Understanding Chronic Bank Failures in Minnesota

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Abstract

This paper examines the causes of chronic bank failures in Minnesota as means to develop an early warning mechanism to help state policymakers identify fragile banks and uncover the key factors that influence banking crises. The study relies on the cox proportional-hazard model to estimate the factors that influence the survival distribution function of Minnesota's banks during the Great Recession period of 2008-2015. The key bank-specific variables that affect the instantaneous rate of bank failure include: credit risk exposure to real estate loans, profitability, operating costs, and earnings coverage for loan losses. More importantly, the empirical results derived here show that those banks that faced higher portfolio exposure to real estate prior to the start of the Great Recession faced a higher probability of failure during the Great Recession. FDIC's insured banks are required to maintain sound written lending policies. However, aggregate loan portfolio in Minnesota remains highly concentrated in real estate loans, which means that there is room for regulation at the state level. Consequently, this study also discusses a proposal for stronger loss contingency regulations as means to address loan concentration risks for state-chartered banks. The policy proposal provides some elementary guidelines to help those state-chartered banks that are most likely to be vulnerable to concentration risks in the prospect of increased macroeconomic stress.

Keywords: Minnesota, bank failure, banking regulations

JEL Codes: G01, G21, C14

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1 Introduction

Macroeconomic stability is conditional on the survival of banks [2]. Particularly, because bank failures are costly in the sense that they increase discretionary spending, affect employment conditions, and the investment climate. The global financial crisis of 2007-2008 catalyzed a period of persistent bank failures in the United States, in which more than 552 banks failed sporadically from 2008 to 2015. At the state level, Minnesota was ranked fifth in terms of bank failures during that latter period (for example, see Figure 1). Moreover, banking statistics portray an alarming situation in Minnesota during the Great Recession period of 2008-2015: Table 2 shows that approximately 26 percent of all active banks either failed or closed due to merger or acquisition. More importantly, the episode of chronic bank failures that occurred in Minnesota during the Great Recession was closely associated with a persistent deterioration in the State's real gross domestic product (GDP). Evidently, data suggest that chronic bank failures are more prevalent amid periods of heightened macroeconomic instability (for example, see Figure 6 in Appendix A). For Minnesota, the specific causes of chronic bank failures remain unknown: more specifically, the empirical literature lacks state-level evidence regarding the key factors that influence bank failures in Minnesota.

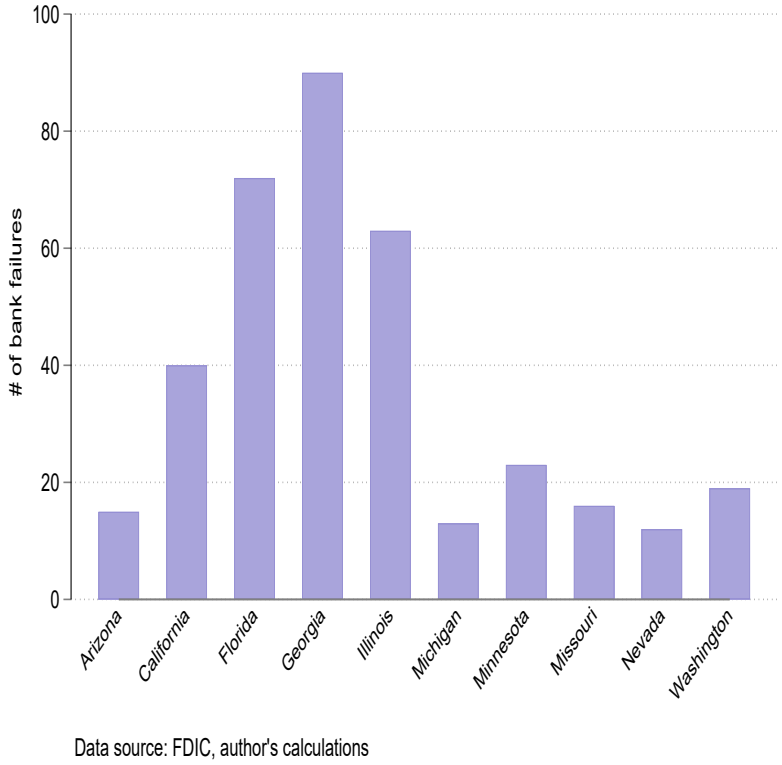

Figure 1: Bank Failures (2008-2015)

Consequently, understanding the relative importance of acute bank crises in explaining macroeconomic performance, this study examines the determinants of chronic bank failures in Minnesota as means to better understand the banking sector and provide effective macroprudential policies to prevent further banking crises amid future economic downturns. At the country level, the determi-

nants of bank failures in the United States are well addressed in the empirical literature. However, more empirical evidence is needed at the state level. Particularly, because state-level findings may provide different conclusions to aggregate country-level evidence, mainly due to the existing structural differences across states that cannot be fully captured by the data. For instance, during the Great Recession, California, Florida, Arizona, and Nevada accounted for nearly half of all foreclosures in the United States. Which implies that the relative importance of credit risk exposure to real estate during that latter period is likely to be stronger for these latter states when compared to other states such as Vermont or South Dakota, which recorded the lowest foreclosures during the global financial crisis of 2007-2008. Consequently, following [6], this study relies on the cox proportional-hazard model to examine the determinants of chronic bank failures in Minnesota during a specific period of heightened macroeconomic uncertainty. Here, the main case study focuses on the Great Recession period of 2008-2015; particularly because the latter period coincides with the last time in history in which the state of Minnesota experienced chronic bank failures. For Minnesota, Figure 2 shows that the banks that survived the Great Recession had robust economic profits, a high earnings coverage ratio, and better liquidity prior to the start of Great Recession. Whereas those banks that failed during the Great Recession recorded higher operating costs and higher credit risk exposure to real estate loans prior to 2008.

Overall, the empirical literature provides mixed evidence about the key variables that influence bank failures in the United States: hence another reason to analyze bank failures on the individual state level. For instance, [7] finds that higher equity capital reduces the probability of bank failure. However, for the specific case of Minnesota, firstly, Table 1 shows that the banks that failed during the Great Recession had a higher equity capital ratio relative to those that survived. Secondly, Tables 3 shows that equity capital is insignificant in explaining the probability of bank failures in Minnesota. [3] finds that bank liquidity is insignificant in explaining bank failure in the United States; but this latter result was found for a sample period that did not account for the Great Recession period. Here, this study finds that bank liquidity is weakly significant in explaining bank failures in Minnesota (for example, see Tables 3, 5, 6, and 7). [4] examined the causes of bank failures in the United States: they find that credit risk exposure to real estate loans increases the probability of bank failure in the United States during the Great Recession. However, Cole and White's (2012) findings also evince that US banks' exposure to (1/4) family residential mortgages reduce the probability of bank failure in 2008. Here, this study shows the opposite effect for Minnesota: higher exposure to (1/4) family residential loans increases the probability of bank failure in Minnesota during the Great Recession period of 2008-2015.

[1] shows the relative importance of bank capital in explaining bank survival amid financial crises. Here, this study provides contrary results regarding the impact of bank capital in explaining bank survival in Minnesota: Table 3 shows that a higher equity ratio or tier 1 risk-based capital ratio does not increase the probability of bank survival in Minnesota amid periods of heightened financial uncertainty. For Minnesota, this latter conclusion stems from the stylized fact that the banking sector is well capitalized and the mean difference in bank capital between those banks that survived and failed during the Great Recession is relatively insignificant (for example, see Table 1). Here, this is the first study in the financial literature to examine the causes of bank failures in Minnesota at the state level. More importantly, this paper considers a time period that has yet to be considered in the empirical literature for Minnesota. Ultimately, this study shows that the strongest determinants of bank survival in Minnesota during the Great Recession period of 2008-2015 include: profitability, coverage for loan losses, operating costs (for example, interest expense

on deposits), and credit risk exposure to real estate. Section 2 analyzes Minnesota's banking sector as means to better understand the conditions of banks. Section 3 discusses the main assumptions behind the cox proportional-hazard model and reports the main findings. The last section discusses key policy implications.

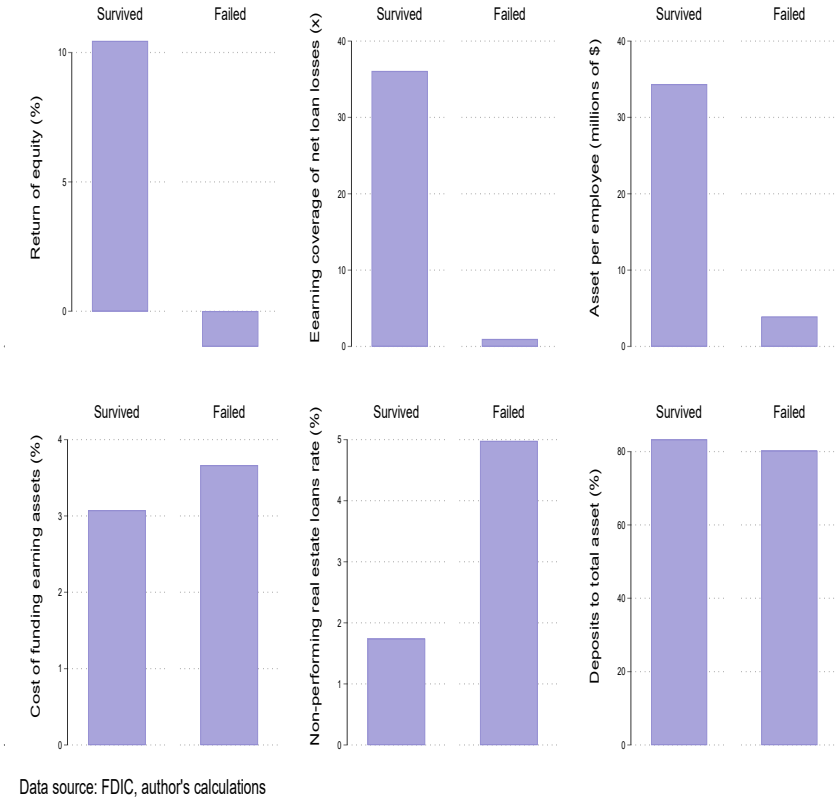

Figure 2: Bank Conditions, Averages (Minnesota, 2007q4)

2 Minnesota's Banking Sector

Understanding the characteristics of Minnesota's banking sector is imperative for identifying the key variables that influence banking performance in the state: hence the importance of this section. Currently, Minnesota's banking sector includes approximately 310 active banks, including saving and credit institutions. The overall banking sector remains stable despite the tumultuous episode of bank failures that occurred during the Great Recession period of 2008-2015. The level of insured commercial banks declined significantly, but the average number of active commercial branches remains fairly stable (for example, this is shown in Figure 5 in Appendix A). This latter finding suggest that Minnesota's banking sector is increasingly becoming more concentrated. Nonetheless, the state's average banking profit rate remains positive and relatively stronger in contrast to the nation's average. Recent annual data indicates that the average equity ratio in the banking sector is approximately nine percent. This implies that the capital structure of banks in Minnesota depends

less on equity and more on debt or deposits (for example, demand deposits account for roughly 26.5 percent of total bank assets in 2022).

Figure 3 depicts the level of bank failures and closures in Minnesota during the Great Recession period of 2008-2015. For Minnesota, Hennepin County experienced the most closures and failures during that latter period. Consequently, the closest areas to Hennepin County experienced the brunt of the contagion, apart from Saint Louis County. An alarming fact about Minnesota's banking sector is that aggregate loan portfolio is highly concentrated, which pauses a significant diversification risk for the entire banking sector. In 2022, aggregate real estate loans account for approximately 70 percent of total loans and leases and about 47 percent of total bank assets. The main implication is that the housing sector is likely to be a potent source of systemic risk for banks in Minnesota: this latter hypothesis is strongly corroborated in Section 3. The largest proportion of banks in Minnesota are state chartered banks, which mainly specialize in commercial lending. Additionally, the main federal regulator for the largest proportion of banks in Minnesota is the Federal Deposit Insurance Corporation (FDIC).

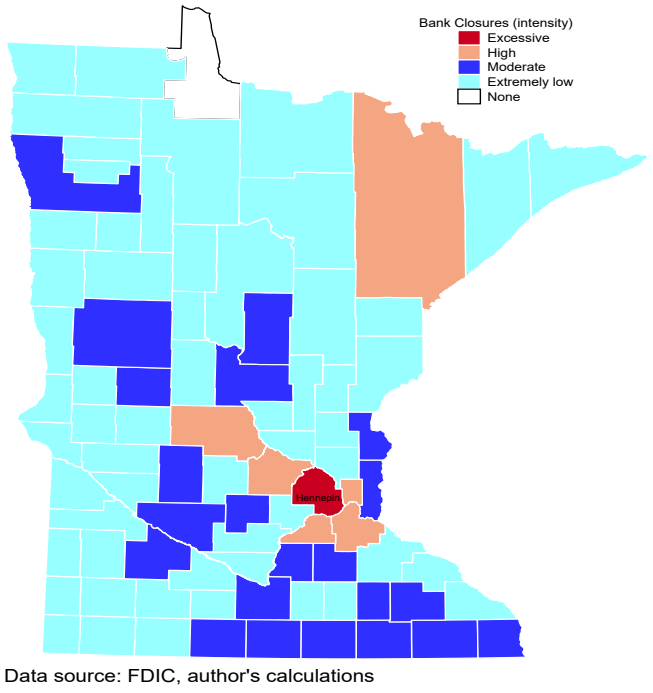

Figure 3: Bank Closures and Failures (Minnesota, 2008-2015)

3 Survival Analysis

3.1 Bank-Specific Variables

Here, the firm-level bank variables are defined and explained thoroughly. For Minnesota, given the relative importance of the real estate sector in explaining diversification risk, credit risk is proxy as follows

$$creditrisk = \frac{(1/4)\ family\ residential\ laons}{(1/4)\ family\ residential\ mortage\ loans}$$

$$\{npres(1/4)loans\} = \frac{\textit{net charge-off (1/4) familiy residential loans}}{\textit{(1/4) family residential laons}}$$

$$npALLresloans = \frac{\textit{real estate laons past due (90+)}}{\textit{real estate loans}}$$

furthermore, the following variables are also used as additional proxies for modeling credit risk: net charge-offs as a percent of average total loans (*charge*), net loans and leases to total assets ($loanr$), and individual loans past due (90+) as a percent of consumer loans ($npInDloans$) .[1] Here profitability is measured as follows

$$profit = \frac{\textit{net income (annualized)}}{\textit{average total equity}}$$

for additional robustness, return on assets (*roa*), net operating income to total assets (*nopinc*), and net interest margin (*nim*) are also considered here. Here, bank liquidity is measured by relying on bank deposits without making any distinction between liquid or illiquid deposits. Hence liquidity is measured as follows

$$liquidity = \frac{\textit{deposits}}{\textit{total assets}}$$

where a higher level of deposits as a percent of total assets either means more available funds to sustain the bank's operating activities or it may imply higher rising interest expense. Nonetheless, $liquidity$ is expected to improve the ability of the bank to remain in business amid poor macroeconomic performance. Here the bank cost proxy is measured as follows

$$costs = \frac{\textit{interest expense on deposits (annualized)}}{\textit{average earning assets}}$$

Here the size of the bank (*size*) is measured by dividing total assets (millions \$) by the number of full-time employees. Larger banks have more assets and more deposits, which means that they are more likely to be better in absorbing credit losses in contrast to smaller banks. Higher provision for loan losses can mitigate bank failures: consequently, coverage for loan losses is modeled as follows

$$coverage = \frac{\textit{pre-tax income + provisions for losses+ risk reserves+ gain(loss) on securities}}{\textit{net loan and leases charge-offs}}$$

where *coverage* is defined as the earnings coverage ratio, which defines the ability of a bank to absorb credit losses. *coverage* is extremely important for bank survival, especially during an economic recession. A higher capital buffer could provide a stronger cushion for banks amid poor economic conditions. Alternatively, excessive capital requirements could reduce the ability of banks to generate loans when the economy is not doing well. Nonetheless, the main proxy for bank capital is measured as follows

$$capital = \frac{\textit{tier 1 core capital}}{\textit{risk-weighted assets}}$$

[1]Note that $creditrisk$ is computed without accounting for home equity loans.

additionally, total equity capital to total assets (*car*) is used as an additional proxy for modeling bank capital. All bank-specific data are expressed in percent (%) with the exception bank size (*size*) and the earnings coverage ratio (*coverage*). The entire data set is collected from FDIC's BankFind database. Table 1 provides an overview of the descriptive statistics, including the difference in means analysis. The signs associated with the difference in means estimates are consistent with theoretical expectations. Here, the main event period begins after the fourth quarter of 2007, which is expected, because the Great Recession officially started in December 2007. Consequently, the independent variables used in the empirical analysis can be viewed as predetermined regressors: this latter condition alleviates any concerns for endogeniety that could arise in modeling bank failures. This study relies on quarterly data and Table 1 reflects the conditions of all active banks at the end of the fourth quarter in 2007; which reflects the last quarter prior to the start of the Great Recession period of 2008-2015. The Great Recession officially ended in 2009, but for many states, including Minnesota, it took longer for their economies to revert to pre-recession levels (for example, see Figure 6 in Appendix A).

	(Failed)	(Survived)	(T-Test)	
	mean(μ_f)	mean(μ_s)	$(\mu_f - \mu_s)$	t-stat
Cost of Funding Earning Assets (*costs*	3.66	3.07	0.59***	(4.33)
Net Interest Margin (*nim*)	4.14	4.16	-0.01	(-0.09)
Net Operating Income to Assets (*nopinc*)	-0.10	1.04	-1.15***	(-5.35)
Return on Assets (*roa*)	-0.08	1.05	-1.13***	(-5.24)
Return on Equity ($profit$)	-1.36	10.44	-11.80***	(-6.32)
Net Charge-Offs to Loans and Leases (*charge*)	0.67	0.33	0.34***	(2.72)
All Other 1-4 Family $\{npres(1/4)loans\}$	0.54	0.17	0.36***	(2.62)
Earnings Coverage of Net Loan Charge-Offs (*coverage*)	0.96	36.06	-35.10	(-1.41)
Assets Per Employee (*size*)	3.91	34.34	-30.43	(-0.27)
All Real Estate Loans (*npALLresloans*)	4.98	1.74	3.24***	(6.00)
1-4 Family Residential ($creditrisk$)	2.23	1.17	1.06**	(2.39)
Loans to Individuals (*npInDloans*)	1.77	0.92	0.85**	(2.07)
Domestic Deposits to Total Assets ($liquidity$)	80.21	83.27	-3.07**	(-1.98)
Equity Capital to Assets (*car*)	11.42	10.89	0.52	(0.61)
Tier 1 Risk-Based Capital Ratio ($capital$)	15.49	14.66	0.83	(0.45)
Net Loans and Leases to Assets ($loanr$)	75.53	68.80	6.74**	(2.27)
Observations	24	328	352	

Table 1: Summary Statistics (Minnesota Banks, 2007q4)

The level of real GDP in Minnesota was on downward trend from 2008 until 2014, when the output gap finally stabilized. In addition, the episode of chronic bank failures that started in Minnesota in 2008 ended in 2015. Data suggest that mergers are frequent in Minnesota, but according to the FDIC's database, Minnesota did not experience another bank failure since 2015. Here, the financial institutions that closed due to merger and acquisition are not included in the main analysis. Following [8], this paper focuses extensively on those banks that failed or closed and liquidated their assets due to reasons other than mergers. Consequently, the sample of banks in this analysis satisfy the following conditions: (i) each bank was reported to be active on December

31st 2007, (ii) no bank was established after December 31st 2007, (iii) lastly, each bank was reported to be either active or failed by December 31st 2015.

Status	*Freq.*	*Percent*	*Cum*
Active	328	74.04	74.04
Closed and liquidiated assets	2	0.45	74.49
Closed and merged	92	20.77	95.26
Failed and closed	1	0.23	95.49
Failed and merged	20	4.51	100.00
Total	443	100.00	

Table 2: Bank Sample Data (Minnesota, 2008-2015)

3.2 Cox Proportional Hazard Model

Here, survival analysis examines the bank-specific factors that influence the survival distribution function of banks during the Great Recession period of 2008-2015. The exact time of failure and the number of failed banks during Great Recession period of 2008-2015 is well documented. Furthermore, none of the banks that survived the end of 2015 failed by 2023. Nonetheless, some of these latter banks did experience some mergers after 2015. But qualitative data support that these mergers were caused by factors other than failure. Consequently, the data set is more appropriate for a survival analysis. Let T represents a continuous random variable, denoting the survival time, such that

$$T \geq 0$$

The probability of bank failure is given by the following cumulative distribution function (cdf)

$$F(t) = Pr\{T \leq t\}$$

from which the survival function is computed as follows

$$S(t) = 1 - F(t) \equiv \int_t^{\infty} f(x)d(x) \tag{1}$$

where equation (1) denotes the probability that the bank survives past t. On the other hand, the instantaneous rate of bank failure at time (t) (for example, this is referred to as the hazard function) can be defined as the conditional probability of bank failure at time (t), given that the bank did not fail before (t). Alternatively, the hazard function can be directly estimated by differentiating both sides in equation (1) as follows

$$\frac{d}{dt}S(t) = -f(t)$$

using the derivative of the log of $S(t)$, the above can be rewritten as follows

$$\frac{d}{dt}logS(t) = \frac{d}{dt}S(t) \cdot \frac{1}{S(t)} \equiv -\frac{f(t)}{S(t)}$$

simplifying the above, the hazard function can be re-expressed as follows

$$h(t) \equiv \frac{f(t)}{S(t)} = -\frac{d}{dt} logS(t) \tag{2}$$

where equation (2) denotes the hazard function (h_t) or the instantaneous rate of bank failure. Some assumptions can be made about the functional form of the probability density function of events $\{f(t)\}$. Alternatively, $\{f(t)\}$ can be left unspecified [5], which is where the main empirical benefits lie: the semi-parametric approach does not suffer from the assumption bias that arises from imposing a specific probability density function on the baseline hazard function. Here, the main focus is to identify the bank-specific factors that influence the hazard function or in other words, the instantaneous rate of bank failure at time (t). Hence the Cox proportional-hazard model

$$h(t) = h_0(t) e^{\{\gamma_1 Z_1 + \gamma_2 Z_2 + ... + \gamma_p Z_p\}} \tag{3}$$

where $h_0(t)$ denotes the baseline hazard function which is time-dependent, Z_p denotes the bank-specific covariates which are time independent, and γ_p are the coefficients to be estimated via maximum likelihood. Here, the main empirical model is defined as semi-parametric, because γ_p are linear in parameters, but the baseline hazard function remains unspecified or can take any form. Here, the estimated parameters are interpreted as hazard ratios, which measure the relative risk of bank failure for all banks given the bank-specific variables. Therefore, an estimated hazard ratio that is greater than one indicates a higher probability of bank failure. On the other hand, a hazard ratio that is less than one indicates a higher probability of bank survival. Lastly, a hazard ratio of 1 indicates no difference in failure rates given the specific explanatory variable of interest.

Here, the robustness check is conducted as follows. Firstly, different proxy for profitability, credit risk, and bank capital are used in Tables 3, 4, 5, 6, and 7. Secondly, some distribution assumptions are made regarding the functional form of the baseline hazard function in Tables 5, 6, and 7 in Appendix A. Here, Table 3 shows that stronger profitability and higher earnings coverage for loan losses are the strongest determinants of bank survival in Minnesota. On the other hand, the strongest determinants of chronic bank failures include operating deposit costs, non-performing real estate loans, and credit risk exposure to (1/4) family residential loans. Bank size and liquidity increase the probability of bank survival, but their effects are weakly significantly. Furthermore, bank capital is weakly significant in explaining chronic bank failures in Minnesota. More empirical robustness is conducted in Table 4, where the sample size only includes those observations that are consistent with the tumultuous period of 2008-2010. Nonetheless, the results are robust and consistent with the previous results derived in Table 3. However, this section finds that the empirical estimates tend to be stronger with more observations. Furthermore, the parametric-based results are reported in Tables 5, 6, and 7 in Appendix A. These latter results are consistent with the main empirical results found in Tables 3 and 4.

	(1) $h(t)$	(2) $h(t)$	(3) $h(t)$	(4) $h(t)$	(5) $h(t)$	(6) $h(t)$	(7) $h(t)$	(8) $h(t)$	(9) $h(t)$	(10) $h(t)$	(11) $h(t)$	(12) $h(t)$
profit	0.946**	0.945**	0.944***	0.933***	0.936***	0.936***						0.929***
	(0.0238)	(0.0228)	(0.0190)	(0.0142)	(0.0168)	(0.0152)						(0.0146)
coverage	0.977***	0.977***	0.977***	0.977***	0.980***	0.981***						
	(0.00638)	(0.00637)	(0.00593)	(0.00600)	(0.00582)	(0.00573)						
npALLresloans	1.133***	1.131***	1.137***				1.145***	1.145***				
	(0.0413)	(0.0399)	(0.0409)				(0.0440)	(0.0442)				
costs	2.433**	2.276**	2.142**	2.238***	2.176**	2.272***	2.526***	2.547***		3.579***	3.305***	3.097***
	(0.970)	(0.871)	(0.683)	(0.617)	(0.660)	(0.662)	(0.837)	(0.853)		(1.608)	(1.181)	(1.044)
liquidity	0.959**	0.954**	0.951*	0.962	0.960	0.959*	0.953*	0.952**				
	(0.0204)	(0.0212)	(0.0244)	(0.0230)	(0.0253)	(0.0240)	(0.0238)	(0.0240)				
size	0.999***	0.999***	0.999***	0.999*	0.999**	0.999**	0.999***	0.999***		0.999		
	(0.000216)	(0.000209)	(0.000208)	(0.000360)	(0.000244)	(0.000256)	(0.000213)	(0.000228)		(0.000559)		
capital	1.027									1.049*	1.037*	1.037*
	(0.0294)									(0.0275)	(0.0193)	(0.0194)
car		1.028							1.060			
		(0.0883)							(0.0620)			
creditrisk				1.160***							1.160***	1.150***
				(0.0656)							(0.0621)	(0.0547)
$\{npres(1/4)loans\}$					1.348*					1.402**		
					(0.226)					(0.238)		
npInDloans						1.072						
						(0.0479)						
nopinc							0.642**				0.575***	
							(0.124)				(0.0998)	
roa								0.646**		0.619**		
								(0.126)		(0.120)		
nim									0.719			
									(0.187)			
charge									2.067**			
									(0.612)			
loanr									1.050**			
									(0.0222)			
N	352	352	352	352	352	352	352	352	352	352	352	352

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 3: Cox Proportional Hazard Regression Model Estimates (2008-2015)

	(1) $h(t)$	(2) $h(t)$	(3) $h(t)$	(4) $h(t)$	(5) $h(t)$	(6) $h(t)$	(7) $h(t)$	(8) $h(t)$	(9) $h(t)$	(10) $h(t)$	(11) $h(t)$	(12) $h(t)$
profit	0.940***	0.941***	0.941***	0.931***	0.932***	0.934***						0.920***
	(0.0168)	(0.0163)	(0.0129)	(0.0110)	(0.0116)	(0.0107)						(0.0115)
coverage	0.967	0.965	0.958*	0.956*	0.963*	0.956**						
	(0.0233)	(0.0225)	(0.0245)	(0.0226)	(0.0195)	(0.0199)						
npALLresloans	1.126***	1.119***	1.131***				1.148***	1.148***				
	(0.0410)	(0.0409)	(0.0413)				(0.0463)	(0.0463)				
costs	2.192**	2.049**	1.865*	2.162***	1.931**	2.054**	2.095**	2.094**		2.879***	2.821***	2.648***
	(0.812)	(0.725)	(0.598)	(0.641)	(0.588)	(0.588)	(0.775)	(0.774)		(1.101)	(0.925)	(0.878)
liquidity	1.003	0.994	0.973	0.975	0.987	0.982	0.983	0.982				
	(0.0403)	(0.0452)	(0.0494)	(0.0452)	(0.0549)	(0.0485)	(0.0546)	(0.0546)				
size	1.000	1.000	1.000	1.000	1.000	1.000	0.999*	0.999*		0.993		
	(0.000251)	(0.000291)	(0.000288)	(0.000277)	(0.000338)	(0.000302)	(0.000327)	(0.000327)		(0.121)		
capital	1.043*									1.053**	1.036***	1.040***
	(0.0247)									(0.0220)	(0.0139)	(0.0141)
car		1.066							1.070			
		(0.105)							(0.0749)			
creditrisk				1.202***							1.214***	1.196***
				(0.0645)							(0.0554)	(0.0485)
$\{npres(1/4)loans\}$					1.419**					1.529**		
					(0.241)					(0.256)		
npInDloans						1.052						
						(0.0483)						
nopinc							0.608***				0.526***	
							(0.116)				(0.0804)	
roa								0.608***		0.566***		
								(0.116)		(0.100)		
nim									1.105			
									(0.344)			
charge									1.969**			
									(0.647)			
loanr									1.027			
									(0.0265)			
N	344	344	344	344	344	344	344	344	344	344	344	344

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 4: Cox Proportional Hazard Regression Model Estimates (2008-2010)

4 Regulation Implications

Banking regulations can be instrumental in preventing and stopping a banking crisis. For instance, regulatory capital requirements help banks in dealing with losses, boost shareholders' confidence, prevent excessive loan supply, and provide capital reserves for depositors in the event that the bank experiences a failure. Furthermore, another vital aspect of banking regulations includes ensuring optimal allowances for loan losses. Which is essential for shielding the banking sector from excessive credit losses. The largest proportion of banks in Minnesota are supervised by FDIC, but because most banks in Minnesota are state-chartered banks; it implies that they are also subject to the state's organizational regulations, which are enforced by the Department of Commerce of Minnesota. For Minnesota, the banking sector is well capitalized and did not require prompt corrective action prior to the start of the Great Recession: for instance, the average tier 1 risk-based capital ratio stood well above 10 percent on December 31st, 2007.

Furthermore, currently, the average capital leverage ratio stands well above the FDIC's minimum requirement of four percent. More importantly, this study does not find strong empirical evidence to support the view that higher capital requirements increase the probability of bank survival in Minnesota. Concomitantly, the empirical results do indicate that excessive tier 1 risked-based capital requirements can be counter-productive in Minnesota. Nonetheless, the effect of tier 1 risked-based capital requirements on bank failure is weakly significant and the direction of causality could be largely influenced by the fact that the banking sector is already well capitalized. For the Great Recession period, the empirical results derived here show that those banks that faced higher portfolio exposure to real estate were highly vulnerable to failure. Consequently, this section argues for improved loss contingency regulations as means to provide adequate capital buffer for banks in Minnesota. FDIC's regulations aimed to quench credit risks mainly focus on ensuring strong allowances for loan losses and making sure that the loan approval process is conditional on the ability of borrowers to meet the lending terms. However, these current regulations do not explicitly emphasize polices that aim to contain aggregate concentration risks, which are always induced by a lack of portfolio diversification.

Recent data suggest that aggregate real estate loans account for more than 70 percent of aggregate loans and leases in Minnesota: this implies that aggregate loan portfolio is highly concentrated. FDIC's insured banks are required to maintain sound written lending policies. However, aggregate loan portfolio in Minnesota remains highly concentrated, which means that there is room for regulation at the state level. FDIC requires all insured banks to maintain adequate allowances for all current loans, including for potential increases in future loan losses. Furthermore, allowances for loan losses are designed to immerse credit losses over an operating cycle of at least 12 months. However, these specific allowances are computed based on expected credit losses, which depend on the ability of management to properly estimate the latter. Hence the issues: failure to properly estimate the probability of default could underestimate or overestimate allowances for loan losses and secondly: having a higher rate of allowances for loan losses does not fully guarantee that the bank will be safe. Instead, an excessive rate of allowances for loan losses can also be viewed as an indicator of bank stress.

For instance, those banks that failed in Minnesota during the Great Recession period of 2008-2015 had a higher average rate of allowances for loan losses on December 31st, 2007 (for example, see Figure 4). Moreover, these failed banks registered a lower average earnings coverage ratio relative to those banks that survived the Great Recession period. Consequently, this section argues

that regulators should focus more on ensuring that banks have a stronger capacity to generate higher coverage earnings to cover net losses, especially in the prospect of poor macroeconomic performance. For instance, First Integrity Bank failed during the Great Recession period on June 3rd, 2008. Nonetheless, data show that prior to the Great Recession, this latter bank had the highest delinquency rate in Minnesota, coupled with the highest rate of allowances for loan losses. Furthermore, First Integrity's earnings coverage ratio was also found to be negative prior to the start of the Great Recession, which is approximately six months before it failed. Here, this section argues for additional steps to be undertaken at the state level to better protect banks in Minnesota from exposure to concentration risks induced by a lack of portfolio diversification.

State regulators should implement an automatic stabilizer mechanism for loan loss provisions as means to quench concentration risks in the banking sector either when the economy is already under stress or in the prospect of a serious economic recession. For example, in the event of a looming economic recession, the state could impose a temporary loan concentration ratio ceiling in the banking sector and then enforce it with higher loan loss reserve requirements. More specifically, state regulators would be compelled to estimate expected credit losses differently, specifically for those fragile banks that have been identified as facing higher loan concentration risks: one way to do this would be to automatically assume a probability of default that is higher than normal for all fragile banks (for example, the state could impose a minimum rate of 50 percent or higher, depending on the condition of each fragile bank). Doing so, would directly increase provisions for loan losses and bad debt expenses, which would inevitably incentivize these fragile banks to restructure their loan portfolios and divert loanable funds to least risky areas.

Furthermore, the state would have to create an assistance liquidity facility only designed for fragile banks that are state chartered and are operating under a negative earnings coverage ratio. Particularly, because these latter banks would face a higher probability of failure, as shown in Table 3. For Minnesota, 49 percent of the banks that had a negative earnings coverage ratio prior to the start of the Great Recession failed right after (for example, Northern Star Bank, Pinehurst Bank, Jennings State Bank, and First Integrity Bank). The assistance liquidity facility would serve the sole purpose of providing stabilizing funds needed to bring back the earnings coverage ratio to positive standing. Ultimately, the policy proposal derived here provides some elementary guidelines to help state-chartered banks that are most likely to be vulnerable to concentration risks amid poor economic performance or in the prospect of a long economic recession. However, the effectiveness of such a proposal would depend on three key factors.

Firstly, successful implementation of the mechanism would depend on the ability of state regulators to efficiently forecast economic downturns on a timely basis. Secondly, regulators would have to be extremely proficient in identifying fragile banks and in estimating credit losses for these fragile banks. Lastly, the effectiveness of the automatic loss provision mechanism would depend on the fiscal stance of the state and its ability to generate funds to support the assistance liquidity facility. Nonetheless, the main idea established here is that the state should rely on stronger loss contingency policies to protect banks from concentration risks in the event of a looming economic recession. Particularly, because proceeding in this manner, would minimize the probability of experiencing an episode of sporadic bank failures. The empirical results are critical, because they estimate the determinants of bank failures for Minnesota. But more importantly, the cox proportional-hazard model allows one to predict the hazard ratio for each bank, which helps policymakers to identify those banks that are stressed but did not fail but remain highly vulnerable to failure.

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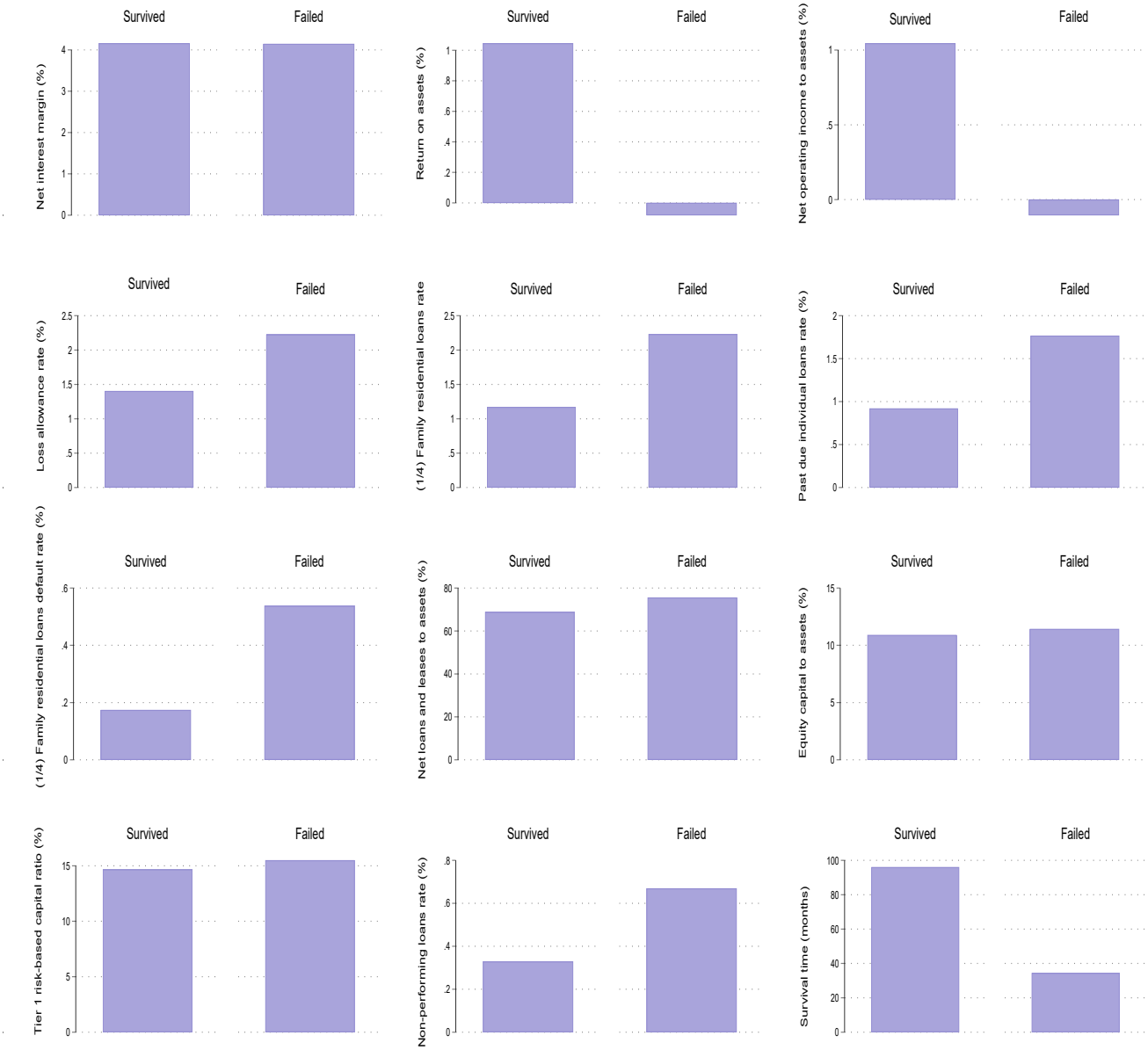
Appendix A



Data source: FDIC, author's calculations

Figure 4: Additional Condition Ratios (Minnesota, 2007q4)

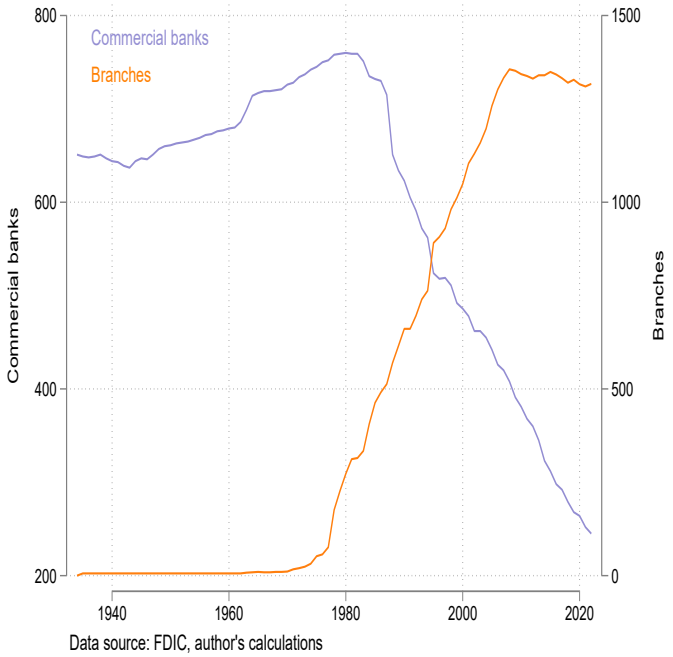


Figure 5: Commercial Banks and Branches in Minnesota

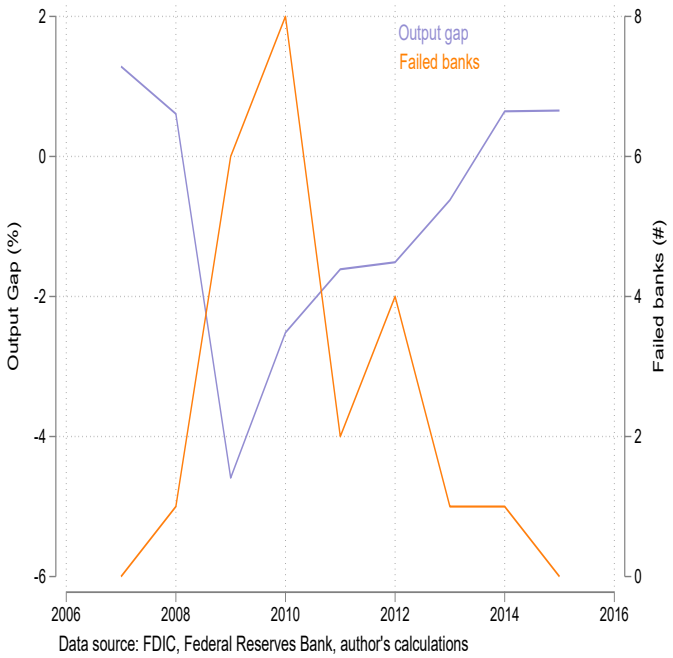


Figure 6: Bank Failures and Macroeconomic Performance in Minnesota

	(1) $h(t)$	(2) $h(t)$	(3) $h(t)$	(4) $h(t)$	(5) $h(t)$	(6) $h(t)$	(7) $h(t)$	(8) $h(t)$	(9) $h(t)$	(10) $h(t)$	(11) $h(t)$	(12) $h(t)$
profit	0.947**	0.947**	0.946***	0.937***	0.938***	0.938***						0.933***
	(0.0215)	(0.0211)	(0.0179)	(0.0127)	(0.0153)	(0.0138)						(0.0119)
coverage	0.977***	0.977***	0.977***	0.977***	0.979***	0.981***						
	(0.00639)	(0.00645)	(0.00610)	(0.00608)	(0.00599)	(0.00600)						
npALLresloans	1.138***	1.136***	1.142***				1.149***	1.150***				
	(0.0404)	(0.0395)	(0.0399)				(0.0438)	(0.0439)				
costs	2.454**	2.341**	2.215**	2.343***	2.250***	2.362***	2.574***	2.595***		3.537***	3.309***	3.245***
	(0.931)	(0.863)	(0.723)	(0.669)	(0.706)	(0.712)	(0.877)	(0.895)		(1.584)	(1.206)	(1.084)
liquidity	0.955**	0.951**	0.948**	0.958*	0.957*	0.956*	0.950**	0.949**				
	(0.0206)	(0.0214)	(0.0240)	(0.0223)	(0.0250)	(0.0239)	(0.0235)	(0.0237)				
size	0.999***	0.999***	0.999***	0.999**	0.999***	0.999***	0.999***	0.999***		0.999		
	(0.000209)	(0.000207)	(0.000201)	(0.000302)	(0.000234)	(0.000242)	(0.000208)	(0.000220)		(0.000414)		
capital	1.021									1.044*	1.030*	1.031**
	(0.0236)									(0.0231)	(0.0164)	(0.0151)
car		1.028							1.061			
		(0.0783)							(0.0610)			
creditrisk				1.148**							1.145***	1.129***
				(0.0622)							(0.0561)	(0.0493)
$\{npres(1/4)loans\}$					1.349*					1.399*		
					(0.230)					(0.240)		
npInDloans						1.073						
						(0.0495)						
nopinc							0.645**				0.581***	
							(0.124)				(0.0972)	
roa								0.649**		0.619**		
								(0.127)		(0.119)		
nim									0.714			
									(0.189)			
charge									2.065**			
									(0.608)			
loanr									1.050**			
									(0.0225)			
Shape parameter	0.988*	0.988*	0.988*	0.987**	0.986**	0.987**	0.986**	0.986**	0.983***	0.985**	0.986**	0.987**
	(0.00618)	(0.00641)	(0.00631)	(0.00608)	(0.00620)	(0.00633)	(0.00654)	(0.00653)	(0.00634)	(0.00608)	(0.00582)	(0.00563)
N	352	352	352	352	352	352	352	352	352	352	352	352

Exponentiated coefficients (hazard ratios); Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 5: Cox Proportional Hazard Regression Model Estimates (2008-2015, Gompertz Distribution)

	(1) $h(t)$	(2) $h(t)$	(3) $h(t)$	(4) $h(t)$	(5) $h(t)$	(6) $h(t)$	(7) $h(t)$	(8) $h(t)$	(9) $h(t)$	(10) $h(t)$	(11) $h(t)$	(12) $h(t)$
profit	0.945**	0.944**	0.943***	0.933***	0.935***	0.934***						0.929***
	(0.0250)	(0.0240)	(0.0206)	(0.0147)	(0.0184)	(0.0163)						(0.0139)
coverage	0.977***	0.977***	0.978***	0.977***	0.979***	0.981***						
	(0.00693)	(0.00696)	(0.00645)	(0.00632)	(0.00645)	(0.00615)						
npALLresloans	1.148***	1.147***	1.151***				1.159***	1.160***				
	(0.0432)	(0.0414)	(0.0428)				(0.0466)	(0.0467)				
costs	2.467**	2.320**	2.226**	2.345***	2.239**	2.368***	2.641***	2.665***		3.667***	3.391***	3.200***
	(1.033)	(0.925)	(0.774)	(0.693)	(0.752)	(0.754)	(0.946)	(0.968)		(1.783)	(1.324)	(1.149)
liquidity	0.952**	0.948**	0.946**	0.956*	0.954*	0.953*	0.947**	0.947**				
	(0.0211)	(0.0219)	(0.0246)	(0.0232)	(0.0259)	(0.0246)	(0.0244)	(0.0245)				
size	0.999***	0.999***	0.999***	0.999**	0.999***	0.999***	0.999***	0.999***		0.999		
	(0.000213)	(0.000206)	(0.000206)	(0.000266)	(0.000230)	(0.000226)	(0.000212)	(0.000222)		(0.000395)		
capital	1.022									1.048*	1.033*	1.032*
	(0.0293)									(0.0283)	(0.0194)	(0.0183)
car		1.022							1.061			
		(0.0868)							(0.0614)			
creditrisk				1.159**							1.157***	1.143***
				(0.0673)							(0.0641)	(0.0550)
$\{npres(1/4)loans\}$					1.349*					1.399*		
					(0.240)					(0.246)		
npInDloans						1.081						
						(0.0514)						
nopinc							0.642**				0.575***	
							(0.130)				(0.106)	
roa								0.647**		0.620**		
								(0.133)		(0.127)		
nim									0.711			
									(0.194)			
charge									2.079**			
									(0.639)			
loanr									1.050**			
									(0.0230)			
N	352	352	352	352	352	352	352	352	352	352	352	352
R^2												

Exponentiated coefficients (hazard ratios); Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 6: Cox Proportional Hazard Regression Model Estimates (2008-2015, Exponential Distribution)

	(1) $h(t)$	(2) $h(t)$	(3) $h(t)$	(4) $h(t)$	(5) $h(t)$	(6) $h(t)$	(7) $h(t)$	(8) $h(t)$	(9) $h(t)$	(10) $h(t)$	(11) $h(t)$	(12) $h(t)$
profit	1.055***	1.056***	1.057***	1.072***	1.079***	1.076***						1.080***
	(0.0189)	(0.0196)	(0.0186)	(0.0149)	(0.0160)	(0.0170)						(0.0136)
coverage	1.024***	1.023***	1.026***	1.027***	1.024***	1.026***						
	(0.00766)	(0.00742)	(0.00835)	(0.00886)	(0.00845)	(0.00922)						
npALLresloans	0.851***	0.854***	0.840***				0.818***	0.818***				
	(0.0511)	(0.0507)	(0.0539)				(0.0573)	(0.0573)				
costs	0.373***	0.351***	0.419***	0.384***	0.383***	0.373***	0.374***	0.372***		0.250***	0.279***	0.297***
	(0.121)	(0.121)	(0.126)	(0.112)	(0.112)	(0.109)	(0.117)	(0.117)		(0.0864)	(0.0883)	(0.0942)
liquidity	1.029	1.027	1.048	1.037	1.047	1.046	1.048	1.050				
	(0.0236)	(0.0264)	(0.0312)	(0.0255)	(0.0362)	(0.0348)	(0.0321)	(0.0321)				
size	1.000**	1.000*	1.000***	1.000	1.001**	1.001**	1.001***	1.001***		1.020		
	(0.000174)	(0.000215)	(0.000184)	(0.000322)	(0.000255)	(0.000234)	(0.000197)	(0.000198)		(0.107)		
capital	0.978									0.958**	0.973*	0.974*
	(0.0168)									(0.0165)	(0.0155)	(0.0151)
car		0.939							0.882			
		(0.0484)							(0.0704)			
creditrisk				0.862**							0.871**	0.892*
				(0.0608)							(0.0556)	(0.0531)
$\{npres(1/4)loans\}$					0.633*					0.573**		
					(0.162)					(0.156)		
npInDloans						0.961						
						(0.0606)						
$nopinc_i$							1.671***				1.918***	
							(0.332)				(0.314)	
roa								1.665**		1.946***		
								(0.334)		(0.313)		
nim									1.406			
									(0.440)			
charge									0.368***			
									(0.124)			
loanr									0.944***			
									(0.0176)			
Shape parameter	1.785***	1.800***	1.851***	1.862***	1.926***	1.968***	1.941***	1.943***	2.413***	1.916***	1.914***	1.823***
	(0.212)	(0.215)	(0.231)	(0.219)	(0.263)	(0.266)	(0.240)	(0.239)	(0.271)	(0.228)	(0.231)	(0.225)
N	352	352	352	352	352	352	352	352	352	352	352	352

Exponentiated coefficients (time ratios); Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 7: Cox Proportional Hazard Regression Model Estimates (2008-2015, Log-normal Distribution)