnings management hypothesis. The Bushman and Williams (2012) model exhibits a similar forecasting ability for LLP. $\Delta NPA_{i,t+1}$, $\ln(AT_{i,t-1})$, and $CAP_{i,t-1}$ show significant explanatory power. It is worth mentioning that the estimated coefficient of shareholder capital (CAP) is significantly negative, suggesting that when capital is insufficient, banks are motivated to supplement capital through LLP.

Now we turn to analyze which component of LLPs are affiliated with individual banks' tail risks. In Table 9, we include both $DLLP1$ and $NDLLP1$ and both $DLLP2$ and $NDLLP2$, respectively. We find that the estimated coefficient for $DLLP1$ is positive and significant for both unconditional and conditional tail risk, while $NDPLLP1$ appears to have no effect on

TABLE 9 The effects of discretionary and nondiscretionary loan loss provisions on bank tail risk.

	Collins et al. (1995) model				Bushman and Williams (2012) model			
	Unconditional		Conditional		Unconditional		Conditional	
	PB_UP	*PB_DOWN*	*PB_UP|MPOS*	*PB_DOWN|MNEG*	*PB_UP*	*PB_DOWN*	*PB_UP|MPOS*	*PB_DOWN|MNEG*
Intercept	−7.579*	−2.824	−8.210**	−2.482	−8.330	−1.639	−9.852	1.752
	(−2.06)	(−0.68)	(−2.20)	(−0.58)	(−1.48)	(−0.28)	(−1.74)	(−0.29)
CAPR	11.103**	8.584**	11.723**	9.010**	6.603*	3.471	7.471*	3.533
	(3.26)	(2.46)	(3.32)	(2.52)	(1.76)	(1.38)	(1.98)	(1.47)
ALLOW	4.465	−2.199	5.058	−3.381	−16.254*	−18.995**	−15.164	−20.339**
	(0.82)	(−0.47)	(0.90)	(−0.67)	(−1.94)	(−2.38)	(−1.68)	(−2.32)
*DLLP*1	58.736*	80.400**	61.401*	76.717**				
	(1.96)	(3.61)	(2.00)	(3.41)				
*NDLLP*1	37.308	20.777	38.103	17.940				
	(1.58)	(0.74)	(1.51)	(0.62)				
*DLLP*2					17.002	18.527	15.125	17.205
					(1.18)	(1.59)	(1.07)	(1.47)
NDLLP2					1.730	3.216	1.264	1.017
					(0.21)	(0.30)	(0.14)	(0.10)
R^2	0.500	0.468	0.547	0.498	0.401	0.379	0.426	0.443
Observations	199	199	199	199	144	144	144	144
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 9 (Continued)

	Collins et al. (1995) model				Bushman and Williams (2012) model			
	Unconditional		Conditional		Unconditional		Conditional	
	PB_UP	***PB_DOWN***	***PB_UP|MPOS***	***PB_DOWN|MNEG***	***PB_UP***	***PB_DOWN***	***PB_UP|MPOS***	***PB_DOWN|MNEG***
Fixed effect	Year	Year	Year	Year	Year	Year	Year	Year
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: The sample consists of 31 Chinese listed banks over the period from January 2007 to December 2019. The pooled time-series and cross-sectional regressions models use ln(1 + $PB\_UP \times 250$), ln(1 + $PB\_DOWN \times 250$), ln(1 + $PB\_UP/MPOS \times 250$), and ln(1 + $PB\_DOWN/MNEG \times 250$) as the dependent variable, respectively, where *PB_UP* and *PB_DOWN* are unconditional tail risk probabilities. *PB_UP/MPOS* and *PB_DOWN/MNEG* are conditional tail risk probabilities. The left panel reports results from the Collins et al. (1995) model and the right panel reports results from the Bushman and Williams (2012) model. The high and low tail thresholds are the 95th percentile and 5th percentile values of daily bank stock returns in each fiscal year for each bank group. The tail thresholds of risk factors vary across fiscal years. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*). * and ** indicate significance at the 10% and 5% levels, respectively.

TABLE 10 Lagged bank accounting information and risk-taking activities.

	Unconditional tail risk		Conditional tail risk	
	***RET* ≥ 95th percentile (*PB_UP*)**	***RET* ≤ 5th percentile (*PB_DOWN*)**	***RET* ≥ 95th percentile (*PB_UP*/*MPOS*)**	***RET* ≤ 5th percentile (*PB_DOWN*/*MNEG*)**
LLP_{-1}	74.875**	81.372***	72.662**	73.852**
	(2.52)	(3.08)	(2.24)	(2.75)
A_SHARE_ONLY	0.292**	0.348**	0.293**	0.338**
	(2.56)	(2.46)	(2.45)	(2.27)
$A\_SHARE\_ONLY \times LLP_{-1}$	−41.054	−51.064*	−40.005	−44.504
	(−1.38)	(−1.88)	(−1.28)	(−1.58)
R^2	0.365	0.437	0.429	0.494
Observations	194	194	194	194
Other variables	Yes	Yes	Yes	Yes
Fixed effect	Year	Year	Year	Year
Cluster	Firm	Firm	Firm	Firm

Note: The sample consists of 31 Chinese-listed banks over the period from January 2007 to December 2019. The table reports the estimated coefficients (*t*-statistics) for lagged 1-year loan loss provision (LLP_{-1}). The pooled time-series and cross-sectional regression models use ln(1 + *PB_UP* × 250), ln(1 + *PB_DOWN* × 250), ln(1 + *PB_UP*/*MPOS* × 250), and ln(1 + *PB_DOWN*/*MNEG* × 250) as the dependent variable, respectively, where *PB_UP* and *PB_DOWN* are unconditional tail risk probabilities and *PB_UP*/*MPOS* and *PB_DOWN*/*MNEG* are conditional tail risk probabilities. The high and low tail thresholds are the 95th percentile and 5th percentile values of daily bank stock returns in each fiscal year for each bank group. The tail thresholds of risk factors vary across fiscal years. All banks are classified into the following three groups: large state-owned banks (*SOB*), joint-stock banks (*JOB*), and small-and-medium city commercial banks (*CCB*). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

individual banks' tail risks. This indicates that the positive association between loan loss provision and tail risk is driven mainly by the discretionary component. Discretionary loan loss provisions play an important role in earnings management. Discretionary loan loss provision is associated with diminished transparency and dampens the discipline of bank risk-taking activities.[8]

5.4 | Endogeneity issues

There is an important issue of endogeneity or reverse causality in our empirical analysis. We address the endogenous issue in two ways. First, banks may adjust financial accruals based on their stock's extreme performance in the previous year. To this end, we regress tail risk probabilities on bank characteristics with a 1-year lag. This alleviates concerns about an endogeneity problem. Table 10 shows that the estimated coefficients for LLP_{-1} are highly significant from the unconditional models. The estimated coefficients for LLP_{-1} are also highly significant from the conditional models. The R^2 value is only slightly lower than that in Tables 6 and 7. The estimates on *A_SHARE_ONLY* remain positive and highly significant at

[8]We also add the following interactive terms: *A_SHARE_ONLY*, *DLLP1* × *A_SHARE_ONLY*, *NDLLP1* × *A_SHARE_ONLY*, *DLLP2* × *A_SHARE_ONLY*, and *DLLP2* × *A_SHARE_ONLY*. The estimates of these interactive terms are not significant.

the 5% level in all model specifications. The estimates for the interaction term $LLP_{-1} \times A\_SHARE\_ONLY$ are not significant.

Second, the tail risk in the banking sector may reversely affect the tail risk from other risk factors. Thus, we measure tail risk probabilities for each risk factor within each fiscal year. The exceedance probability of each risk factor is then regressed on the exceedance probability of the market excess return factor (*EXMRET*) and the banking sector risk factor (*BANK*):

$$P\_DOWN_{Risk\_Factor,t} = \lambda_0 + \lambda_1 P\_DOWN_{EXMRET,t} + \lambda_2 P\_DOWN_{BANK,t} + \varepsilon_t, \tag{13}$$

$$P\_UP_{Risk\_Factor,t} = \delta_0 + \delta_1 P\_UP_{EXMRET,t} + \delta_2 P\_UP_{BANK,t} + \varepsilon_t. \tag{14}$$

The annual regressions cover 13 fiscal year observations from 2007 to 2019. Table 11 summarizes the results or risk factors with significant δ_2 and λ_2. Once the exceedance probability of the market excess return factor (*EXMRET*) is controlled, the exceedance probability of the banking sector factor (*BANK*) will only significantly affect the exceedance probabilities of nine other risk factors, which are concentrated in industries closely related to the banking sector, including *REAL, B_SMB, B_ROE, SECUR*, and *INSUR*. Since these industries are closely related to the banking sector, their exceedance probabilities are closely tied to the exceedance probabilities of the bank sector. During our sample period, we find no evidence that extreme returns in the banking sector have a broad effect on the remaining 26 risk factors.

TABLE 11 The impact of banking sector tail events on other risk factors.

	Upper tail exceedance probabilities δ_2	**Lower tail exceedance probabilities λ_2**
LT_REV	0.775**	0.870**
	(2.71)	(3.05)
REAL	0.398**	0.284**
	(4.81)	(5.89)
B_SMB	0.817**	
	(2.73)	
B_ROE	1.178**	1.678**
	(2.78)	(3.71)
SECUR	0.863**	0.958**
	(8.42)	(13.50)
INSUR	0.500**	0.485*
	(6.03)	(1.84)
OIL	0.664**	0.604**
	(3.07)	(2.39)
EMG_REAL		0.888*
		(2.20)
Observations	13	13

Note: The sample period is from January 2007 to December 2019. The table reports the response of the probability of a tail event in each risk factor to the probability of a tail event in the bank industry return. That response is given by λ_2 or δ_2 in the following regressions. The table reports only the estimates for risk factors that have significant λ_2 and δ_2 using annual data. * and ** indicate significance at the 10% and 5% levels, respectively.

6 | CONCLUSIONS

This paper employs unconditional and conditional exceedance models to study the tail dependency between bank stocks and risk factors in China. The unconditional exceedance model assesses the probability of extreme daily returns while the conditional exceedance model assesses the likelihood of extreme daily returns given extreme outcomes from risk factors. We choose listed bank stocks in China and empirically investigate their tail co-movement with 35 risk factors from the stock, bond, and commodity markets. The aim of this paper is to examine the tail linkage between individual bank stocks and those 35 common risk factors. Univariate conditional exceedance probability focuses on the effect of one particular risk factor and evaluates the relative importance of different risk resources. Multivariate conditional exceedance probability examines the joint effect when multiple risk factors realize extreme values.

In our sample period, we identify several systematically important industries whose tail behaviors are strongly associated with the tail behaviors of individual bank stocks. Tail events from the banking, security trading, real estate, and energy industries significantly influence tail risk probabilities of bank stocks listed in China. Our results indicate that univariate conditional tail risk is significantly higher than unconditional tail risk. The influence of simultaneous tail outcomes from several risk factors is much stronger than tail outcomes from one single risk factor.

We also find that the cross-market tail linkage between individual bank stocks listed in China and emerging market risk factors is much stronger than the tail linkage between individual stocks listed in China and developed market risk factors. This is consistent with evidence from the contagion literature that, in general, the linkage between stocks listed in China and developed market risk factors is loose. But during crisis periods, we find greater tail dependence between individual bank stocks and developed market risk factors.

We consistently find that bank specific financial ratios such as capital ratio, non-performing assets, leverage, and growth of earnings per share play important roles in determining the tail risk of individual bank stocks. Loan loss provision is the most important determinant of bank tail risk among all bank specific financial ratios we consider. The positive influence of loan loss provision on tail risk is mainly driven by the discretionary component.

AUTHOR CONTRIBUTIONS

Huan Yang: Data curation; formal analysis; software; writing—original draft. **Jun Cai**: Conceptualization; methodology; resources; supervision. **Lin Huang**: Funding acquisition; resources; supervision; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

ETHICS STATEMENT

Not applicable.

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APPENDIX: CONSTRUCTION OF RISK FACTORS, MARKET VARIABLES, AND ACCOUNTING VARIABLES

See Table A1.

TABLE A1 Panel A of the Appendix provides the details of data sources and construction of risk factors. Panel B provides definitions, references, and details of the CAMAR data items used to construct the financial variables.

Panel A: Risk factors

Risk factor	Data source and construction of risk factors
EXMRET	The data source is CSMAR. *EXMRET* is the daily excess return in the market index.
SMB	The data source is CSMAR. *SMB* is the daily difference in returns on diversified portfolios of stocks with small-versus-large market capitalization.
HML	The data source is CSMAR. *HML* is the daily difference in returns on diversified portfolios of stocks with high-versus-low book-to-market ratios.
RMW	The data source is CSMAR. *RMW* is the difference in daily returns on diversified portfolios of stocks with robust-versus-weak profitability.
CMA	The data source is CSMAR. *CMA* is the difference in daily returns on diversified portfolios of stocks with low-versus-high investment.
MOM	The data source is CSMAR. *MOM* is the average return on the two high-prior-return portfolios minus the average return on the two low-prior-return portfolios. Prior daily returns are measured over prior month 2 to prior month 12.
ST_REV	The data source is CSMAR. *ST_REV* is the average return on the two high-prior-return portfolios minus the average return on the two low-prior-return portfolios. Prior daily returns are measured over the prior single month.
LT_REV	The data source is CSMAR. *LT_REV* is the average return on the two high-prior-return portfolios minus the average return on the two low-prior-return portfolios. Prior returns are measured over prior month 13 to prior month 60.
LIQ	The *LIQ* factor is constructed using data from CAMAR, following the method described on Kenneth French's webpage. Liquidity is measured by the Amihud (2002) measure. *LIQ* is the average return on the two most illiquid portfolios minus the average return on the two most liquid portfolios.
DIV	The *DIV* factor is constructed using data from CSMAR, following the method described on Kenneth French's webpage. Dividend yield is measured by the total dividend paid divided by the beginning of the fiscal year market value. *DIV* is the average return on the two highest dividend yield portfolios minus the average return on the two lowest dividend yield portfolios.
B_SMB	The *B_SMB* factor is constructed using banking sector stocks. The data source is CSMAR. The *B_SMB* factor is constructed following the method described in Kenneth French's webpage. *B_SMB* is the return on a small bank portfolio minus the return on a large bank portfolio.
B_ROE	The *B_ROE* factor is constructed using banking sector stocks. The data source is CSMAR. The *B_ROE* factor is constructed following the method described in Kenneth French's webpage. *B_ROE* is the average return on more profitable bank portfolios minus the average return on less profitable bank portfolios.

TABLE A1 (Continued)

Panel A: Risk factors	
Risk factor	**Data source and construction of risk factors**
BANK	The data source is CSMAR. *BANK* is the value-weighted return on the banking industry.
SECUR	The data source is CSMAR. *SECUR* is the value-weighted return on the financial industry.
INSUR	The data source is CSMAR. *INSUR* is the value-weighted return on the insurance industry.
REAL	The data source is CSMAR. *REAL* is the value-weighted return on the real estate industry.
REAL_LEV	The *REAL_LEV* factor is constructed using real estate sector stocks. The data source is CSMAR. The *REAL_LEV* factor is constructed following the method described in Kenneth French's webpage. *REAL_LEV* is the average return on high-levered real estate stocks minus the average return on low levered real estate stocks.
BONDDRET	The data source is CSI. *BONDDRET* is the daily return on the China Aggregate Bond Index.
TERM	The data source is WIND. *TERM* is the difference between 10-year Treasury bond and 1-year Treasury note daily yields.
CREDIT	The data source is CSI. *CREDIT* is the difference between AAA and A bond daily yields.
COMMDRET	The data source is WIND. *COMMDRET* is the daily return on the CRB commodity market index.
GOLDDRET	The data source is WIND. *GOLDDRET* is the daily return on gold futures contracts traded on the COMEX.
GOLD	The data source is CSMAR. *GOLD* is the value-weighted return on the gold-mining industry.
OILDRET	The data source is WIND. *OILDRET* is the daily return on light crude oil futures contracts traded on the NYMEX.
OIL	The data source is CSMAR. *OIL* is the value-weighted return on the oil industry.

Panel B: Bank financial variables	
Variable names	**Descriptions**
Market variables	
Market value of equity (*ME*)	*ME* = market equity at the end of the fiscal year = fiscal year-end stock price × common shares outstanding
Beta (*BETA*)	*BETA* = $\beta_1 + \beta_2 + \beta_3$ from the following regression: $r_{i,t} = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{m,t+1} + \beta_3 r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is daily individual stock returns within the fiscal year and $r_{m,t}$ is the corresponding daily return on value-weighted market portfolio.
Idiosyncratic volatility (*IVOL*)	*IVOL* is from the following regression: $r_{i,t} = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{m,t+1} + \beta_3 r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is daily individual stock returns within the fiscal year and $r_{m,t}$ is the corresponding daily return on value-weighted market portfolio.
Price synchronicity (*R2*)	*R2* = *R*-squared from the following regression: $r_{i,t} = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{m,t+1} + \beta_3 r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is daily individual stock returns within the fiscal year and $r_{m,t}$ is the corresponding daily return on value-weighted market portfolio.
Bank accounting variables	
Total assets (*AT*)	*AT* = total assets
Capital ratio (*CAPR*)	*CAPR* = tier 3 capital ratio

(Continues)

TABLE A1 (Continued)

Panel B: Bank financial variables

Variable names	Descriptions
Loan loss provisions (*LLP*)	*LLP* = provision for loan losses/total assets In models decomposing *LLP* into discretionary and nondiscretionary components: Collins et al. (1995) model, *LLP* = provision for loan losses/total assets = *PCL*/*AT* Bushman and Williams (2012) model, *LLP* = provision for loan losses/lagged total loans = $PCL/LNTAL_{-1}$
Loan loss allowance (*ALLOW*)	*ALLOW* = total allowance for loan loss/total assets = *RCL*/*AT*
Net interest margin (*NIM*)	*NIM* = net interest margin/total assets
Earnings-per-share growth (*EPSG*)	*EPSG* = growth of earnings per share
The ratio interest income to total income (*ININC*)	*ININC* = total interest income/total income
Leverage ratio (*LEV*)	*LEV* = total liabilities/total assets = *LT*/*AT*
Nonperforming assets (*NPA*)	*NPA* = total nonperforming assets/total assets = *NPAT*/*AT*
An indicator variable to capture the period of financial crisis (*CRISIS*)	*CRISIS* = 1 for fiscal year 2008; 0 otherwise.
Earnings before loan loss provision (*EBLLP*)	*EBLLP* = (income before extraordinary + loan loss provisions)/total assets = (*IB* + *PCL*)/*AT* in the Collins et al. (1995) model *EBLLP* = (income before extraordinary + loan loss provisions)/lagged total loans = $(IB + PCL)/LNTAL_{-1}(IB + PCL)/LNTAL_{-1}$ in the Bushman and Williams (2012) model
Discretionary LLP (*DLLP*1)	*DLLP*1 = residual value from the Collins et al. (1995) LLP model
Nondiscretionary LLP (*NDLLP*1)	*NDLLP*1 = predicted value from the Collins et al. (1995) LLP model
Discretionary LLP (*DLLP*2)	*DLLP*2 = residual value from the Bushman and Williams (2012) model
Nondiscretionary LLP (*NDLLP2*)	*NDLLP*2 = predicted value from the Bushman and Williams (2012) model.