Understanding Chronic Bank Failures in Minnesota

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Abstract

Minnesota experienced 23 bank failures during the Great Recession. However, the internal causes of these failures are not well addressed in the empirical literature: we contribute to the literature by addressing this issue. This study relies on survival analysis to model the risk of bank failure in Minnesota during the Great Recession. We explore the econometric gains of incorporating several parametric distributions in modeling the baseline hazard function. For the Great Recession, we show the importance of the lognormal distribution in modeling the baseline hazard rate. We find that the key bank-specific factors that inflate the instantaneous rate of bank failure include higher exposure to nonperforming real estate loans, moral hazard in bank lending, poor earning capacity to cover loan defaults, and inefficiency in managing interest expenses on deposits. For macroprudential implications, we find some weak evidence of contagion in the banking sector and we highlight the importance of regulatory capital in explaining bank survival in Minnesota during the Great Recession.

Keywords: Bank failures, Minnesota, applied financial modeling, Great Recession, survival analysis.

JEL Codes: G01, G21, C14

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1 Introduction

The Great Recession catalyzed a long period of macroeconomic instability and bank failures across the United States. Minnesota's banking sector bears the brunt of this latter crisis: one fourth of all active lending institutions either failed or merged during the Great Recession. More importantly, the internal causes of Minnesota's banking crisis during the Great Recession are not well documented in the empirical literature: hence the opportunity to contribute. Moreover, highlighting the causes of bank failures during the last major economic crisis offers an opportunity to policymakers to prevent future banking crises in Minnesota: hence the relative importance of this study.

According to the Federal Reserve Bank (FED), the Great Recession officially ended in 2009. However, for Minnesota, it took longer for its economy to recover. Annual data show that the economy slowed down in 2008, but the real output gap eventually collapsed in 2009, and it did not return to positive status until 2014. Clearly, Minnesota experienced poor economic performance between 2008 and 2014. This poor economic performance also coincided with a severe banking crisis that started on May 30^{th} 2008 and ended in December 19^{th} 2014. Eventually, Minnesota has not experienced another bank failure since then. For these latter reasons, this study considers the 2008-2014 timeline as the main period for analyzing the causes of bank failures in Minnesota during the Great Recession. Additionally, for empirical robustness, this paper considers the early stages of the Great Recession (for example, the 2008-2010 timeline) as a separate additional event to focus on.

Ultimately, the main empirical objective is to uncover the bank-specific factors that affect the risk of bank failure in Minnesota during the Great Recession. Consequently, following Kočenda and Iwasaki (2020): this study relies on survival analysis to examine the bank-specific variables that affect the risk of bank failure in Minnesota during the Great Recession. For the United States, the studies that rely on survival analysis to examine the risk of bank failure provide few details on the specification of the baseline hazard function (Cox et al., 2017). Here, this study discusses the relative importance of the lognormal distribution in modeling the baseline hazard function for the Great Recession timeline.

Another key objective is to examine the relevance of contagion in the banking sector during the Great Recession. However, estimating the lagged effect of the dependent variable within a standard survival model poses some technical limitations. Therefore, to examine the relevance of contagion: this study proposes a dynamic generalized linear model (GLM) with the Poisson distribution as the underlying parametric distribution of the count of bank failures.[1] The key empirical results found in this paper can be summarized as follows:

- The key bank-specific factors that affect the instantaneous rate of bank failure during the Great Recession include exposure to nonperforming real estate loans, moral hazard in bank lending, poor earning capacity to cover loan defaults, and inefficiency in managing interest expenses on deposits.
- Regulatory capital is positively associated with bank survival. Hence the importance of macroprudential policies in explaining bank survival in Minnesota during the Great Recession.

[1] See Schoenmaker (1996) for more information the GLM approach.

- The semiparametric model (for example, the Cox proportional hazard model) and the parametric survival model (for example, the lognormal survival model) yield similar empirical conclusions. Although the Cox proportional hazard assumption is satisfied. The parametric model is relatively more useful, particularly because it offers more insights into the behavior of the hazard rate and the survival experience of banks during the Great Recession. The empirical results show that the instantaneous rate of bank failure is unimodal, and the size of the shape parameter ($\sigma > 1$) implies that there is strong heterogeneity in survival time during the Great Recession.

- The GLM Poisson estimates show that the instantaneous rate of bank failure is concave downward, which reinforces credibility in the lognormal survival estimates. The autoregressive parameter of the GLM model is highly significant. Despite the limitations of the GLM approach: the significance of the lagged dependent variable provides enough empirical evidence to support evidence of contagion in the banking sector during the Great Recession.

The empirical results have several implications. For bank managers: the key findings highlight the importance of profit conditions, operational efficiency, and portfolio diversification in minimizing the risk of bank failure. For local government officials: this study highlights the key structural issues (for example, portfolio concentration in the real estate sector) that influence the risk of bank failure in Minnesota. For regulators at the Federal Deposit Insurance Corporation (FDIC), the evidence of contagion in a banking crisis reiterates the need for timely prompt corrective actions and the importance of strong capital buffers in minimizing the risk of bank failure in Minnesota during the Great Recession. The rest of this paper is organized as follows. Section 2 examines the empirical literature on bank failures in United States. Section 3 describes the survival analysis framework and reports the key empirical results. Section 4 discusses the key policy implications behind the key empirical results. Lastly, Appendix A provides a detailed overview of the GLM Poisson regression model.

2 Literature review

This section analyzes the empirical literature on bank failures in the United States. Cebula (2010) examines the determinants of bank failures in the United States for the period of 1970-2007: Cebula's 2010 study reveals the importance of nonperforming loans and bank costs in predicting bank failures. Here, this study considers key bank-specific characteristics such as noncurrent loans and interest expenses on deposits in modeling the risk of bank failure in Minnesota. Abou-El-Sood (2016) describes the ambiguous effect of regulatory capital in understanding bank distress in the United States. Overall, Abou-El-Soud's 2016 study shows the importance of regulatory capital in reducing bank distress when a bank is undercapitalized (for example, when the tier 1 risk-based capital ratio is below six percent). Additionally, for the specific financial crisis period of 2007-2009: Abou-El-Soud's 2016 study shows that regulatory capital reduces bank distress only when the tier 1 risk-based capital ratio exceeds eight percent.

Abou-El-Soud's 2016 study is fundamental for understanding the effect of regulatory capital on bank failures. Particularly, because it underscores the importance of threshold effects and the benefits of enforcing stronger capital buffers in a financial crisis. Berger and Bouwman (2013) show the importance of equity capital in explaining bank survival in a banking crisis. Overall, the empirical literature evinces the significance of equity capital and regulatory capital in explaining the likelihood of bank survival in a banking crisis. Wheelock and Wilson (2000) find that exposure to real estate loans increase the probability of bank failures in the United States between 1983 and 1993: Wheelock and Wilson's 2000 study demonstrates the importance of accounting for concentration risks in modeling bank failures in Minnesota. Here, Table 2 in Section 3 reiterates the significance of loan concentration in understanding the risk of bank failure in Minnesota.

Calomiris and Mason (2003) show the relevance of profitability in understanding bank survival during the Great Depression. Additionally, Calomiris and Mason's 2000 findings deemphasize the significance of bank size in understanding the risk of bank failure. For Minnesota, Section 3 does not corroborate this latter result: on the contrary, bank size, which is proxy by total assets per employee is weakly significant in explaining the risk of bank failure in Minnesota. Cole and White (2012) examine the causes of bank failures in the United States: overall, they find that exposure to real estate loans increase the probability of bank failure during the Great Recession. Similarly, Section 3 finds that exposure to nonperforming real estate loans increases the probability of bank failure in Minnesota during the Great Recession.

Additionally, Cole and White (2012) find an insignificant relationship between reserves for loan losses and the risk of bank failure during the Great Recession. For Minnesota, Section 3 does not corroborate this latter result. Furthermore, Cole and White's 2012 paper illustrates a key limitation that arises in modeling the risk of bank failure with the logistic regression: the cumulative logistic distribution does not account for time to failure, which makes it less effective in predicting the risk of bank failure. The logistic model estimates the probability of bank failure at a fixed point in time. Whereas the survival model estimates the probability of bank failure within a given time period, conditional on the bank having survived up to that period. Therefore, because survival analysis focuses on time to failure, this paper argues that the survival model provides a better alternative for modeling the risk of bank failure in contrast to the standard logistic model. Berger and Bouwman (2013) rely on the ratio of Basel 1 risk-weighted assets to gross total assets as a proxy for credit risks.

However, they find no significant relationship between the latter and the risk of bank failure during the Global Financial Crisis. Evidently, Berger and Bouwman's 2013 study illustrates the dilemma that arises in selecting the appropriate proxy for modeling credit risks. Here, Section 3 shows that nonperforming loans and loan defaults are significant predictors of bank failures and consequently useful in modeling credit risks for Minnesota. The empirical literature strengthens the relative importance of survival analysis in modeling bank failures in the United States. Moreover, the empirical literature emphasizes the importance of relying on bank-specific characteristics such as credit risks, concentration risks, non-operating costs, and profitability in modeling bank failures in the United States.

3 Survival analysis

3.1 Bank-specific variables

This section discusses the data and describes the key variables employed in the main empirical analysis. According to the FDIC database, mergers are frequent in Minnesota, but bank failures are less frequent: Minnesota has not experienced a bank failure since December 19^{th} 2014. Following

Kočenda and Iwasaki (2020), this paper focuses exclusively on failed banks: these are the banks that closed and liquidated their assets due to reasons other than mergers. The financial institutions that closed due to mergers and acquisitions are not included in the main analysis. The banks that are included in the main analysis satisfy the following conditions: each bank is reported to be active on December 31st, 2007, the established date is not greater than December 31st, 2007, (iii) each bank is reported to be either active or failed by December 31st, 2014. Table 1 provides an overview of the status of all banks in Minnesota from 2008 to 2014.

Status	*Freq.*	*Percent*	*Cum*
Closed: stopped reporting	1	0.23	0.23
Closed: liquidated assets, relinquished insurance	1	0.23	0.45
Closed: merged or acquired	82	18.51	18.96
Failed: received government assistance	23	5.19	24.15
Survived	336	75.85	100.00
Total	443	100.00	

Table 1: Bank Status (Minnesota, 2008-2014)

The bank-specific variables are collected from the FDIC database. Here, the survival models are estimated with year-to-date quarterly data. More precisely, the cross-sectional data set reflects balance sheet information for the last quarter prior to the start of the Great Recession. Consequently, the bank-specific covariates can be viewed as predetermined regressors (Kočenda and Iwasaki, 2020): this latter condition relaxes concerns of reverse causation in estimating the survival regressions. For Minnesota, prior to the start of the Great Recession: real estate loans accounted for more than 65 percent of total loans and leases. Aggregate loan portfolio in Minnesota remains highly concentrated in the real estate sector. In 2024, exposure to real estate loans reached about 70 percent of total loans and leases. This latter statistic reiterates that the housing sector remains a potent source of systematic risk for the banking sector. For Minnesota, given the structural importance of the real estate sector in explaining moral hazard in bank lending: the credit risk variables are measured as follows

$$(1/4)FamilyResloansNP = \frac{\textit{noncurrent (1/4) family residential properties loans}}{\textit{total (1/4) family residential mortgage loans}}$$

$$(1/4)FamilyResloansDefaults = \frac{\textit{net charge-off (1/4) family residential properties loans}}{\textit{average total loans (1/4) family residential properties}}$$

$$allResloansNP = \frac{\textit{Real estate loans past due 90 days or more plus loans placed in non-accrual status}}{\textit{total real estate loans}}$$

For empirical reliability, this paper relies on additional variables for credit risks, namely: net charge-offs as a percentage of average total loans and leases ($loanDefaults$), net loans and leases to total assets ($loanConcentration$), total noncurrent loans to gross loans and leases ($nonperFloans$), and allowance for loan losses to loans and leases ($allowance$).[2] According to FIDC, an allowance

[2]Net charge-offs are gross loans and leases financing receivable charge-offs, adjusted for gross recoveries, (annualized). Note that $(1/4)FamilyResloansNP$ does not include noncurrent home equity loans.

for loan losses is 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 the allowance for loan losses. Moreover, a high rate of allowance 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 had a relatively higher average rate of allowance for loan losses on December 31st, 2007. Here profitability is measured as follows

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

This section relies on returns to assets (*roa*) as an additional measure of profitability. Net operating income to total assets (*nopinc*) is utilized as an indirect proxy for cash flow. Bank liquidity is measured by relying on core deposits, which are relatively more liquid, and provide an adequate source for funding loans. The bank liquidity proxy is measured as follows

$$liquiDity = \frac{\textit{core deposits}}{\textit{total assets}}$$

A higher level of core deposits as a percentage of total assets means more available funds to sustain the bank's operating activities or higher interest expenses on deposits. Nonetheless, $liquiDity$ is expected to improve the ability of the bank to remain in business during poor macroeconomic performance. The ability of the bank to immerse indirect costs by generating higher revenues from earning assets depends on the efficiency of management. Therefore, efficient banks are more likely to survive during a banking crisis. The proxy for efficiency is measured as follows

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

Here, bank size (*size*) is measured by the ratio of total assets to the number of full-time employees. The size of the bank can be useful in understanding the risk of bank failure: larger banks have more assets, which enhances the probability of surviving a long period of poor economic performance. However, for Minnesota, the data paint a different narrative: the banks that failed in the Great Recession were relatively larger in terms of size. A stronger earning capacity to cover loan defaults enhances the ability of the bank to survive in a banking crisis. Here, the loan coverage ratio is measured 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* defines the ability of a bank to absorb loan losses. *coverage* is important for bank survival, especially during an economic recession. A capital buffer provides a cushion for banks during a financial crisis. Alternatively, excessive capital requirements can reduce the ability of banks to generate earning assets, which could worsen efficiency and increase the risk of failure.

The main proxy for regulatory capital is measured as follows

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

According to FDIC: regulatory capital requirements strengthen the banking sector by enhancing shareholders' confidence and by providing capital reserves for depositors when the bank experiences failure. Additionally, this study relies on the ratio of equity capital to total assets as a proxy for bank capital (*eqCapital*). Table 1 provides an overview of the first moment statistics, including the difference in means analysis. The independent two-sample t-tests are reported in Table 2, and these results are highly sensitive to abnormal data distributions. Some bank-specific variables are highly skewed (for example, *coverage*, *size*, *regCapital*, *eqCapital*, and 1/4 *FamilyResloansNP*); which makes the independent two-sample t-tests less reliable for these latter variables.

	(Failed)	(Survived)	(T-Test)	
	mean(μ_f)	mean(μ_s)	($\mu_f - \mu_s$)	Test Statistics
Cost of Funding Earning Assets (*EFFratio*)	3.72	3.08	0.64***	(4.63)
Net operating income (*nopinc*)	-0.08	1.04	-1.12***	(-5.15)
Return on assets (*roa*)	-0.06	1.04	-1.10***	(-5.04)
Return on equity (*profit*)	-1.12	10.33	-11.44***	(-6.08)
Net charge-offs to loans and leases (*loanDefaults*)	0.73	0.33	0.41**	(3.21)
(1/4)*FamilyResloansNP*	1.77	1.18	0.59	(1.36)
coverage	0.99	35.74	-34.75	(-1.38)
Assets per employees (*size*)	4.28	3.76	0.52	(1.45)
Nonperforming real estate loans (*allResloansNP*)	4.88	1.76	3.12***	(5.69)
Core deposits to assets (*liquiDity*)	67.00	71.44	-4.44*	(-2.28)
Equity capital to assets (*eqCapital*)	10.21	10.90	-0.69	(-0.87)
Tier 1 risk-based capital ratio (*regCapital*)	11.23	14.63	-3.40*	(-2.33)
Net loans and leases to assets (*loanConcentration*)	78.42	68.82	9.60**	(3.24)
Loss allowance to Loans and Leases (*allowance*)	1.76	1.41	0.35	(1.93)
Noncurrent loans and leases % gross loans (*nonPerfloans*)	3.82	1.57	2.25***	(5.53)
(1/4)*FamilyResloansDefaults*	0.57	0.19	0.38**	(2.79)
Observations	23	336	359	

Table 2: Independent Two-Sample T-Tests

For the profit variables, the difference in means are highly significant and large. The banks that survived the Great Recession have a higher average profit rate in contrast to the 23 banks that failed during the Great Recession. For the rate of nonperforming real estate loans, the difference in means is relatively large and highly significant. The 23 banks that failed during the Great Recession were comparatively highly exposed to nonperforming real estate loans: hence the importance of credit risks in understanding bank failures in Minnesota. The difference in means for the loan concentration ratio is significant: the banks that survived the Great Recession were comparatively less exposed to concentration risks, which made them less vulnerable to failure.

3.2 Survival analysis

Let $T \geq 0$ denote survival time with a nonparametric probability density function given by $f(t)$. The probability that a bank fails by time t is given by the cumulative distribution function as follows

$$F(t) = P(T \leq t)$$

from which the survival function is computed as follows

$$S(t) = 1 - F(t) \equiv P(T > t) \tag{1}$$

where equation (1) denotes the probability that the bank survives past t. Differentiating both sides of the survival function yields

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

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 conditional probability of bank failure a time t, given that the bank survives up to t. Here, the hazard function measures the instantaneous rate of bank failure. Consider the Cox proportional hazard model

$$h(t) = h_0(t)e^{\{b_1x_1+b_2x_2+...+b_px_p\}} \tag{3}$$

where $h_0(t)$ denotes the time-varying baseline hazard function, $(x_1 + x_2 + ... + x_p)$ are the time-independent bank-specific variables, whose coefficients are to be estimated via maximum likelihood. For the Cox proportional hazard model, the parameters of the model are linear, but the baseline hazard function remains nonparametric: hence the semiparametric approach. According to Cox (1972), the Cox proportional hazard model does not suffer from the assumption bias that arises by imposing a specific parametric distribution on the baseline hazard function. Nonetheless, the main assumption of the Cox proportional hazard model is that the hazard ratio is constant over time. The coefficients of the model are interpreted as hazard ratios, which measure the relative risk of bank failure due to a one-unit change in the bank-specific factors. A hazard ratio that is greater than one indicates a higher relative risk of bank failure. Alternatively, a hazard ratio that is less than one indicates a lower relative risk of bank failure. Lastly, a hazard ratio that is equal to 1 indicates no differences in the relative risk of bank failure.

65 percent of all bank failures in Minnesota occurred during the early stages of the Great Recession, between 2008 and 2010. For empirical robustness, this section considers the 2008-2010 timeline as a separate event to study. For diagnostics purposes, this section relies on the global proportional hazard test to examine the relevance of the Cox proportional hazard assumption. The survival regressions are estimated with robust standard errors to address heteroscedasticity concerns. The empirical estimates of a survival model are highly sensitive to multicollinearity, which inflates the standard errors, especially for short samples. To alleviate this issue: this section does not include highly correlated regressors in the same survival regression. Tables 3 and 4 report the Cox proportional hazard estimates with the hazard ratios. For the semiparametric model, the key bank-specific factors that increase the risk of bank failure during the Great Recession are:

- Credit risk exposure to the real estate market, moral hazard in bank lending proxy by the loan concentration ratio, nonperforming loans, and banking inefficiency.

Alternatively, the key factors that lower the risk of bank failure during the Great Recession include:

- Regulatory capital, profitability, and the coverage for loan losses.

Bank size and liquidity did not pass the empirical robustness check: particularly, because the two variables are not statistically significant in explaining the risk of bank failure during the early stages of the Great Recession. Equity capital passed the robustness check, but the latter variable is weakly significant. For the Cox proportional hazard model, the baseline hazard function is not assumed to be constant, but it remains unparameterized. For empirical reliability, this study emphasizes the relative importance of identifying the parametric distribution that best fits the instantaneous rate of bank failure.

For the United States, the key studies that rely on survival analysis to analyze the risk of bank failure do not consider the need to parameterize the baseline hazard function. For instance, Cox et al. (2017) leave the baseline hazard function unparameterized and provide no discussion on the empirical benefits of using the appropriate parametric distribution to model the baseline hazard function. Here, this study discusses the empirical benefits of using the appropriate parametric distribution to model the baseline hazard function. For Minnesota, the FDIC data show a rapid exponential increase in bank failures from 2008 to 2010, followed by a sharp progressive decline in bank failures until 2014. Furthermore, the FIDC dataset provides strong evidence of heterogeneity in bank survival during the Great Recession.

For these latter reasons, this study recommends to rely on the lognormal distribution to model the baseline hazard function for the Great Recession timeline. Particularly, because the shape of the lognormal distribution implies that the instantaneous rate of bank failure follows a unimodal process: it increases exponentially towards an absolute maximum and then declines over time. For the Great Recession timeline, this study considers the following hazard function

$$h(t,\sigma) \equiv \frac{f(t)}{S(t)} \dashrightarrow \frac{\frac{1}{\sigma(t)\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{ln(T)-\mu}{\sigma}\right)^2}}{\left(1-\Phi(z)\left\{\frac{ln(t)-\mu}{\sigma}\right\}\right)} \tag{4}$$

where $ln(T)$ denotes the natural log of survival time. σ is an important parameter of the lognormal hazard function: it measures the curvature of the hazard function. Φ is the standard normal cumulative distribution function. Here, the location parameter (μ) is a linear function of the bank-specific covariates ($\mu = b_0 + b_1x_1 + b_2x_2 + ... + b_px_p$). The lognormal acceleration failure time (AFT) regression can be expressed as follows

$$Ln(T) = b_0 + b_1x_1 + b_2x_2 + ... + b_px_p + \sigma e \tag{5}$$

where e is a normally distributed error term. σ is the standard deviation of the error term, which measures the curvature of the lognormal distribution of survival time.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$
profit	0.947***	0.950***	0.912***	0.929***								
	(0.0160)	(0.0180)	(0.0175)	(0.0177)								
coverage	0.975***	0.971***	0.979***	0.977***	0.965***		0.970***	0.975***				0.972***
	(0.00662)	(0.00732)	(0.00693)	(0.00671)	(0.00634)		(0.00798)	(0.00721)				(0.00734)
allResloansNP	1.138***				1.149***	1.175***	1.162***					
	(0.0456)				(0.0451)	(0.0461)	(0.0401)					
EFFratio	2.332**	2.940**									2.451**	
	(0.983)	(1.303)									(0.916)	
regCapital	0.838**	0.863**	0.808***	0.800***	0.790***	0.745***		0.764***			0.820***	0.775***
	(0.0605)	(0.0515)	(0.0621)	(0.0676)	(0.0564)	(0.0645)		(0.0610)			(0.0556)	(0.0664)
allowance		1.750**									2.162***	
		(0.400)									(0.506)	
{(1/4)*FamilyResloansNP*}			1.139**									
			(0.0732)									
liquiDity			0.961**	0.957**		0.942***	0.951**	0.953**			0.952**	0.955**
			(0.0185)	(0.0195)		(0.0197)	(0.0207)	(0.0211)			(0.0183)	(0.0209)
size			1.169*	1.194**						1.165**		1.169**
			(0.0937)	(0.0879)						(0.0776)		(0.0755)
nonperFloans				1.237***								1.253***
				(0.0666)								(0.0652)
nopinc					0.584***	0.498***	0.579***	0.497***				
					(0.0963)	(0.0932)	(0.118)	(0.0865)				
eqCapital							0.854*			0.875*		
							(0.0727)			(0.0631)		
{(1/4)*FamilyResloansDefaults*}								1.358**				
								(0.189)				
roa									0.717***	0.506***	0.551***	0.555***
									(0.0914)	(0.0870)	(0.104)	(0.103)
loanDefaults									1.707**			
									(0.409)			
loanConcentration									1.054***	1.035*		
									(0.0181)	(0.0192)		
N	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	23	23	23	23	23	23	23	23	23	23	23	
Global test (p-value)	0.1163	0.1293	0.2108	0.3254	0.6749	0.2015	0.0769	0.1076	0.1361	0.3046	0.0893	0.1611
Log pseudolikelihood	-106.41	-107.1689	-107.6773	-104.8985	-110.08143	-109.192	-112.72633	-110.59018	-121.032	-118.91068	-108.65252	-106.59123
Akaike information criterion (AIC)	222.8214	224.3378	227.3547	221.7971	228.1629	226.384	235.4527	231.1804	248.064	245.8214	227.305	225.1825

Hazard ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 3: Cox Proportional Hazard Regression (Great Recession)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$
profit	0.940***	0.946***	0.914***	0.931***								
	(0.0143)	(0.0187)	(0.0196)	(0.0193)								
coverage	0.981	0.975*	0.983	0.982	0.975*		0.975*	0.979*				0.977*
	(0.0124)	(0.0132)	(0.0114)	(0.0119)	(0.0139)		(0.0134)	(0.0125)				(0.0135)
allResloansNP	1.159***				1.174***	1.182***	1.163***					
	(0.0509)				(0.0538)	(0.0531)	(0.0371)					
EFFratio	1.467	1.829									1.862*	
	(0.549)	(0.675)									(0.650)	
regCapital	0.787***	0.822**	0.775**	0.759**	0.742***	0.732***		0.740***			0.800***	0.730***
	(0.0691)	(0.0643)	(0.0822)	(0.0883)	(0.0629)	(0.0716)		(0.0837)			(0.0636)	(0.0888)
allowance		1.919**									2.124***	
		(0.557)									(0.617)	
$\{(1/4)FamilyResloansNP\}$			1.170***									
			(0.0562)									
liquiDity			0.996	0.994		0.986	1.001	1.001			0.990	0.997
			(0.0274)	(0.0294)		(0.0278)	(0.0302)	(0.0285)			(0.0241)	(0.0300)
size			1.053	1.068						1.050		1.057
			(0.127)	(0.139)						(0.0962)		(0.122)
nonperFloans				1.224***								1.235***
				(0.0750)								(0.0775)
nopinc					0.563***	0.514***	0.550***	0.474***				
					(0.116)	(0.122)	(0.103)	(0.106)				
eqCapital							0.883			0.869*		
							(0.0946)			(0.0701)		
$\{(1/4)FamilyResloansDefaults\}$								1.419**				
								(0.224)				
roa									0.651***	0.486***	0.556**	0.539**
									(0.0909)	(0.0779)	(0.137)	(0.131)
loanDefaults									1.580**			
									(0.354)			
loanConcentration									1.038**	1.028		
									(0.0170)	(0.0187)		
γ	0.00283***	0.00289***	0.00308***	0.00290***	0.00274***	0.00282***	0.00227***	0.00268***	0.00201***	0.00220***	0.00286***	0.00273***
	(0.000615)	(0.000624)	(0.000682)	(0.000623)	(0.000630)	(0.000655)	(0.000485)	(0.000629)	(0.000486)	(0.000485)	(0.000645)	(0.000626)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	15	15	15	15	15	15	15	15	15	15	15	
Global test (p-value)	0.8375	0.3500	0.8988	0.8331	0.5171	0.3665	0.0031	0.5951	0.3139	0.0541	0.1776	0.5956
Log pseudolikelihood	-66.166507	-66.858855	-68.116636	-66.663882	-67.361279	-68.148535	-72.413878	-69.613185	-78.174958	-76.748201	-68.2773	-67.740512
Akaike information criterion (AIC)	142.333	143.7177	148.2333	145.3278	142.7226	144.2971	154.8278	149.2264	162.3499	161.4964	146.5546	147.481

Hazard ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 4: Cox Proportional Hazard Regression (Great Recession, Early Stages)

For the early stages of the Great Recession, the number of bank failures in Minnesota follows an exponential trend. For the 2008-2010 timeline, the implication is that the lognormal distribution remains useful, but not necessarily optimal in modeling the baseline hazard function. To test the exponential assumption: this study considers the Gompertz parametric distribution in modeling the baseline hazard function for the 2008-2010 timeline. Hence the Gompertz survival regression model

$$h(t,\gamma) = \lambda e^{\gamma(t)} \tag{6}$$

where λ is parameterized as follows: $e^{(b_1x_1+b_2x_2+\ldots+b_px_p)}$. The baseline hazard function is modeled as an exponential function with γ acting as the shape parameter. Table 5 reports the empirical estimates of the lognormal AFT regressions with the time ratios. Table 6 reports the Gompertz survival regressions with the hazard ratios. The parametric results mirror the semiparametric results. Moreover, the parametric survival regressions can be summarized as follows:

- For the lognormal AFT regression, the shape parameter (σ) is statistically significant and greater than 1. This implies that the instantaneous rate of bank failure follows a unimodal process, which is consistent with the theoretical conclusions established for the Great Recession timeline.

- For the Gompertz survival regression, the shape parameter (γ) is statistically significant and greater than zero. As expected, this finding implies that the hazard rate is exponentially increasing in the early stages of the Great Recession. For the 2008-2010 timeline, the Gompertz survival results are relatively more efficient than the Cox proportional hazard estimates found in Table 4.

The lognormal survival functions for the key bank-specific factors are plotted in Figure 5 in Appendix A. As expected, the banks that are undercapitalized and highly exposed to nonperforming real estate loans have a lower probability of survival during the Great Recession. Alternatively, the banks with a positive coverage ratio and stronger profits show a higher probability of survival during the Great Recession. There are multiple parametric distributions that can be used to model the baseline hazard function for the Great Recession timeline. However, this paper stresses the importance of partially relying on theory to select the appropriate parametric distribution to model the baseline hazard function. For instance, the exponential distribution implies a constant hazard rate, which is less likely to hold during the Great Recession timeline. The Weibull distribution implies a monotonic hazard rate of failure, which makes less theoretical sense for the Great Recession timeline. Nonetheless, the Weibull survival regressions are reported in Table 13 in Appendix A: as excepted, the empirical estimates for the shape parameter (p) are widely insignificant and unstable. The generalized gamma distribution can assume different shapes. However, given the available data, this study finds that the generalized gamma distribution is not useful in modeling the hazard rate due to the inability to estimate stable coefficients via maximum likelihood.

The Gompertz survival model assumes that the hazard rate either increases or decreases exponentially over time, which makes the Gompertz distribution less practical in modeling the baseline hazard function for the Great Recession timeline. As expected, Table 11 in Appendix A evinces that the Gompertz distribution is not useful in modeling the baseline hazard function for the Great Recession timeline: all estimates of the shape parameter (γ) are negative, which implies that the hazard rate is exponentially decreasing over time. But none of the estimated values of (γ) are statistically significant.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$
profit	1.040***	1.039**	1.062***	1.045***								
	(0.0146)	(0.0164)	(0.0117)	(0.0125)								
coverage	1.024***	1.028***	1.028***	1.027***	1.037***		1.034***	1.033***				1.034***
	(0.00874)	(0.00932)	(0.00955)	(0.00933)	(0.0118)		(0.0106)	(0.0108)				(0.0114)
allResloansNP	0.878**				0.861***	0.837***	0.828***					
	(0.0456)				(0.0481)	(0.0472)	(0.0460)					
EFFratio	0.471**	0.413***									0.465**	
	(0.148)	(0.131)									(0.148)	
regCapital	1.118*	1.126**	1.165***	1.168***	1.179***	1.196***		1.207***			1.148***	1.187***
	(0.0697)	(0.0559)	(0.0668)	(0.0680)	(0.0631)	(0.0663)		(0.0706)			(0.0547)	(0.0670)
allowance		0.583*									0.482**	
		(0.165)									(0.143)	
(1/4)*FamilyResloansNP*			0.911									
			(0.0524)									
liquiDity			1.032*	1.034*		1.047***	1.045**	1.037**			1.031**	1.036*
			(0.0180)	(0.0182)		(0.0166)	(0.0183)	(0.0184)			(0.0158)	(0.0189)
size			0.880*	0.867**						0.863**		0.873**
			(0.0597)	(0.0584)						(0.0600)		(0.0578)
nonperFloans				0.816***								0.793***
				(0.0518)								(0.0569)
nopinc					1.361*	1.512**	1.403*	1.574***				
					(0.225)	(0.244)	(0.255)	(0.223)				
eqCapital							1.092			1.051		
							(0.0667)			(0.0747)		
(1/4)*FamilyResloansDefaults*								0.640*				
								(0.162)				
roa									1.503**	1.862***	1.512**	1.382*
									(0.289)	(0.272)	(0.262)	(0.235)
loanDefaults									0.619*			
									(0.173)			
loanConcentration									0.945***	0.958***		
σ	1.509***	1.508***	1.553***	1.507***	1.574***	1.572***	1.684***	1.623***	1.757***	1.768***	1.549***	1.573***
	(0.183)	(0.171)	(0.193)	(0.193)	(0.192)	(0.207)	(0.192)	(0.195)	(0.205)	(0.224)	(0.182)	(0.205)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	23	23	23	23	23	23	23	23	23	23	23	
Log pseudolikelihood	-80.608096	-81.472474	-83.984	-80.767165	-84.8744	-84.752728	-86.583242	-85.418897	-92.404186	-92.222384	-84.135503	-82.332468
Akaike information criterion (AIC)	175.2162	176.9449	183.968	177.5343	181.7489	181.5055	187.1665	184.8378	194.8084	196.4448	182.271	180.6649

time ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 5: Lognormal AFT Regressions (Great Recession)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$
$profit$	0.942***	0.949***	0.932***	0.945***								
	(0.0119)	(0.0153)	(0.0126)	(0.0131)								
$coverage$	0.981	0.975*	0.977*	0.977*	0.974*		0.975*	0.976*				0.974*
	(0.0124)	(0.0133)	(0.0126)	(0.0132)	(0.0145)		(0.0136)	(0.0128)				(0.0137)
$allResloansNP$	1.169***				1.185***	1.197***	1.165***					
	(0.0498)				(0.0518)	(0.0517)	(0.0375)					
$EFFratio$	1.584	2.022*									2.139**	
	(0.611)	(0.760)									(0.765)	
$regCapital$	0.777***	0.810***	0.789**	0.769**	0.737***	0.734***		0.757***			0.794***	0.743***
	(0.0719)	(0.0615)	(0.0798)	(0.0844)	(0.0678)	(0.0712)		(0.0693)			(0.0546)	(0.0787)
$allowance$		2.107***									2.295***	
		(0.529)									(0.608)	
$(1/4)FamilyResloansNP$			1.166**									
			(0.0713)									
$liquiDity$			1.003	1.000		0.990	1.002	1.004			0.996	1.001
			(0.0262)	(0.0282)		(0.0269)	(0.0299)	(0.0285)			(0.0229)	(0.0292)
$size$			1.065	1.087						1.051		1.069
			(0.107)	(0.118)						(0.0960)		(0.110)
$nonperFloans$				1.238***								1.246***
				(0.0782)								(0.0798)
$nopinc$					0.593***	0.559***	0.551***	0.521***				
					(0.0759)	(0.0740)	(0.0894)	(0.0629)				
$eqCapital$							0.883			0.871*		
							(0.0918)			(0.0655)		
$(1/4)FamilyResloansDefaults$								1.438**				
								(0.228)				
roa									0.650***	0.490***	0.584***	0.600***
									(0.0918)	(0.0675)	(0.106)	(0.0851)
$loanDefaults$									1.581*			
									(0.375)			
$loanConcentration$									1.038**	1.028		
									(0.0172)	(0.0194)		
γ	0.00283***	0.00289***	0.00308***	0.00290***	0.00274***	0.00282***	0.00227***	0.00268***	0.00201***	0.00220***	0.00286***	0.00273***
	(0.000615)	(0.000624)	(0.000682)	(0.000623)	(0.000630)	(0.000655)	(0.000485)	(0.000629)	(0.000486)	(0.000485)	(0.000645)	(0.000626)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	15	15	15	15	15	15	15	15	15	15	15	
Log pseudolikelihood												
Akaike information criterion (AIC)												

Hazard ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 6: Gompertz Survival Regressions (Great Recession, Early Stages)

Table 12 in Appendix A shows that the loglogistic distribution is useful in modeling the baseline hazard function for the Great Recession timeline. However, the estimates of the shape parameter are inconsistent and weakly significant. Overall, this study finds that the lognormal parametric distribution offers a better alternative for modeling the baseline hazard function for the Great Recession timeline. A few parametric survival models reported in Appendix A provide lower AIC estimates in contrast to the lognormal survival model. Nonetheless, the differences in the AIC estimates between those latter models and the lognormal model are relatively low.[3] Both the semiparametric approach and the full parametric approach provide useful insights. The diagnostic tests suggest that the cox proportional hazard assumption is satisfied in Tables 4 and 5. However, the lognormal survival model is relatively more useful. Particularly, because it provides more insights into the behavior of the hazard rate during the Great Recession. For instance, the size of the shape parameter of the lognormal survival model is relatively large. This implies that there is strong heterogeneity in survival time in the banking sector during the Great Recession timeline. For the early stages of the Great Recession, the Gompertz survival model complements the Cox proportional hazard findings by providing meaningful insights about the shape of the hazard function during the 2008-2010 timeline.

4 Conclusion

This study examines the causes of bank failures in Minnesota during the Great Recession by relying on survival analysis. The key empirical findings imply that both the semiparametric and parametric models provide useful and consistent results. However, this study finds that the lognormal parametric distribution fits the data best. The underlying policy implications of the key empirical results can be explained as follows. Lower credit risks are associated with a lower instantaneous rate of bank failure. Consequently, this paper argues that banks should strive for portfolio diversification, stronger credit screening, and rely on sound restrictive covenants to minimize the effect of nonperforming loans and on the risk of bank failure.

For banking regulation purposes, the key findings imply that the tier-1 risk based capital ratio is positively associated with bank survival during the Great Recession. Factually, First Integrity Bank is the only bank in Minnesota whose tier 1 risk-based capital ratio fell below FDIC's minimum capital requirements in December 31^{st} 2007. Coincidentally, First Integrity Bank also recorded the lowest survival time during the Great Recession: the bank failed on May 30^{th}, 2008. Therefore, this study derives enough qualitative and empirical evidence to support the view that banking regulations can be instrumental in reducing the risk of chronic bank failures in Minnesota. Efficient banks with better cash flow, and a stronger earning capacity to cover loan defaults have a higher probability of survival during the Great Recession. For Minnesota, these latter findings highlight two essential points. Firstly, it is vital for community banks to incorporate an effective strategy to better manage interest rate risks. Balance sheet mismatches are more prevalent during recessions. Community banks rely heavily on short-term liabilities (for example, core deposits) to fund fixed-term loans with longer maturities. Hence the issue: rising interest rates can reduce liquidity given declining loan demand and the inability to efficiently absorb rising deposit costs.

Secondly, portfolio diversification can alleviate the probability of loan defaults and therefore

[3] On average, the difference in the AIC estimates is less than five on average.

minimize the risk of bank failure. In general, the main empirical results are consistent with the empirical literature. However, this paper makes several contributions. Firstly, this is the first study to examine the causes of bank failures in Minnesota during the Great Recession period of 2008-2014. Secondly, this study demonstrates the econometric gains achieved by relying on the lognormal parametric distribution to model the baseline hazard function for the Great Recession timeline.[4] Lastly, this paper considers various bank-specific variables that have never been considered in analyzing the causes of bank failures in Minnesota.

Overall, the robustness check shows that the survival estimates are robust and consistent. The underlying assumptions of the dynamic GLM Poisson model are discussed in Appendix A. However, this paper also recognizes the limitations that arise in modeling the expected count of bank failure with the dynamic GLM Poisson model. The issue of dynamic endogeneity exposes the empirical results to biasedness. Therefore, this study recommends that the readers consider the uncertainty surrounding the autoregressive parameter estimates by focusing on the confidence intervals reported in Table 8. Nonetheless, the significance of the autoregressive parameter estimates strengthens the hypothesis of contagion in the banking sector during the Great Recession timeline.

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[4] For example, the AIC estimates of the lognormal model are relatively lower than the AIC estimates for the Cox proportional hazard model.

Appendix A

Dynamic Poisson Regression

The actual quarterly count of bank failures during the Great Recession closely resembles a Poisson process with a low mean. Consequently, this section examines the relevance of Poisson parametric distribution in modeling the quarterly count of bank failures by relying on a standard chi-square test of goodness of fit. Figure 1 summarizes the chi-square test results, which demonstrate the relative importance of the Poisson distribution in modeling the quarterly count of bank failures in Minnesota during the Great Recession. [5]

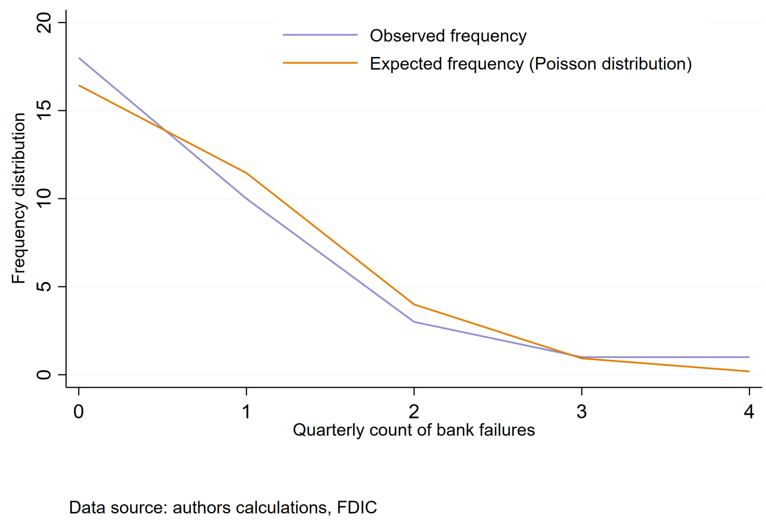

Figure 1: Quarterly Count of Bank Failures (2008-2015)

Bank failures are not frequent in Minnesota: the rare count of bank failures is a desired characteristic of the Poisson distribution. However, the study does not assume that the rate of bank failure is constant during the Great Recession timeline. Furthermore, it is also reasonable to assume that bank failures are not independent during a financial crisis. Evidently, Figure 2 plots the partial autocorrelation function of bank failures, which shows that the first lag is highly significant. Consequently, following Schoenmaker (1996), this section argues that a first-order Poisson regression model might be more appropriate to model bank failures during the Great Recession. This section acknowledges that the number of zeros accounts for 55 percent of the observed frequency. However, the dispersion ratio is 1.38. Which is relatively close to one, indicating that a zero-inflated Poisson model may not necessarily be needed, especially in the presence of severe autocorrelation. Nonetheless, the standard errors of the dynamic Poisson regression may be inconsistent. To address the latter, this section relies on heteroscedasticity and autocorrelation consistent standard errors.

This section proposes a generalized linear regression model (GLM) with the following Poisson distribution as the underlying parametric distribution of the quarterly count of bank failures:

[5]For the chi-square test of goodness of fit, the chi-square test statistic is 4.12 with 2 degrees freedom.

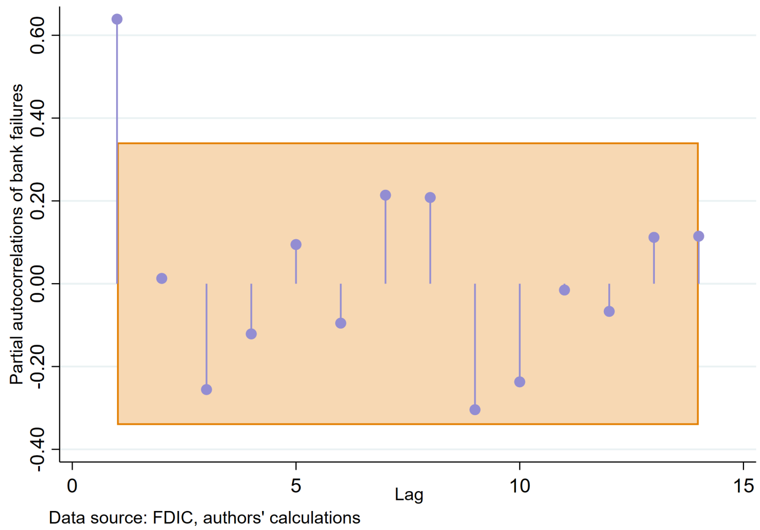

Figure 2: Partial Autocorrelation Function

$$P(Z_t = z_t) = \frac{\theta_t^{z_t} e^{-\theta_t}}{z_t!} \tag{7}$$

where equation (7) denotes the probability of obtaining z number of bank failures in each quarter. θ is the Poisson mean, which is not constant. The log link function is given as follows

$$ln(\theta_t) = f(t, X_{t-1}\Gamma, Z_{t-1}) \tag{8}$$

from which the dynamic GLM Poisson regression model can be expressed as follows

$$ln\{E(Z_t)\} \equiv ln(\theta_t) = \gamma_0 + \rho Z_{t-1} + \sum_{i=1}^{k} \sum_{p=1}^{j_i} \Gamma_{i,p} X_{i,t-p} + \alpha_1 t + \alpha_2 t^2 \tag{9}$$

where ρ denotes the autoregressive parameter, which captures the relative importance of contagion in explaining bank failures during the Great Recession period. t denotes a time trend. The section assumes that the rate of bank failure is not constant but is likely to increase at a decreasing rate over the Great Recession period. To test this latter hypothesis, this study considers a quadratic time trend (t^2) to examine the curvature of the instantaneous rate of bank failure during the Great Recession period. $X_{i,t-p}$ includes the bank-specific factors, including the real output gap (*ogap*), which is a macroeconomic variable. This section does not assume a contemporaneous relationship between the covariates and the expected count of bank failures. Instead: the regressors are assumed to be predetermined and the number of lags (p) starts at 1.

This section relies on year-to-date quarterly data sampled from the fourth quarter of 2007 to the last quarter of 2015. Minnesota did not experience a bank failure in 2015. However, this study extends the sample size to 2015 as a means to increase precision in the parameters estimates. The bank-specific variables are aggregated quarterly averages of all reporting banks in each quarter. Table 7 reports the correlation matrix for all the variables. On one hand, the correlation matrix shows that coverage for loan defaults, profitability, regulatory capital, and the real output gap are negatively correlated with bank failures during the Great Recession. On the other hand, exposure to nonperforming real estate loans, aggregate loan defaults, and nonperforming (1/4) single family residential loans are all positively associated with bank failures during the Great Recession. Table 2 reports the dynamic GLM Poisson estimates with heteroscedasticity and autocorelation consistent standard errors (HAC). The empirical results can be explained as follows. ρ is highly significant and positive: this implies that past quarterly failures are significantly associated with current quarterly failures. A highly significant ρ provides evidence of contagion in the banking sector during the Great Recession. More importantly, the data show that contagion is more prevalent in areas such as Hennepin County and Washington county (for example, see Figure 3).

	Z_t
regCapital	-0.457***
roa_t	-0.629***
$ogap_t$	-0.480***
$coverage_t$	-0.433**
allResloansNP	0.576***
(1/4)*FamilyResloansNP*	0.572***
loanDefaults	0.647***
N	33

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 7: Quarterly Bank Data (Pearson Correlation Matrix)

Overall, the time trends are statistically significant in modeling the expected count of bank failures. α_1 is positive and α_2 is negative, which indicates that the curvature of the instantaneous rate of bank failure is concave-downward. This latter result is consistent with the results found in Section 3, which reinforces the credibility of the lognormal survival model. For macroprudential implications: the lagged effect of regulatory capital is significant in explaining the expected count of quarterly bank failures during the Great Recession. This latter finding evinces the role of regulatory capital in slowing the momentum of bank failures during the Great Recession. More importantly, a one-percent increase in the tier 1 risk-based capital ratio in the previous quarter reduces the expected count of bank failures in the following quarter by 65 percent. Similar to the findings of Wu and Cole (2024), this section shows that macroeconomic conditions are statistically useful in understanding bank failures. A one-percent increase in the real output gap in the previous quarter reduces the expected count of bank failures in the following quarter by 30 percent.

Overall, the bank-specific effects are consistent with economic theory. However, it is important to recognize that the empirical framework is limited in addressing concerns of endogeneity. This section aims at reverse causation by imposing a backward lag order on the relationship between the expected count of bank failures and the regressors. The identification scheme assumes that previous banking conditions or macroeconomic activities are not influenced by current bank failures. Econometrically, the identification scheme is reasonable, but it is likely true that there may be other unobserved factors that are correlated to both current bank failures and the lags of the bank-specific covariates and macroeconomic regressors.

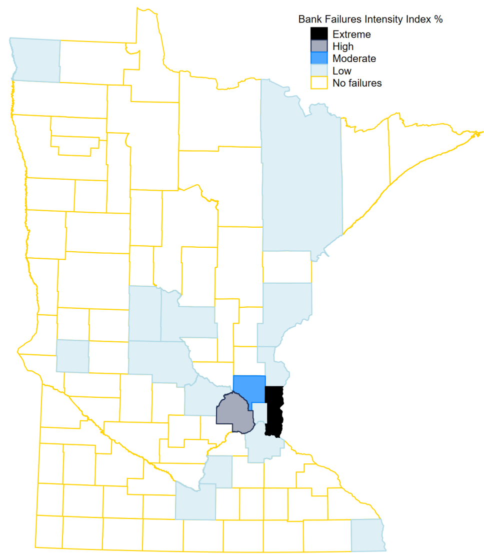

Figure 3: Bank Failures Index (Great Recession)

If so, then the strength and direction of this latter covariance would impact the strength and the direction of the potential bias. Nonetheless, Table 8 reports a 95 percent confidence interval associated with each coefficient estimate as a means to allow the readers to gauge the uncertainty around the parameter estimates. This section relies on the deviance test of goodness of fit to examine the fit of the empirical estimates. The p-values associated with the chi-square test statistics are reported in Table 8, and these latter statistics show that equation (9) fits the observed data reasonably well.

Contagion in the banking sector implies that a single bank failure can cause systemic risks in the entire banking sector. These findings highlight the need for policymakers to be more proactive in supporting and identifying unhealthy community banks before a major economic crisis occurs. Monitoring credit risks can be useful in identifying those community banks that are mostly likely to fail during a looming recession. Furthermore, imposing stronger capital buffers in a banking crisis can reduce moral hazard in bank lending and decrease the likelihood of bank failures.

	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$	$ln\{E(Z_t)\}$
Z_{t-1}	0.315***	0.154**	0.317***	0.120**	0.217***	0.238***	0.206***	0.297***	0.309***	0.198***	0.271***	0.218***
	[0.227,0.402]	[0.038,0.270]	[0.203,0.431]	[0.030,0.210]	[0.117,0.316]	[0.160,0.315]	[0.143,0.269]	[0.153,0.441]	[0.225,0.392]	[0.125,0.271]	[0.156,0.387]	[0.154,0.282]
t	0.236***	0.250*	0.156*	0.184*	0.072	-0.154	0.165*	0.233***	0.255***	0.249***	0.542***	0.177*
	[0.156,0.316]	[0.051,0.450]	[0.004,0.308]	[0.014,0.355]	[-0.103,0.247]	[-0.565,0.256]	[0.006,0.324]	[0.157,0.309]	[0.113,0.398]	[0.142,0.355]	[0.305,0.779]	[0.037,0.318]
t^2	-0.010***	-0.009**	-0.007**	-0.006	-0.002	0.003	-0.006*	-0.010***	-0.010***	-0.005*	-0.016***	-0.007*
	[-0.012,-0.007]	[-0.015,-0.003]	[-0.012,-0.002]	[-0.012,0.000]	[-0.009,0.005]	[-0.011,0.016]	[-0.012,-0.000]	[-0.012,-0.007]	[-0.013,-0.007]	[-0.011,-0.000]	[-0.022,-0.009]	[-0.012,-0.001]
$ogap_{t-1}$		-0.352***										
		[-0.454,-0.249]										
$coverage_{t-1}$			-0.026*									
			[-0.052,-0.001]									
$loanDefaults_{t-2}$				2.611***								
				[1.095,4.128]								
$allResloansNP_{t-1}$					1.122**							
					[0.356,1.888]							
$(1/4)FamilyResloansNP_{t-1}$						2.320*						
						[0.182,4.458]						
roa_{t-1}							-1.671**					
							[-2.757,-0.584]					
$profit_{t-1}$								-0.006				
								[-0.044,0.032]				
$loanConcentration_{t-1}$									0.018			
									[-0.099,0.134]			
$regCapital_{t-1}$										-1.047**		
										[-1.678,-0.417]		
$liquiDity_{t-1}$											-0.191***	
											[-0.260,-0.122]	
$nopinc_{t-1}$												-1.370*
												[-2.596,-0.145]
_cons	-1.515***	-1.998**	-0.497	-3.252***	-4.179***	-3.770***	-0.349	-1.468***	-2.844	13.088**	10.278***	-0.579
	[-2.065,-0.965]	[-3.385,-0.611]	[-1.779,0.785]	[-4.356,-2.149]	[-6.313,-2.046]	[-5.826,-1.714]	[-1.556,0.859]	[-1.970,-0.966]	[-11.466,5.779]	[4.161,22.015]	[6.689,13.868]	[-1.683,0.524]
Observations	32	32	32	31	32	32	32	32	32	32	32	32
Deviance test (p-value)	0.803	0.946	0.795	0.876	0.822	0.821	0.837	0.762	0.762	0.824	0.8987	0.804
Log likelihood	-27.806	-25.213	-27.455	-25.047	-27.153	-27.164	-26.975	-27.804	-27.804	-27.130	-26.130	-27.357

HAC standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 8: Dynamic Poisson Regression (Great Recession)

Additional Tables

Financial institutions	Key details
1st American state Bank of Minnesota	This is a state chartered bank located in Hancock, Minnesota. The FDIC Unique Number (UNINUM) is 9760. The bank failed on February 5^{th}, 2010. By December 31^{st} 2009, the earnings coverage ratio turned negative, return on equity fell to –159.37 %, and the bank equity capital ratio collapsed to 1.61%.
1st Regents Bank	This is a state chartered bank located in Andover, Minnesota. The FDIC Unique Number (UNINUM) is 358656. The bank failed on January 18^{th}, 2013. By December 31^{st} 2012, the earnings coverage ratio collapsed below zero and the tier 1 risk-based capital ratio fell to .77 %, which is well below the Basel III capital requirement of 6 %.
Access Bank	This is a state chartered bank located in Champlin, Minnesota. The FDIC Unique Number (UNINUM) is 423257. The bank failed on May 7^{th}, 2010. By March 31^{st} 2010, equity capital dropped below zero, return on equity fell to -1185 %, and the earning coverage for loan losses turned negative.
Brickwell Community Bank	This is a state chartered bank located in Woodbury, Minnesota. The FDIC Unique Number (UNINUM) is 423257. The bank failed on September 11^{th}, 2009. By June 30^{th} 2009, net loans and leases reached about 129 % of core deposits, the tier 1 risk-based capital ratio fell below zero, and return on assets collapsed to -10.67 %.

Community National Bank	This is a national bank regulated by the Controller of the Currency and located in Lino Lakes, Minnesota. The FDIC Unique Number (UNINUM) is 16336. The bank failed on December 17th, 2010. By September 30st 2010, the earnings coverage ratio fell to - 34% and return on equity collapsed to – 68 %.
Community Security Bank	This is a state chartered bank located in New Prague, Minnesota. The FDIC Unique Number (UNINUM) is 57677. The bank failed on July 23rd, 2010. By June 30th 2010, the tier 1 risk-based capital dropped below zero and net operating income to total assets collapsed to -13.71 %.
First Commercial Bank	This is a state chartered bank located in Bloomington, Minnesota. The FDIC Unique Number (UNINUM) is 76803. The bank failed on September 7th, 2012. By June 30st 2012, the earnings coverage ratio turned negative, and the tier 1 risk-based capital ratio fell below 6 %.
First Integrity Bank, National Association	This is a state chartered bank located in Staples, Minnesota. The FDIC Unique Number (UNINUM) is 8073. The bank failed on May 30th, 2008. By March 31st 2008, return on equity fell to -638.90 % and the tier 1 risk-based capital ratio fell below zero.
Home Savings of America	This is a federal savings bank located in Little Falls, Minnesota. The FDIC Unique Number (UNINUM) is 42012. The bank failed on February 24th, 2012. By December 31st 2011, the tier 1 risk-based capital ratio turned negative and return on equity collapse to - 206.67 %.

Horizon Bank	This is a state chartered bank located in Pine City, Minnesota. The FDIC Unique Number (UNINUM) is 6232. The bank failed on June 26^{th}, 2009. By March 31^{st} 2009, the tier 1 risk-based capital ratio collapsed to 1.50% and the earnings coverage ratio turned negative.
Inter Savings Bank, fsb D/B/A Interbank, fsb	This is a federal savings bank located in Maple Grove, Minnesota. The FDIC Unique Number (UNINUM) is 44329. The bank failed on April 27^{th}, 2012. By March 31^{st} 2012, return on asset collapse to -2.45 % and the tier 1 risk-based capital ratio fell below 6 %.
Jennings state Bank	This is a state chartered bank located in Spring Grove, Minnesota. The FDIC Unique Number (UNINUM) is 7288. The bank failed on October 2^{nd}, 2009. By September 30^{st} 2009, net operating income fell below zero and return on equity collapsed to -134.10 %.
Mainstreet Bank	This is a state chartered bank located in Forest Lake, Minnesota. The FDIC Unique Number (UNINUM) is 1274. The bank failed on August 28^{th}, 2009. By June 30^{th} 2009, equity capital turned negative and return on assets collapsed to -9.93 %.
Marshall Bank, National Association	This is a national bank located in Hallock, Minnesota. The FDIC Unique Number (UNINUM) is 10348. The bank failed on January 29^{th}, 2010. By December 31^{st} 2009, the tier 1 risk-based capital ratio fell to zero % and return on equity collapsed to -110.01 %.
Northern Star Bank	This is a state chartered bank located in Mankato, Minnesota. The FDIC Unique Number (UNINUM) is 73805. The bank failed on December 19^{th}, 2014. By September 30^{st} 2014, return on asset turned negative and tier 1 risk-based capital ratio fell below FDIC's minimum regulatory capital requirements.

Patriot Bank Minnesota	This is a state chartered bank located in Forest Lake, Minnesota. The FDIC Unique Number (UNINUM) is 61735. The bank failed on January 27^{th}, 2012. By December 31^{st} 2011, the earnings coverage ratio turned negative and return on equity collapsed to -137.65 %.
Pinehurst Bank	This is a state chartered bank located in Saint Paul, Minnesota. The FDIC Unique Number (UNINUM) is 423249. The bank failed on May 21^{st}, 2010. By March 31^{st} 2010, equity capital turned negative and returned on equity collapse to -3119.74 %.
Prosperan Bank	This is a state chartered bank located in Oakdale, Minnesota. The FDIC Unique Number (UNINUM) is 74649. The bank failed on November 6^{th}, 2009. By September 30^{th} 2009, return on equity collapsed to -501.83 % and the tier 1 risk-based capital ratio fell below zero.
Riverview Community Bank	This is a state chartered bank located in Otsego, Minnesota. The FDIC Unique Number (UNINUM) is 364862. The bank failed on October 23^{rd}, 2009. By September 30^{th} 2009, the tier 1 risk-based capital ratio fell below its regulatory level and the earnings coverage ratio turned negative. More importantly, 18 % of loans dedicated to finance commercial real estates were nonperforming by December 31^{st} 2007.
Rosemount National Bank	This is a national bank located in Rosemount, Minnesota. The FDIC Unique Number (UNINUM) is 16797. The bank failed on April 15^{th}, 2011. By March 31^{st} 2011, the earnings coverage ratio collapsed drastically to -28 and the tier 1 risk-based capital ratio fell below its regulatory level.

St. Stephen state Bank	This is a state chartered bank located in Saint Stephen, Minnesota. The FDIC Unique Number (UNINUM) is 11502. The bank failed on January 15^{th}, 2010. By December 31^{st} 2009, equity capital turned negative and return on equity collapsed to -438.49%.
state Bank of Aurora	This is a state chartered bank located in Aurora, Minnesota. The FDIC Unique Number (UNINUM) is 5244. The bank failed on March 19^{th}, 2010. By December 31^{st} 2009, the earnings coverage ratio turned negative and return on assets collapsed to -6.56 %.
The RiverBank	This is a state chartered bank located in Wyoming, Minnesota. The FDIC Unique Number (UNINUM) is 6553. The bank failed on October 7^{th}, 2011. By September 30^{th} 2011, the tier 1 risk-based capital ratio fell below FDIC regulatory capital requirements and return on equity collapsed to -142.58 %.

Table 9: Qualitative Analysis of Bank Failures (Minnesota)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$
profit	1.025***	1.021***	1.031***	1.026***								
	(0.00723)	(0.00796)	(0.00453)	(0.00616)								
coverage	1.007	1.009	1.007	1.007	1.011		1.011*	1.009				1.011*
	(0.00458)	(0.00548)	(0.00494)	(0.00495)	(0.00697)		(0.00590)	(0.00591)				(0.00649)
allResloansNP	0.942**				0.930**	0.928**	0.922***					
	(0.0273)				(0.0321)	(0.0312)	(0.0289)					
EFFratio	0.872	0.782*									0.748*	
	(0.133)	(0.116)									(0.118)	
regCapital	1.091**	1.096***	1.085**	1.093**	1.113***	1.108***		1.108***			1.101***	1.108***
	(0.0395)	(0.0361)	(0.0356)	(0.0386)	(0.0375)	(0.0388)		(0.0393)			(0.0385)	(0.0391)
allowance		0.724*									0.676**	
		(0.120)									(0.127)	
(1/4)*FamilyResloansNP*			0.947**									
			(0.0234)									
liquiDity			0.999	0.999		1.002	0.999	0.996			1.000	0.998
			(0.00992)	(0.0107)		(0.0105)	(0.0115)	(0.0110)			(0.00894)	(0.0114)
size			0.971	0.962						0.975		0.965
			(0.0369)	(0.0425)						(0.0401)		(0.0430)
nonperFloans				0.926**								0.911**
				(0.0332)								(0.0404)
nopinc					1.218**	1.259**	1.270**	1.300***				
					(0.121)	(0.115)	(0.129)	(0.0906)				
eqCapital							1.038			1.036		
							(0.0387)			(0.0420)		
(1/4)*FamilyResloansDefaults*								0.795*				
								(0.102)				
roa									1.275**	1.383***	1.219**	1.222**
									(0.134)	(0.119)	(0.115)	(0.115)
loanDefaults									0.819			
									(0.125)			
loanConcentration									0.981***	0.985**		
									(0.00652)	(0.00682)		
σ	0.705**	0.688***	0.673**	0.692**	0.753	0.747*	0.841	0.738*	0.869	0.863	0.720**	0.749
	(0.110)	(0.0956)	(0.116)	(0.112)	(0.131)	(0.132)	(0.118)	(0.130)	(0.114)	(0.144)	(0.102)	(0.135)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	15	15	15	15	15	15	15	15	15	15	15	
Log pseudolikelihood	-44.267607	-43.663125	-46.248474	-45.085604	-46.143575	-47.073618	-50.405446	-47.124136	-54.423542	-54.422188	-45.53188	-46.79478
Akaike information criterion (AIC)	102.5352	101.3262	108.4969	106.1712	104.2871	106.1472	114.8109	108.2483	118.8471	120.8444	105.0638	109.5896

time ratios; robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 10: Lognormal AFT Regressions (Great Recession, Early Stages)

	(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	0.955***	0.958***	0.939***	0.952***								
	(0.0124)	(0.0138)	(0.0101)	(0.0110)								
coverage	0.974***	0.969***	0.971***	0.970***	0.961***		0.969***	0.971***				0.968***
	(0.00691)	(0.00735)	(0.00753)	(0.00708)	(0.00629)		(0.00743)	(0.00705)				(0.00716)
allResloansNP	1.145***				1.160***	1.190***	1.168***					
	(0.0461)				(0.0453)	(0.0494)	(0.0418)					
EFFratio	2.611**	3.375***									3.023***	
	(1.071)	(1.404)									(1.063)	
regCapital	0.853**	0.874**	0.833**	0.821**	0.814***	0.781***		0.795***			0.844***	0.800***
	(0.0598)	(0.0467)	(0.0613)	(0.0643)	(0.0542)	(0.0580)		(0.0506)			(0.0471)	(0.0584)
allowance		1.823***									2.253***	
		(0.403)									(0.545)	
(1/4)*FamilyResloansNP*			1.120									
			(0.0788)									
liquiDity			0.958**	0.954**		0.941***	0.950**	0.951**			0.954**	0.953**
			(0.0189)	(0.0198)		(0.0201)	(0.0213)	(0.0216)			(0.0183)	(0.0208)
size			1.170**	1.201***						1.162**		1.185***
			(0.0849)	(0.0819)						(0.0800)		(0.0745)
nonperFloans				1.270***								1.278***
				(0.0715)								(0.0692)
nopinc					0.669***	0.594***	0.619***	0.578***				
					(0.0676)	(0.0618)	(0.0897)	(0.0518)				
eqCapital							0.870*			0.890*		
							(0.0636)			(0.0548)		
(1/4)*FamilyResloansDefaults*								1.377**				
								(0.187)				
roa									0.728***	0.538***	0.616***	0.644***
									(0.0882)	(0.0636)	(0.0855)	(0.0747)
loanDefaults									1.644**			
									(0.366)			
loanConcentration									1.055***	1.039**		
									(0.0179)	(0.0188)		
γ	-0.000173	-0.000160	-0.000176	-0.000144	-0.000201	-0.000174	-0.000266	-0.000249	-0.000352*	-0.000314	-0.000142	-0.000173
	(0.000200)	(0.000205)	(0.000206)	(0.000218)	(0.000198)	(0.000212)	(0.000203)	(0.000198)	(0.000198)	(0.000207)	(0.000221)	(0.000219)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	23	23	23	23	23	23	23	23	23	23	23	
Log pseudolikelihood	-80.5193	-81.2447	-83.5229	-79.9001	-84.7103	-84.2275	-86.547412	-85.3573	-94.8037	-92.8515	-82.8258	-80.9183
Akaike information criterion (AIC)	175.0387	176.4896	183.0458	175.8001	181.4206	180.455	187.0948	184.7147	199.6073	197.7031	179.6516	177.8367

Hazard ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 11: Gompertz Survival Regressions (Great Recession)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$	$Ln(T)$
$profit$	1.043***	1.039**	1.061***	1.046***								
	(0.0126)	(0.0164)	(0.0113)	(0.0110)								
$coverage$	1.021**	1.028***	1.024**	1.023**	1.032***		1.029**	1.028**				1.028**
	(0.00982)	(0.00932)	(0.0117)	(0.0108)	(0.0110)		(0.0115)	(0.0124)				(0.0123)
$allResloansNP$	0.892***				0.877***	0.859***	0.853***					
	(0.0366)				(0.0364)	(0.0361)	(0.0380)					
$EFFratio$	0.442**	0.413***									0.432***	
	(0.159)	(0.131)									(0.130)	
$regCapital$	1.134*	1.126**	1.164**	1.178**	1.196***	1.229***		1.228***			1.149***	1.208***
	(0.0784)	(0.0559)	(0.0731)	(0.0794)	(0.0712)	(0.0725)		(0.0712)			(0.0584)	(0.0758)
$allowance$		0.583*									0.518***	
		(0.165)									(0.126)	
$(1/4)FamilyResloansNP$			0.915									
			(0.0509)									
$liquiDity$			1.034**	1.037**		1.050***	1.049***	1.042**			1.037**	1.040**
			(0.0171)	(0.0182)		(0.0167)	(0.0192)	(0.0193)			(0.0153)	(0.0194)
$size$			0.885**	0.872**						0.872**		0.880**
			(0.0520)	(0.0478)						(0.0557)		(0.0470)
$nonperFloans$				0.825***								0.812***
				(0.0444)								(0.0459)
$nopinc$					1.433***	1.586***	1.534***	1.670***				
					(0.151)	(0.160)	(0.208)	(0.142)				
$eqCapital$							1.130*			1.101		
							(0.0765)			(0.0886)		
$(1/4)FamilyResloansDefaults$								0.727*				
								(0.138)				
roa									1.520*	1.890***	1.541***	1.478***
									(0.336)	(0.180)	(0.197)	(0.157)
$loanDefaults$									0.669			
									(0.225)			
$loanConcentration$									0.946***	0.959**		
									(0.0159)	(0.0175)		
σ	0.754**	1.508***	0.745**	0.727**	0.767**	0.744**	0.826*	0.800**	0.871	0.842	0.740**	0.756**
	(0.0870)	(0.171)	(0.0873)	(0.0905)	(0.0935)	(0.0975)	(0.0949)	(0.0902)	(0.0960)	(0.103)	(0.0924)	(0.0947)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	23	23	23	23	23	23	23	23	23	23	23	
Log pseudolikelihood	-80.6646	-81.47247	-83.76728	-80.1727	-84.98585	-84.01326	-86.8239	-85.61789	-94.00431	-92.3797	-83.191811	-81.4520
Akaike information criterion (AIC)	175.3293	176.9449	183.5346	176.3455	181.9717	180.0265	187.6478	185.2358	198.0086	196.7594	180.3836	178.904

Hazard ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 12: Loglogistic Survival Regressions (Great Recession)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$	$h(t)$
profit	0.949***	0.953***	0.929***	0.942***								
	(0.0144)	(0.0156)	(0.0111)	(0.0122)								
coverage	0.975***	0.971***	0.974***	0.973***	0.964***		0.970***	0.973***				0.970***
	(0.00700)	(0.00744)	(0.00750)	(0.00703)	(0.00643)		(0.00797)	(0.00719)				(0.00729)
allResloansNP	1.152***				1.164***	1.193***	1.173***					
	(0.0492)				(0.0483)	(0.0519)	(0.0444)					
EFFratio	2.540**	3.368***									2.980***	
	(1.077)	(1.456)									(1.088)	
regCapital	0.840**	0.863***	0.821**	0.813**	0.802***	0.765***		0.780***			0.828***	0.789***
	(0.0631)	(0.0491)	(0.0634)	(0.0657)	(0.0568)	(0.0607)		(0.0531)			(0.0511)	(0.0601)
allowance		1.914***									2.410***	
		(0.431)									(0.592)	
(1/4)*FamilyResloansNP*			1.132*									
			(0.0833)									
liquiDity			0.958**	0.953**		0.941***	0.950**	0.951**			0.952**	0.952**
			(0.0192)	(0.0200)		(0.0208)	(0.0220)	(0.0223)			(0.0192)	(0.0211)
size			1.181**	1.215***						1.170**		1.195***
			(0.0892)	(0.0869)						(0.0843)		(0.0779)
nonperFloans				1.278***								1.288***
				(0.0763)								(0.0727)
nopinc					0.622***	0.549***	0.592***	0.541***				
					(0.0746)	(0.0658)	(0.105)	(0.0591)				
eqCapital							0.861*			0.881*		
							(0.0695)			(0.0596)		
(1/4)*FamilyResloansDefaults*								1.374**				
								(0.192)				
ROA									0.722***	0.519***	0.583***	0.596***
									(0.0905)	(0.0765)	(0.0897)	(0.0801)
loanDefaults									1.680**			
									(0.398)			
loanConcentration									1.055***	1.037**		
									(0.0184)	(0.0191)		
p	1.193*	1.214*	1.271**	1.272**	1.197	1.240*	1.107	1.163	1.037	1.076	1.236*	1.216
	(0.124)	(0.124)	(0.149)	(0.155)	(0.136)	(0.156)	(0.112)	(0.129)	(0.0900)	(0.109)	(0.143)	(0.147)
# of banks	359	359	359	359	359	359	359	359	359	359	359	359
# of failures	23	23	23	23	23	23	23	23	23	23	23	
Log pseudolikelihood	-80.307146	-80.930941	-83.01144	-79.314443	-84.54494	-83.828116	-86.842374	-85.444136	-95.549362	-93.382292	-82.383341	-80.616274
Akaike information criterion (AIC)	174.6143	175.8619	182.0229	174.6289	181.0899	179.6562	187.6847	184.8883	201.0987	198.7646	178.7667	177.2325

Hazard ratios; robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 13: Weibull Survival Regressions (Great Recession)

Figures

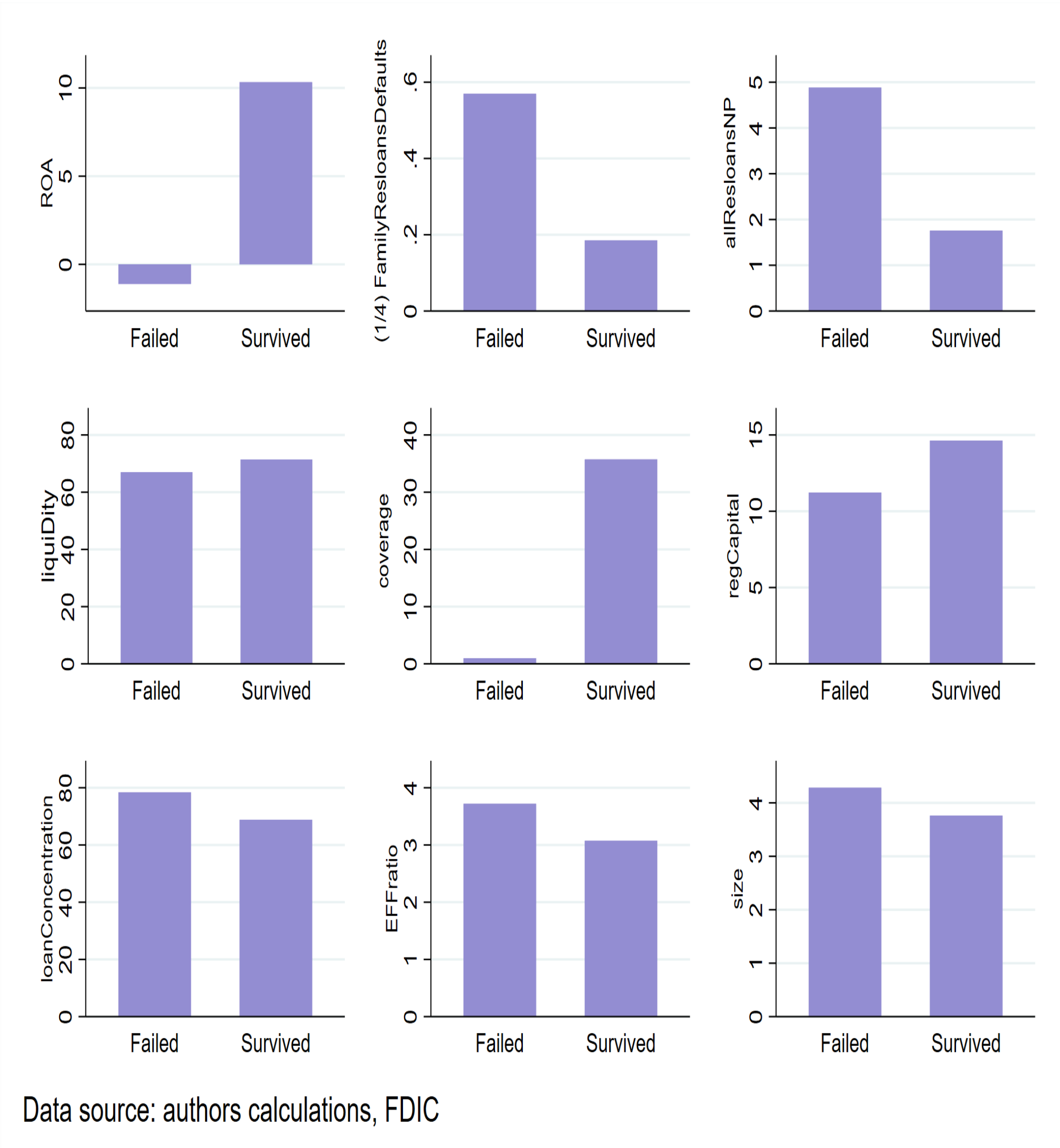

Figure 4: Key Bank-Specific Variables

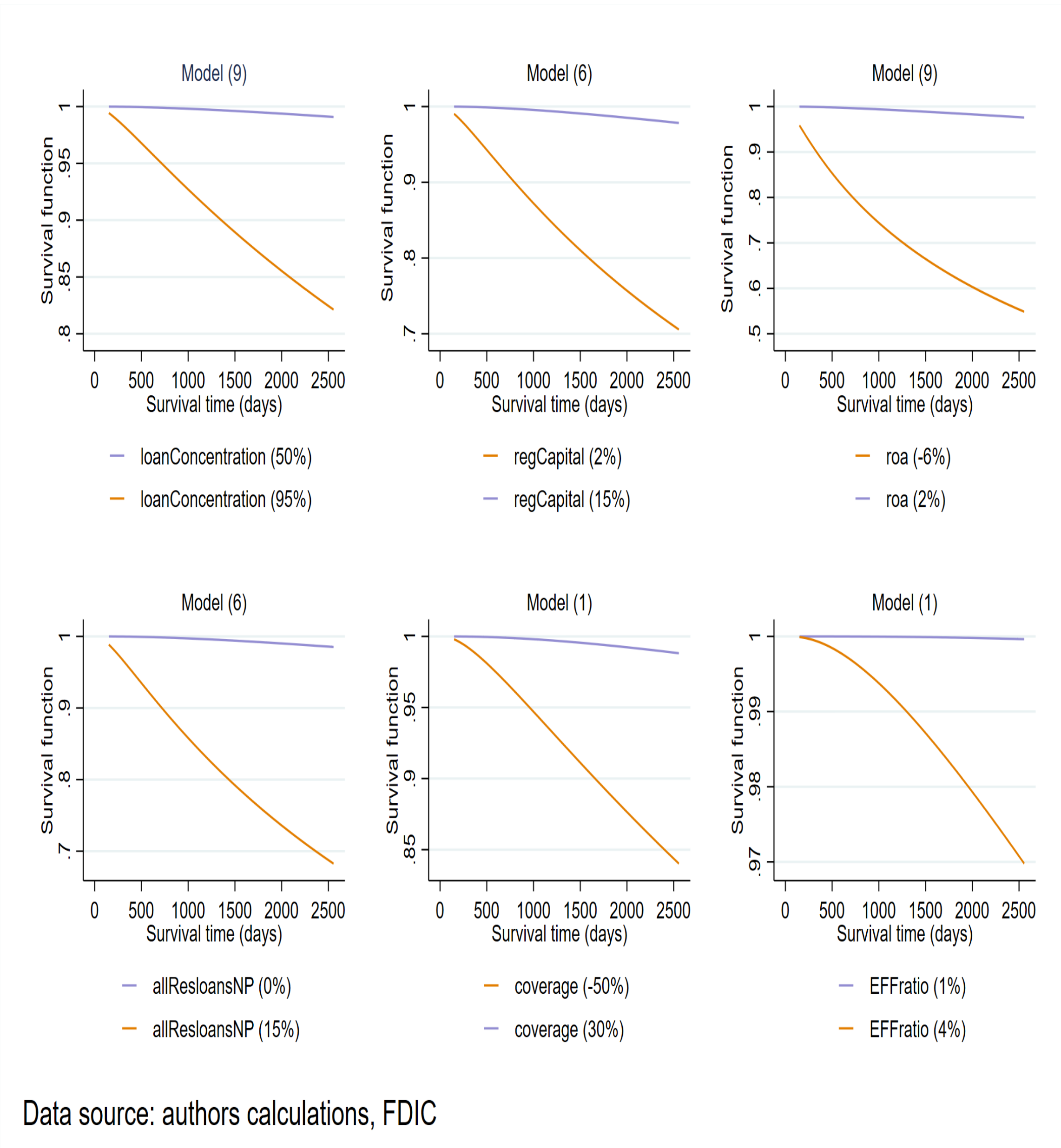

Figure 5: Key Survival Functions (Table 5)

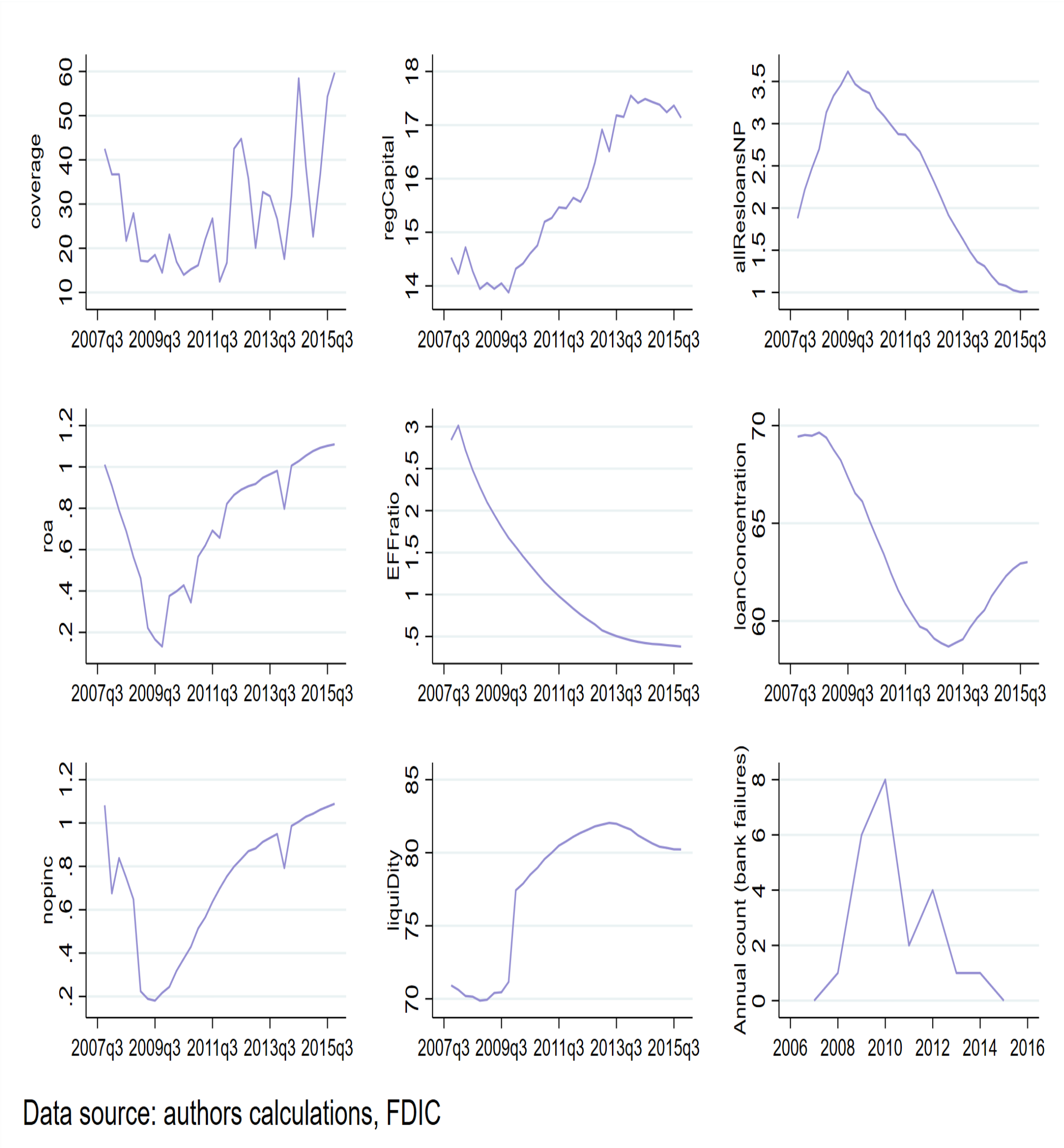

Figure 6: Quarterly Bank Data