Loan loss provisions and bank riskiness at market extreme losses

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Abstract

This paper examines the U.S bank holding companies for the effect of loan loss provisions (LLPs) on systemic risk at market extreme losses over the quarters of 1982-2024 period. An insight into the overall effect is provided by the composition of systemic risk into two subcomponents, systemic linkage and bank-specific risk. Overall, we find that a higher level of LLPs increases bank riskiness when the financial system goes crashes. The decomposition points out that, for all banks regardless of their sizes, setting a larger amount of incomes aside for LLPs significantly increases the number of plunges in their stock prices corresponding to the market extremely downward movements. There is no clear evidence of significant impact of LLPs on bank-individual risk with the whole sample. By further analyses with subsamples based on bank size, we, however, figure out that….

Keywords: Systemic risk, Financial crisis, Market extreme losses, Systemic linkage, Individual risk, Federal Reserve.

1 Introduction

This paper examines the relationship between loan loss provisions (LLPs) and bank systemic risk at financial market extreme losses. This examination is aimed to provide an insight into the systemic risk to macropudential perspectives by looking at the dependency of bank worst returns system-wide large losses. Loan loss provisons help bank to cover the potential losses in their released loans. The provisons are helpful when economics activities suffer sharp falls. As a consequence, bank borrowers are very likely to default in those crisis situations. Widely large drops in stock markets, however, trigger sell-off actions towards the banks indicating high level of LLPs. Those investor reactions to severe market conditions cause plunges in stock prices of financial institutions, i.e. increase bank systemic risk. A system-wide indicator of vulnerability to asset fire sales for the U.S. bank holding companies (BHCs) was documented by (Duarte and Eisenbach, 2021). An almost 30% drop in the total equity of all BHCs due to 1% decline in the prices of all BHCs assets was seen at the peak of the global financial crisis of 2008-2009 (BIS, 2018).

Institutional individual risk taken in isolation is important to bank regulators and policy makers. The unprecedented financial market collapses worldwide after 2008-2009 crisis, however, revealed that the collective fragility of the banks as a whole is also important for financial system stability. The crisis hit the critical vulnerabilities in the final system and sparked intensive debates and conferences on the safety and stability of the financial system by the Basel Committee on Banking Supervision (BCBS), the International Monetary Fund (IMF), the Financial Stability Board (FSB), and Central Banks. Those discussions lead to globally regulatory reforms including Dodd-Frank Wall Street Reform and Consumer Protection Act in the U.S., Basel III framework with the liquidity coverage ratios (LCR) and net stable funding ratios (NSFR) requirements by Basel Committee on Banking Supervision, and international focuses on the systemic risk of SIFIs, and newly introduced regulations on derivatives trading to reduce counterparty risk.

In addition, in the post-crisis period, banks extensively increased expenses for rising credit losses, which implied higher procyclicality of their LLPs (Danisman et al., 2021).

In favor of macroprudential views, if loan loss provisions increase bank systemic risk during economics nagative shocks, how do the provisions affect the linkage of bank stock plunges to the shock events? This study is aimed to adress this question.

Our hypotheses are specified as follows:

Hypothesis 1: Loan loss provisons increases bank systemic risk during market crises.

Hypothesis 2: The linkage between bank stock worst performances and sytem severe losses positively responses to loan loss provison due to market reactions.

Hypothesis 3: There are significant differences in idiosyncratic risk between large and small banks.

2 Data and variables

2.1 Data

The data sample in this study is compiled from two main sources, the Call Reports for Bank Holding Companies according to FR Y-9C reports, and CRSP for daily stock returns. Bank historical daily returns were first retrieved from CRSP from the first of January, 1982 to September 30, 2024 for every US Bank Holding Company. Those returns were selected accordingly to adjusted stock prices which exclude the dividends paid out. In combination with bank equity daily return, the daily value-weighted returns of the money market is then used as the financial system performance in tail beta estimations.[1]

The provided system daily retunrs were aggregated from the firms with SIC codes between 6000 and 6999, covering banking, insurance, real estates, and trading sectors. Both system and bank daily returns within estimation windows of sixteen quarters or four years, ranging from 1982:Q4–1986:Q3 to 2020:Q4–2024:Q3, were used to compute the three main dependent variables, including systemic risk (*tailbeta*), and its two subcomponents, systemic linkage (*tailbetaSL*) and bank-specific tail risk (*tailbetaIR*). —[**cited: Based on the previous empirical research ?**], the length of the rolling windows for tail betas estimating is four years or 16 quarters, which is sufficient to capture the events of financial system crashes.[2] In addition, the CRSP-FRB link file from the Federal Reserve Bank of New York contains RSSD ID-PERMCO connections, bridging the computed tail betas to bank financial records by year and quarter correspondingly.[3]

The link file has several records duplicated in entity and PERMCO fields, indicating the changes in bank PERMCO, or name, or institution type from commercial banks to bank holding companies. Duplication flags according to those records are, therefore, added to the link file in order for the merging of tail betas with financial records not to produce tail beta repeatation in the result.

To guarantee the quality of the data and the liquidity of the collected stocks on the equity market, the data sample includes only the banks that have total assets of at least USD 500 million (Minton et al., 2019) and nonzero returns on at least 60% of the days in every estimation window.[4] Moreover, all observations corresponding to zero estimates of *tailbeta* are excluded from the sample because the decomposition in —**revise: Equation** (5) **?** requires to take natural logarithm of estimated tailbeta and its two subcomponents. To mitigate the impact of outliers, all variables are winsorized at 99% level. The merging and cleaning process produces a final sample of —[**finalize: 1,272**] banks in form of an unbalanced panel of —[**finalize: 69,102**] bank-quarter observations in the period from

[1]The market returns were extracted from 38 Industry Portfolios downloaded from Kenneth R. French - Data Library website at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2]In an additional test, we also calculated tail betas from two years of daily returns for robustness checks.

[3]The latest end date in CRSP-FRB link file at the time of this study was on September 30, 2024.

[4]—**revise: Total assets are measured in real December 2024 dollars using implicit GDP price deflator**. The price deflator is obtained from the St. Louis Fed website (GDPDEF - Gross Domestic Product: Implicit Price Deflator) at https://fred.stlouisfed.org/series/GDPDEF.

1986:Q3 to 2024:Q3. Each record in the final sample presents the tail beta computed from the bank and system returns within the timeframe of sixteen quarters from t to t+15, and fundamental items at time t+15. In other words, the fundamental data is positioned at the quarter 16^{th} of the rolling window which is fitted to the 16-quarter timeframe. In regression analyses, the tail betas and their two subcomponents are, however, regressed on the financial factors at t-1 for identifying which bank fundamental information can help explain the variabilities of the three main risk measures in sixteen-quarter period ahead. Therefore, the fundamental variables are lagged 16 quarters, from t+15 back to t-1 in the majority of our regressions, excluding a few cases when further lags applied to some explantory variables.

2.2 Systemic risk

The main purpose of this empirical study is to examine the impact of market severe downturns on bank stock performance. We therefore use the systemic risk measure of (Van Oordt and Zhou, 2018) as the proxy for bank riskiness. This is because their decomposition of systemic risk provides the advantages in clarification of whether there exists a systemic connection of bank stock price to market negative shocks and how strong it is. As a result, the systemic linkage component significantly improves macro-prudential poin of views. In other words, for banks with the same level of the bank-specific tail risk, the stronger systemic linkage a bank has, the systematically riskier the bank is.

Systemic risk associated with the extreme negative shocks in financial index is the proxy for bank riskiness in our analyses. —**need citations: The beta coefficients from a linear regression across all market observations do not well describe the stock performances at market plunges, although those coefficients are simple and usually used as systemic risk measures as in** [@]. As a result, those betas are inappropriate for this present research situation in which bank stock returns are examined in market crash conditions. This appropriateness is more likely the case in banking literature when systemic risk is ussually related to large and severe shock events in financial markets.

We use the systemic risk measure in (Van Oordt and Zhou, 2018) to proxy the bank riskiness associated with market extreme losses. (Van Oordt and Zhou, 2018) measured the affect of financial system severe downside returns on bank equity performance by tail beta β_i^T in the following linear equation:

$$R_i = \beta_i^T R_m + \epsilon_i \;\; for \;\; R_m < -VaR_m(\alpha) \tag{1}$$

where R_i, and R_m represent bank i^{th}, and market returns respectively. $R_m < -VaR_m(\alpha)$ refers to the extreme losses with a small probability of α corresponding to the tail region on the left of market return probability distribution. $VaR_m(\alpha)$ denotes the value on the rightmost of the region, which is also called the value-at-risk or threshold value of one-dollar equity investment in the financial market. The challenge of estimating —**revise: Equation** (1) **?** is to regress all bank returns on just a small number of observations on system crash events using Ordinary Least Squares (OLS) methodology. (Van Oordt and Zhou, 2018) utilized their methodology developed in (Van Oordt and Zhou, 2017) that derived a consistent and asymptotically normal estimator for β_i^T as the following equation:

$$\beta_i^T = \lim_{\alpha \to 0} \tau(\alpha)^{1/\zeta_m} \frac{VaR_i(\alpha)}{VaR_m(\alpha)} \tag{2}$$

where $VaR_i(\alpha)$ and $VaR_m(\alpha)$ denote the value-at-risks of one-dollar investments in bank stock and market index respectively. ζ_m is the tail index measuring the heavy-tailedness of market return distribution. The higher heavy-tailedness, the higher probability or likelihood of market crashes. β_i^T is a non negative number, i.e. $\beta_i^T \geq 0$. This is because, based on Extreme Value Theory (EVT), it is derived from the worst negative returns R_i, and R_m which follow heavy-tailed distributions with ζ_i, and ζ_m indices respectively. In other words, the tail beta β_i^T measures the downside movements of the worst bank stock performances R_i conditional upon financial market extreme losses R_m. $\tau_i(\alpha)$ represents the tail dependence of bank worst returns on system adverse shocks (see (De Haan and Ferreira, 2006)). The higher $\tau_i(\alpha)$, the more bank worst returns associated with the system downside shock events. This tail dependence is defined as:

$$\tau i(\alpha) = Pr(R_i < -VaR_i(\alpha) | R_m < -VaR_m(\alpha)) \tag{3}$$

The proposed estimator for β_i^T was applied in (Van Oordt and Zhou, 2016), and verified that, at firm level, a higher stock risk premium is associated with its higher β_m^T. β_i^T can be empicically estimated by combining the existing Hill estimator in (Hill, 1975) for $1/\zeta_m$, and the non-parametric estimator in (Embrechts et al., 2000) for $\lim_{\alpha \to 0} \tau(\alpha)$.

With an estimation window of n pairs of observations on (R_i, R_m), and k worst returns for each of the two return series within the window, the empirical estimator $\hat{\beta}_i^T$ can be expressed as:

$$\hat{\beta}_i^T = \hat{\tau}(k/n)^{1/\hat{\zeta}_m} \frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_m(k/n)} \tag{4}$$

In this present study, we follow (Van Oordt and Zhou, 2018) and select 40 worst returns from the rolling window of four years of daily observations, which on average produces a k/n $\approx$ 40/1056 $\approx$ 4%. This ratio is similar to the level of k/n in the studies that determined the optimal thresold value for the left tail as in (Jansen and De Vries, 1991), (Longin and Solnik, 2001), and (Yang et al., 2021). By taking logarithm of the —**revise: Equation** (4) **?**, the systemic risk is decomposed and represented by a linear relationship with its two subcomponents as follow:[5]

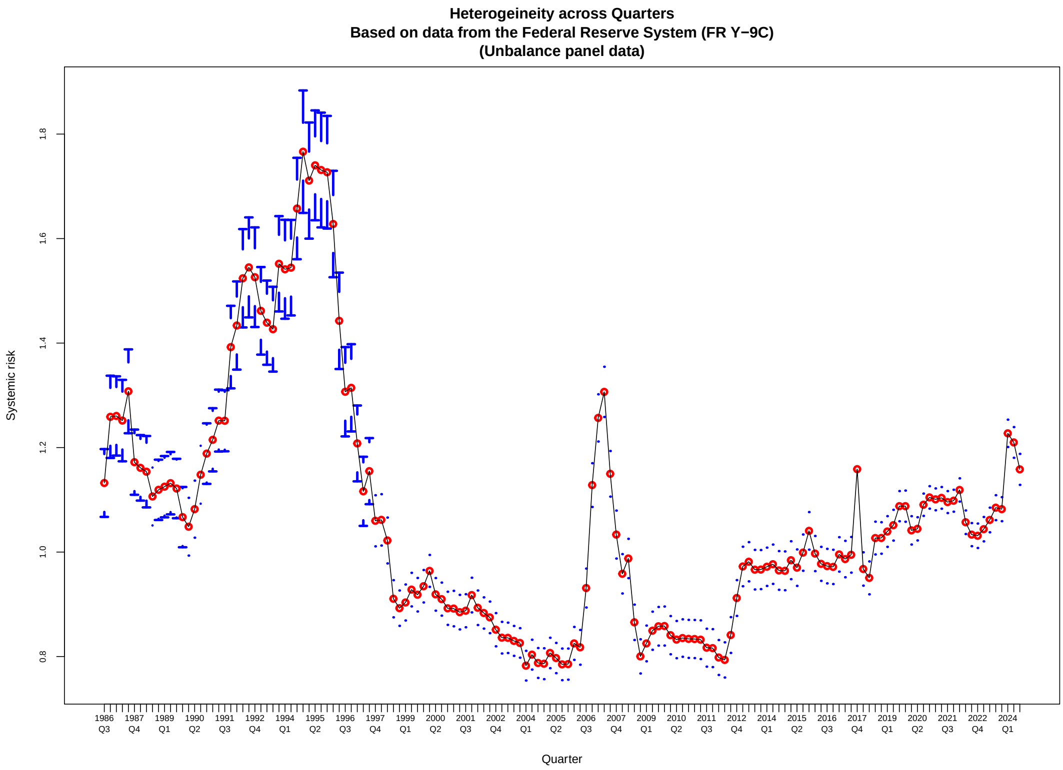
[5] $1/\zeta_m$ indicates the inversion of market tail index, which is also called Hill estimator. Hill estimator is calculated by taking the average differences between each of k extreme losses and the loss at (k+1) position (that is, $VaR_m(\alpha)$) as described in (Van Oordt and Zhou, 2016). $\lim_{\alpha \to 0} \tau(\alpha)$ is the main

$$log\hat{\beta}_i^T = log\hat{\tau}(k/n)^{1/\hat{\zeta}_m} + log\frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_m(k/n)} \tag{5a}$$

$$log\hat{\beta}_i^T = log(Systemic\ Linkage) + log(Individual\ Risk) = logSL_i + logIR_i \tag{5b}$$

where SL_i represents the connection of bank large drops to the system crash events, from the markets. The stronger SL_i is, the higher conditional probability of a sharp drop a bank would face. Meanwhile, IR_i is the remaining portion that indicates individual risk at bank level unconditional on the market plunges. Systemic risk, systemic linkage, and individual risk are the three main risk measures used as dependent variables in our regression analyses.

Figure 2.1: Mean variation in Systemic risk over 1986Q3-2024Q3 period



2.3 Loan loss provision

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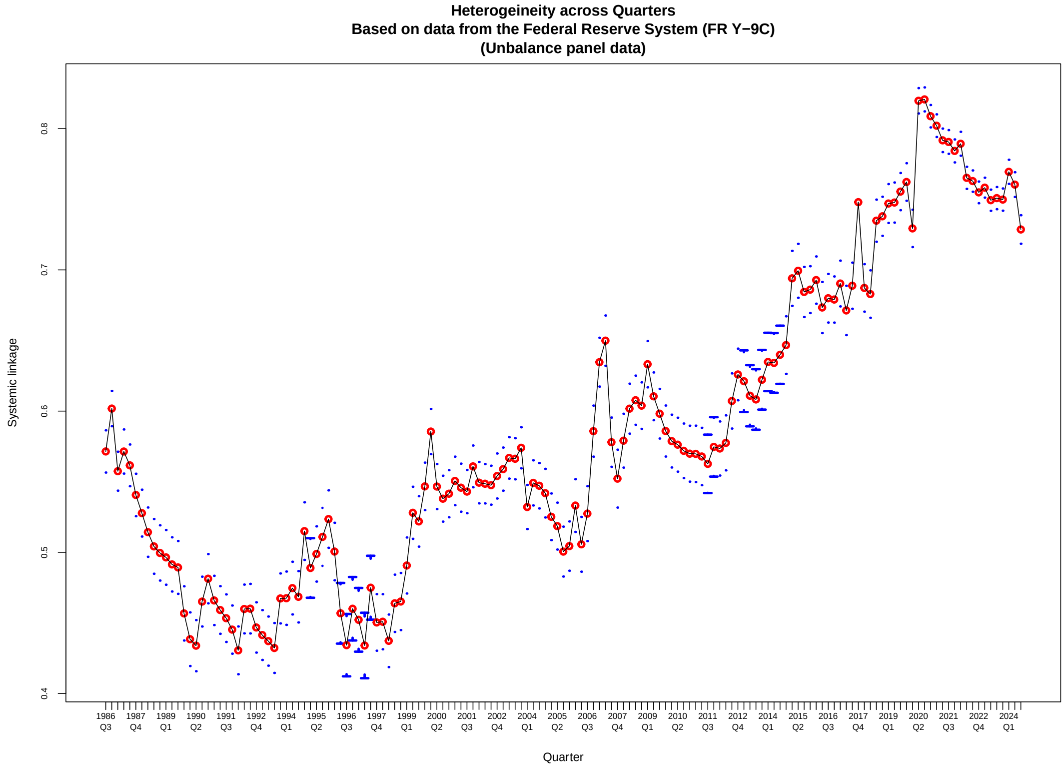
component of $\lim_{\alpha\to 0} \tau(\alpha)^{1/\zeta_m}$ which which is so-called Systemic Linkage. This component represents tail dependences of banks on the system, and it is computed by accumulating the comovements of k worst bank returns with k worst market losses.

Figure 2.2: Mean variation in Systemic linkage over 1986Q3-2024Q3 period



2.4 Control variables

To control the effects of bank-specific characteristics on systemic risk, we include the following variables into regression models: (i) Bank size. Previous studies indicated that banks' choices of business models have direct influences on their size as in (Bolívar et al., 2023), (Coelho et al., 2022), and (Roengpitya et al., 2017). This is indicated by the strong correlations between total assets and all bank characteristics in pairwise correlation in — **revise: Table** 2.3 **?**. Therefore, following (Baele et al., 2014), the logarithm of deflated total assets is first regressed on all bank characteristics in our models.[6] The residuals is then used as the proxy for bank size in regression models to eliminate linear relationships between regressors. (ii) Capital ratio is the ratio of equity capital to total assets, (iii) Profitability. Following ((Yang et al., 2021)) we use return on equity (ROE) instead of return on assets (ROA) although existing literatures indicate significant relationship between these two returns and risks. This is because since 1970s banks started manipulating their ROE as a performance target by taking more risks via leverage as documented in (Pennacchi and Santos, 2021). They also figured out that stock market investors' focus on ROE was the reason why banks manipulated ROE. In addition, the finding of (Moussu and Petit-Romec, 2017) indicates that pre-crisis ROE is a strong predictor of both bank standalone and systemic risks in the two major financial crises of 1998 and 2008-2009. We measure ROE as the ratio of net income to total equity, which assesses the effectiveness in using investors' dollars. (iv) Deposits to assets calculated as total deposits divided by total assets is used as a control for funding structure, (v) Non-interest income cal-

[6]See the Data section for the detailed deflation.

culated as the ratio of non-interest income to interest income is utilized as a proxy for income structure and business model, and (vi) Non-performing loans defined as the ratio of non-performing loans to total loans controls for the quality and riskiness of banks' loan portfolios.

Table 2.1: Definition of the variables

Variables	**Description**	**Type**
Dependent variables		
Systemic Risk: $\beta^T_{i;[t,t+15]}$.	tail beta	Systemic risk
Systemic Linkage: $SL_{i;[t,t+15]}$.	systemic linkage	Systemic linkage
Bank Tail Risk: $IR_{i;[t,t+15]}$.	bank risk	Bank-specific tail risk
Independent variables		
Explanatory variables[a]		
LoanLossProvision$_{t-1}$.	A fund bank set aside to cover potential losses from the current loans.	Loan loss provision
Control variables		
Bank size ($reslnTA_{t-1}$).	Bank size	Bank characteristics
Tangible equity ratio$_{t-1}$.	Capital: Tangible common equity ratio	Bank characteristics
Nonperforming-loans ratio$_{t-1}$.	Asset quality: Non-performing loans ratio	Bank characteristics
CAMEL ratios[c]		
Cost-to-income ratio$_{t-1}$.	Management: cost-to-income ratio	Bank characteristics
Bank size ($reslnTA_{t-1}$).[b]	Earnings: return on total equity	Bank characteristics
Liquid assets$_{t-1}$.	Liquidity: liquid assets ratio	Bank characteristics
Deposit funding gap$_{t-1}$.	Funding structure defined as the difference between total loans and total deposits scaled by total assets	Bank characteristics
Loans to total assets$_{t-1}$.	Loans structure: Loans to total assets	Bank characteristics
Noninterest income share$_{t-1}$.	Income structure defined as a ratio of non-interest income and total income (the sum of non-interest and interest incomes)	Bank characteristics
Growth in total assets$_{t-1}$.	Assets growth	Bank characteristics

Note:
The relationship between the dependent variables, systemic risk, systemic linkage, and bank-specific tail risk, is described in —**revise: Equation** (5) **?**.(.)

[a] *LLP* is the amount of fund a bank sets aside to cover the potential losses from the current loans.(.)

[b] *resLnTotAssets* is bank size defined as the residuals obtained from the regeression of the natural logarithm of total assets on the remaining regressors. This is because banks' choice of their business models tends to directly impact their size, that is, total assets. As a consequence of this procedure, all independent variables this way affect the tail risk measures through total assets.(.)

[c] *TCERatio*, *NPL*, *Cost2Income*, *ROE*, and *LiquidAssetstoAssets* are the *four ratios* of the **CAMEL** model.(.)

2.5 Descriptive statistics and correlations

Table 2.2: Descriptive Statistics

VARIABLES	**Mean**	**Std..Dev.**	**min**	**p10**	**p90**	**max**
PANEL A: Systemic Risk and the subcomponents[a]						
Systemic Risk: $\beta^T_{i;[t,t+15]}$	1.062	0.469	0.138	0.596	1.523	7.438
Systemic Linkage: $SL_{i;[t,t+15]}$	0.595	0.166	0.172	0.370	0.809	0.948
Bank Tail Risk: $IR_{i;[t,t+15]}$	1.920	1.193	0.513	1.142	2.976	15.873
$ln(\beta^T_{i;[t,t+15]})$	-0.019	0.397	-1.980	-0.517	0.421	2.007
$ln(SL_{i;[t,t+15]})$	-0.564	0.306	-1.759	-0.993	-0.212	-0.053
$ln(IR_{i;[t,t+15]})$	0.544	0.419	-0.668	0.133	1.091	2.765
PANEL B: Main Charaterisics[b]						
LoanLossProvision$_{t-1}$[c]	0.347	0.590	-0.210	0.000	0.851	3.535
ln(Total Assets$_{t-1}$)	15.073	1.695	11.887	13.182	17.430	19.853
Tangible equity ratio$_{t-1}$	7.968	2.493	1.782	5.172	10.724	18.446
Nonperforming-loans ratio$_{t-1}$	0.013	0.018	0.000	0.001	0.033	0.099
Cost-to-income ratio$_{t-1}$	0.664	0.142	0.379	0.518	0.818	1.300
Return on equity$_{t-1}$	0.057	0.071	-0.329	0.012	0.129	0.207
Liquid assets$_{t-1}$	0.050	0.086	-0.125	-0.035	0.159	0.387
Deposit funding gap$_{t-1}$	-0.114	0.140	-0.528	-0.295	0.051	0.214
Growth in total assets$_{t-1}$	0.023	0.059	-0.082	-0.023	0.069	0.380
PANEL C: Non-Interest Income[d]						
Noninterest income share$_{t-1}$	0.253	0.149	0.025	0.102	0.423	0.799
Srvc Charges on Deposit Accounts Shr$_{t-1}$	0.063	0.037	0.000	0.017	0.113	0.171
Fiduciary Activities Income Share$_{t-1}$	0.032	0.052	0.000	0.000	0.077	0.324
Trading Revenue Share$_{t-1}$	0.006	0.019	-0.008	0.000	0.014	0.113
Other Non-Interest Income Share$_{t-1}$	0.151	0.129	0.001	0.044	0.281	0.745
PANEL D: Loan Portfolio[e]						
Loans to total assets$_{t-1}$	0.651	0.132	0.177	0.492	0.793	0.878
Real estate Loan Share$_{t-1}$	0.675	0.201	0.051	0.398	0.899	0.992
Commercial & Industrial Loan Shr$_{t-1}$	0.175	0.116	0.000	0.053	0.332	0.588
Consumer Loan Share$_{t-1}$	0.087	0.099	0.000	0.004	0.224	0.507
Agricultural Loan Share$_{t-1}$	0.008	0.019	0.000	0.000	0.024	0.136
Other Loan Share$_{t-1}$	0.055	0.094	-0.011	0.000	0.142	0.552

Note:
The table reports the descriptive statistics for bank holding companies over the period —**finalize: 1986 - 2024** ?. The definitions of all variables in this report table are provided in —**revise: Table 2.1** ?. The dependent variables are computed by the rolling window of sixteen quarters of daily returns, starting fromt the first trading date of an estimation period. The relationship of the three dependent variables is described in —**revise: Equation** (5) ?. ... regressors are determined at the end of each quarter *t-1* preceding the 16-quarter rolling window. All variables are ... at level of ... and ...(.)

[a] *logtailbeta*, *tailbetaSLlog*, and *tailbetaIRlog* are the natual logarithm of systemic risk, systemic linkage, and bank tail risk respectively.(.)

[b] *TCERatio*, *NPL*, *Cost2Income*, *ROE*, and *LiquidAssetstoAssets* are the *four ratios* of the **CAMEL** model.(.)

[c] *LLP* is the amount of fund a bank sets aside to cover the potential losses from the current loans.(.)

[d] The Non-interest income portion of total income, and the sources that constitute the portions of non-interest income.(.)

[e] The ratio of total loans to total assets, and the items of loans portfolio in terms of share values.(.)

Table 2.3: Pairewise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
(1) $ln(\beta^T_{i;[t,t+15]})$.	1.000									
(2) $ln(SL_{i;[t,t+15]})$.	0.311	1								
(3 $ln(IR_{i;[t,t+15]})$.	0.719	-0.437	1							
(4) LoanLossProvision$_{t-1}$.	0.235	0.027	0.203	1						
(5) Bank size ($reslnTA_{t-1}$).	0.193	0.442	-0.164	-0.001	1					
(6) Tangible equity ratio$_{t-1}$.	-0.173	-0.023	-0.147	-0.169	-0.002	1				
(7) Nonperforming-loans ratio$_{t-1}$.	0.149	0.058	0.099	0.468	0	-0.085	1			
(8) Cost-to-income ratio$_{t-1}$.	0.082	-0.165	0.199	0.175	-0.003	-0.202	0.266	1		
(9) Return on equity$_{t-1}$.	-0.120	0.032	-0.137	-0.362	0.001	0.037	-0.365	-0.495	1	
(10) Liquid assets$_{t-1}$.	0.143	-0.213	0.293	0.061	-0.029	0.048	-0.017	0.159	-0.015	
(11) Deposit funding gap$_{t-1}$.	-0.047	0.193	-0.186	0.043	0.001	0.076	0.028	-0.123	-0.032	-
(12) Loans to total assets$_{t-1}$.	-0.042	-0.06	0.004	0.023	0.001	0.055	-0.014	-0.099	-0.073	-0
(13) Noninterest income share$_{t-1}$.	0.096	0.332	-0.154	0.061	0.001	-0.148	0.043	0.184	0.1	
(14) Growth in total assets$_{t-1}$.	-0.008	0	-0.008	-0.087	0	-0.047	-0.133	-0.04	0.108	0

Note:
The table reports pairwise correlations between the variables used in our regression models. The three dependent va
risk: (2) Systemic linkage: (3) Bank-specific tail risk. The loan loss provision is measures as : . The control variable
variables are provided in —**revise: Table 2.1 ?**. They are computed with rolling windows of sixteen quarters a
estimation period. Their relationship is described in —**revise: Equation** (5) **?**. All regressors are calculated at
16-quarter rolling windows.(.)

[a] *resLnTotAssets* is bank size defined as the residuals obtained from the regeression of the natural logarithm of total
is because banks' choice of their business models tends to directly impact their size, that is, total assets. As a conse
variables this way affect the tail risk measures through total assets.(.)

3 Empirical analysis

3.1 Main result

We examine the dependency of bank systemic risk on loan loss provision by estimating the following panel regression equation:

$$\begin{aligned} log(TailRisk_{i,t:t+15}) = \alpha + \beta(LLP)_{i,\ t-k} + \\ \gamma(Bank - specific\ controls)_{i,\ t-1} + \\ \omega(Time\ fixed - effect)_{i,\ t} + \epsilon_{i,\ t} \end{aligned} \tag{6}$$

where dependent variables are : Tail risk measures, including *log(tailbeta)* and its two subcomponents, *log(tailbetaSL)* and *log(tailbetaIR)*. The data used for testing this specification is a bank-quarter sample. The tail measures are therefore calculated from the returns spreading over sixteen quarters, from quarter t*th* to quarter (t+15)*th*.[7] LLP is the loan loss provision of bank i at quarter t).

[7]See definition section for the descriptions and formulas of the tail variables and loan loss provison measures.

The control variables are bank-specific characteristics.[8]

Only Time fixed effects are included to capture the macroeconomy and financial evironment factors that effect across all banks over time. Consistent with (Van Oordt and Zhou, 2018), we obtained systemic linkage as significant predictor of systemic risk in the next 12 quarters. We therefore do not include bank fixed effects to prevent they obsorb the variations in Systemic linkage.[9]

Table 3.1: Baseline results

	(1)	(2)	(3)
VARIABLES	$\mathbf{log}\hat{\beta}^{\mathbf{T}}_{\mathbf{i;[t,t+15]}}$	$\mathbf{logSL_{i;[t,t+15]}}$	$\mathbf{logIR_{i;[t,t+15]}}$
Bank size ($reslnTA_{t-1}$)[a]	0.072***	0.129***	-0.057***
	(0.011)	(0.006)	(0.009)
LoanLossProvision$_{t-1}$	**0.078*****	**0.045*****	**0.034****
	(0.018)	(0.010)	(0.016)
Tangible equity ratio$_{t-1}$	-0.022***	-0.014***	-0.008***
	(0.004)	(0.002)	(0.003)
Nonperforming-loans ratio$_{t-1}$	2.233***	-1.103***	3.336***
	(0.552)	(0.382)	(0.458)
Cost-to-income ratio$_{t-1}$	-0.318***	-0.594***	0.276***
	(0.079)	(0.044)	(0.069)
Return on equity$_{t-1}$	-0.729***	-0.210**	-0.519***
	(0.168)	(0.098)	(0.147)
Liquid assets$_{t-1}$	0.017	-0.191***	0.208**
	(0.111)	(0.066)	(0.096)
Deposit funding gap$_{t-1}$	0.288***	0.316***	-0.028
	(0.091)	(0.061)	(0.086)
Loans to total assets$_{t-1}$	-0.187**	-0.349***	0.163*
	(0.090)	(0.065)	(0.084)
Noninterest income share$_{t-1}$	0.350***	0.578***	-0.228***
	(0.068)	(0.045)	(0.059)
Growth in total assets$_{t-1}$	0.161***	0.034	0.128***
	(0.051)	(0.033)	(0.038)
Constant	0.456	0.126	0.331
	(1,694.650)	(.)	(.)
Observations	27,195	27,195	27,195
Number of Banks	843	843	843
R-squared	0.365	0.561	0.490
Partial R-squared	0.164	0.464	0.177
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Clustering at bank level	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes

[8]Some of the control variables are selected from the CAMEL model. The remaining is based on the previous studies on LLPs and systemic risk of bank stock returns. See —**revise: Table** 2.1 **?** for the definitions of the control variables.

[9]Bank fixed effects are, however, included in our additional regression analyses as futher robustness checks.

Table 3.1: *(continued)*

Note:
Partial R-squared shows the explanatory power of the dummies for time- and bank-fixed effects. Standard errors in parentheses. Adjustes R-squared accounts the explanatory power of the regressors that actually affect the tail risks. Rolling windows of 16 quarters, spreading from the beginning of the quater t to the end of of the quarter $t+15$, are used to computed the three tail risks. All bank characteristics are determined at the end of the quarter $t-1$, preceding the rolling window. The standard errors are robust at time and bank level clustering. The asterisks, *** (p<0.01), ** (p<0.05), and * (p<0.1), indicate significance at 1%, 5%, and 10% levels.(.)

[a] *resLnTotAssets* represents bank size, which is is the residuals obtained from the regression of natural logarithm of total assets on all the other independent variables as decribed in 2.1.(.)

3.2 The consequence of current loan loss provison

something goes here

3.3 Robustness results

3.3.1 Alternative measures of loan loss provision

[A table with three models (the 3 alternative measures) like the one for systemic risk GOES HERE].

3.3.2 Alternative measures of systemic risk

something goes here.

3.3.3 GMM two-step estimations with IVs

Table 3.2: Results with the two-step feasible GMM estimator and instrument variables

	IV-GMM (1)	FE (2)	Zero $beta_s^T$ (3)	Small (4)	Large (5)	FTEs (6)
VARIABLES	$\log\hat{\beta}^{\mathbf{T}}_{\mathbf{i};[\mathbf{t},\mathbf{t+15}]}$	$\log\hat{\beta}^{\mathbf{T}}_{\mathbf{i};[\mathbf{t},\mathbf{t+15}]}$	$\hat{\beta}^{\mathbf{T}}_{\mathbf{i};[\mathbf{t},\mathbf{t+15}]}$	$\log\hat{\beta}^{\mathbf{T}}_{\mathbf{i};[\mathbf{t},\mathbf{t+15}]}$	$\log\hat{\beta}^{\mathbf{T}}_{\mathbf{i};[\mathbf{t},\mathbf{t+15}]}$	$\log\hat{\beta}^{\mathbf{T}}_{\mathbf{i};[\mathbf{t},\mathbf{t+15}]}$
Bank size ($reslnTA_{t-1}$).[a]	0.051***	-0.036**	0.073***	0.089***	0.012	
	(0.009)	(0.015)	(0.010)	(0.016)	(0.015)	
Log(Number of Employees)$_{t-1}$						0.040***
						(0.009)
LoanLossProvision$_{t-1}$	**0.225*** **	**0.031***	**0.079*** **	**0.104*** **	**0.044***	**0.125*** **
	(0.050)	(0.017)	(0.020)	(0.020)	(0.024)	(0.014)
Tangible equity ratio$_{t-1}$	-0.017***	0.001	-0.021***	-0.024***	-0.011*	-0.013***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)
Nonperforming-loans ratio$_{t-1}$	-0.704	2.458***	2.113***	2.735***	0.875	2.582***
	(1.028)	(0.553)	(0.600)	(0.639)	(0.737)	(0.489)
Cost-to-income ratio$_{t-1}$	-0.671***	0.202**	-0.309***	-0.331***	-0.045	-0.193***
	(0.136)	(0.101)	(0.077)	(0.092)	(0.120)	(0.063)
Return on equity$_{t-1}$	-3.672***	-0.281	-0.712***	-0.541***	-0.907***	-0.966***
	(0.610)	(0.206)	(0.184)	(0.182)	(0.247)	(0.126)
Liquid assets$_{t-1}$	-0.108	0.045	0.048	0.009	0.060	-0.067
	(0.135)	(0.146)	(0.120)	(0.134)	(0.174)	(0.102)
Deposit funding gap$_{t-1}$	0.071	-0.365***	0.327***	0.344***	0.319***	0.071
	(0.101)	(0.136)	(0.085)	(0.127)	(0.123)	(0.088)
Loans to total assets$_{t-1}$	-0.213**	0.291	-0.259***	-0.171	-0.307**	0.042
	(0.105)	(0.191)	(0.082)	(0.127)	(0.123)	(0.087)
Noninterest income share$_{t-1}$	0.471***	0.069	0.350***	0.372***	0.091	0.073
	(0.094)	(0.107)	(0.066)	(0.091)	(0.118)	(0.069)
Growth in total assets$_{t-1}$	0.006	-0.042	0.122**	0.202***	0.073	0.136***
	(0.970)	(0.043)	(0.054)	(0.056)	(0.058)	(0.046)

Table 3.2: *(continued)*

Constant	0.805***	-0.366	1.727***	0.477	0.391***	0.111
	(0.144)	(.)	(0.101)	(.)	(0.140)	(0.115)
Hansen J Statistic (p value)	2.4 (0.49)					
Kleibergen-Paap LM (p value)	79.6 (0.00)					
Observations	17,828	27,195	23,136	22,598	4,597	33,974
Number of Banks	640	843	688	777	151	928
R-squared	0.496	0.566	0.330	0.362	0.265	0.399
Partial R-squared	0.363	0.0709	0.169	0.123	0.148	0.142
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering at bank level[*]	Yes	Yes	Yes	Yes	Yes	Yes
Clustering at time level[†]	Yes	Yes	Yes	Yes	Yes	Yes

Note:
The two-step feasible GMM estimator is used for the efficiency of the estimated coefficients and consistent estimates of standard errors. All independent variables are instrumented by the 4-quarter-lagged averaged regressors of *resTotAssets*, *CostToIncome*, *LiquidAssetstoAssets*, and *GrTA*, lagging from the quarter *t-2* to the quarter *t-6*.(.)Partial R-squared shows the explanatory power of the dummies for time- and bank-fixed effects. Standard errors in parentheses. Adjustes R-squared accounts the explanatory power of the regressors that actually affect the tail risks. Rolling windows of 16 quarters, spreading from the beginning of the quater *t* to the end of of the quarter *t+15*, are used to computed the three tail risks. All bank characteristics are determined at the end of the quarter *t-1*, preceding the rolling window. The standard errors are robust at time and bank level clustering. The asterisks, *** (p<0.01), ** (p<0.05), and * (p<0.1), indicate significance at 1%, 5%, and 10% levels.(.)

[a] *resLnTotAssets* represents bank size, which is is the residuals obtained from the regression of natural logarithm of total assets on all the other independent variables as decribed in 2.1.(.)

[*] Hansen J Statistics test rejects the null hypothesis of over-identification.(.)

[†] Kleibergen-Paap rk LM-statistic rejects the null hypothesis of under-identification.(.)

3.3.4 Longer lags

lagging the independent variables back 1, 2, 3, and 4 more quarters

Table 3.3: Regression results with longer lags of the regressors

	(1 qtr)	(2 qtrs)	(3 qtrs)	(4 qtrs)	(5 qtrs)
VARIABLES	**log $\boldsymbol{\beta^{T}_{i;[t;t+15]}}$**	**log $\boldsymbol{\beta^{T}_{i;[t+1;t+16]}}$**	**log $\boldsymbol{\beta^{T}_{i;[t+2;t+17]}}$**	**log $\boldsymbol{\beta^{T}_{i;[t+3;t+18]}}$**	**log $\boldsymbol{\beta^{T}_{i;[t+4;t+19]}}$**
Bank size ($reslnTA_{t-1}$).[a]	0.082***	0.081***	0.081***	0.080***	0.080***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
LoanLossProvision$_{t-1}$	**0.078*** **	**0.070*** **	**0.066*** **	**0.067*** **	**0.068*** **
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Tangible equity ratio$_{t-1}$	-0.023***	-0.023***	-0.023***	-0.022***	-0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Nonperforming-loans ratio$_{t-1}$	2.264***	2.229***	2.092***	1.868***	1.652***
	(0.582)	(0.574)	(0.569)	(0.558)	(0.550)
Cost-to-income ratio$_{t-1}$	-0.363***	-0.363***	-0.360***	-0.349***	-0.339***
	(0.080)	(0.078)	(0.078)	(0.079)	(0.079)
Return on equity$_{t-1}$	-0.682***	-0.626***	-0.568***	-0.510***	-0.448***
	(0.175)	(0.168)	(0.162)	(0.164)	(0.161)
Liquid assets$_{t-1}$	-0.002	-0.007	-0.014	-0.032	-0.044
	(0.114)	(0.112)	(0.112)	(0.112)	(0.111)
Deposit funding gap$_{t-1}$	0.283***	0.288***	0.293***	0.297***	0.299***
	(0.093)	(0.092)	(0.092)	(0.092)	(0.091)
Loans to total assets$_{t-1}$	-0.198**	-0.194**	-0.194**	-0.195**	-0.191**
	(0.093)	(0.092)	(0.092)	(0.092)	(0.092)
Noninterest income share$_{t-1}$	0.370***	0.363***	0.356***	0.349***	0.342***
	(0.069)	(0.068)	(0.068)	(0.069)	(0.069)
Growth in total assets$_{t-1}$	0.161***	0.189***	0.201***	0.221***	0.222***
	(0.051)	(0.051)	(0.051)	(0.049)	(0.051)
Constant	0.575***	0.434	0.467	0.436	0.419
	(0.103)	(.)	(.)	(.)	(278.000)

Table 3.3: *(continued)*

Observations	24,904	25,154	25,154	25,154	25,154
Number of Banks	778	781	781	781	781
R-squared	0.327	0.324	0.320	0.316	0.313
Partial R-squared	0.182	0.176	0.171	0.167	0.162
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Clustering at bank level	Yes	Yes	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes	Yes	Yes

Note:
Partial R-squared shows the explanatory power of the dummies for time- and bank-fixed effects. Standard errors in parentheses. Adjustes R-squared accounts the explanatory power of the regressors that actually affect the tail risks. Rolling windows of 16 quarters, spreading from the beginning of the quater *t* to the end of of the quarter *t+15*, are used to computed the three tail risks. All bank characteristics are determined at the end of the quarter *t-1*, preceding the rolling window. The standard errors are robust at time and bank level clustering. The asterisks, *** ($p<0.01$), ** ($p<0.05$), and * ($p<0.1$), indicate significance at 1%, 5%, and 10% levels.(.)

[a] *resLnTotAssets* represents bank size, which is is the residuals obtained from the regression of natural logarithm of total assets on all the other independent variables as decribed in 2.1.(.)

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