Bank liability structure, FDIC loss, and time to failure: A quantile regression approach

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ABSTRACT

Previous empirical studies that aim to determine factors impacting the deposit insurer's loss arising from bank failures use standard econometric techniques that assume the losses are homogeneously driven by the same set of explanatory variables: However, deposit insurers are particularly concerned about high cost failures. If the factors driving high cost failures differ systematically from the determinants of low and moderate cost failures, an alternative way of estimation is required. Using a sample of more than 1,200 failures of financial institutions in the US between 1984 and 1996, we present a quantile regression approach that illustrates the sensitivity of the loss rate in different quantiles to our explanatory variables. The findings suggest that reliance on standard econometric techniques gives rise to misleading inferences and that loss rates are not homogeneously driven by the same factors across the quantiles. Rather, the funding structure plays a more important role for the high cost failures than it does for less expensive cases. We also find that liability structure affects time to failure and that uninsured depositors are a source of market discipline.

Keywords: bank liability structure; loss given default; market discipline; time to failure; quantile regression

JEL Classification: G21; G28; C41; C49

1. Introduction

Deposit insurers need to determine the losses arising to them from bank failures to adequately price deposit insurance and adjust the resources of the insurance fund accordingly. An ongoing discussion about the setting of the designated reserve ratio and the differentiation of pricing schemes by bank size motivates a recent proposal by the Federal Deposit Insurance Corporation (FDIC) to reform deposit insurance legislation. This debate underscores the continued need to investigate the determinants of losses caused by failures of financial institutions.

While a considerable body of literature exists on the factors impacting deposit insurers' losses, these studies are limited in two distinct aspects: First, they largely focus on the failed banks' asset composition and asset quality as key drivers for the loss incurred. However, the liability structure of a bank also has substantial bearing for the pricing of deposit insurance and therefore also impacts eventually deposit insurers' losses (Pennacchi, 2005). Moreover, Shibut (2002) underscores that the structure of deposits not only determines which depositors have to be compensated in case of failure, but it is furthermore an influential factor for an institution's risk taking behavior.[1] This, in turn, affects potential losses by the insurer. Second, existing work uses standard econometric techniques such as ordinary least squares that do not sufficiently account for the highly skewed distribution of the losses and the heterogeneous population of the failed institutions. Since deposit insurers are particularly concerned about high cost failures due to their possibly adverse impact on the insurance fund, it is pertinent to understand whether losses are homogeneously driven by the same determinants or if factors impacting resolution costs of expensive failures differ systematically from the factors observed in less expensive failures.

This paper contributes to the literature on losses arising to deposit insurers in three distinct ways: First, to differentiate between the factors driving high cost and low cost failures, we introduce a methodological advancement using quantile regression, also referred to as least absolute deviation regression, for a sample of more than 1,200 bank failures in the US during the period 1984 – 1996. This enables us to focus on the tails of the distribution of the loss variable and permits better inferences about the factors contributing to high cost failures. Moreover, employing quantile regression mitigates the problems associated with relying on a single measure of central tendency of the distribution of the loss rate and permits inferences about the relative importance of certain regressors at different points of the distribution of the loss rate. Therefore, quantile regression can be considered superior to the previously used estimation techniques since it provides more precise estimates of the impact of the determinants of losses. Second, we test as to whether bank liability structure plays a role in determining the loss when banks fail. Given the substantial evidence in the literature that ailing institutions tend to substitute uninsured deposits in the run-up to failure with insured deposits, thereby increasing the cost to the insurer, it is critical to focus

[1] King et al. (2006) highlight recent changes in the environment banks operate in. Deeper and wider financial markets offer new opportunities for depositories' liability management. They stress, *inter alia*, that banks are relying increasingly on non-core funding such as jumbo CDs, brokered deposits, and Federal Home Loan Bank (FHLBank) advances. To the extent to which these funds are insured or implicitly guaranteed by the government, e.g. brokered deposits below 100,000 USD and FHLBank advances respectively, they give rise to moral hazard and hence alter the risk profile of financial institutions.

on the extent to which different types of deposits impact upon loss. Finally, the new Basel Capital Accord highlights in Pillar 3 the role of market discipline to constrain risk-taking behavior of financial institutions. Thus, we hypothesize that depositories heavily reliant on uninsured deposits are likely to fail faster than institutions funded by other sources since holders of uninsured claims can respond to impending failure with withdrawal of funds. Alternatively, failing banks will attempt to substitute the cash outflows with insured deposits, thus increasing the deposit insurer's risk exposure. Our hypothesis bears important policy considerations: If such banks tend to fail faster, they would have to be subject to additional measures of prompt corrective action to prevent substitution of uninsured claims with insured deposits. We therefore test the effect of liability structure on time to failure, and estimate an accelerated failure time model with time-varying covariates for those institutions that failed during the period 1984 – 1996. To our knowledge, the nexus between market discipline and liability structure on the one hand and time to failure on the other has not yet been subject to extensive econometric analysis.

We show that the evolution of the loss rate, defined as the ratio of loss incurred by the FDIC divided by total deposits of the failed institution, exhibits considerable variation across different quantiles of the distribution. Our quantile regression results illustrate that the loss rates in different quantiles show significantly different sensitivities to the utilized set of explanatory variables. In particular, Fed funds purchased, real estate owned, depositor preference law, capitalization, unearned income and loans to individuals exhibit varying impact on the loss rate as we move up the distribution. To this extent, our results extend recent work by the FDIC that provides circumstantial evidence for differences of medians of a set of certain balance sheet and income statement variables between low cost and high cost failures (Shibut et al., 2003).[2]

We find that the ratio of Fed funds purchased to total deposits is negatively associated with the loss rate at the lower tail of the distribution. However, Fed funds purchased significantly increase FDIC loss for the high cost failures. This finding is robust to the inclusion of control variables capturing asset composition and asset quality of failed institutions. In terms of the magnitude of the effect of the variables that capture liability structure, our results indicate that the ratio of Fed funds purchased to total deposits has a greater impact on the loss rate for costly failures than most of the previously utilized variables that capture asset quality. This result underscores the importance of considering bank liability structure when analyzing loss rates to deposit insurers.

Likewise, the variables that capture presence of depositor preference law, the ratios of loans to individuals, real estate owned, and total equity capital to total deposits exhibit highly nonlinear relationships with the loss rate and substantiate that an alternative to standard estimation procedures is required when analyzing deposit insurers' loss given default. In addition, our quantile regressions also highlight that certain variables that capture the loan portfolio change the sign of the coefficient as they move along the distribution, suggesting that reliance on estimates obtained with standard econometric techniques gives rise to misleading inferences. Regarding the determinants that drive losses for high cost failures, we show that high cost failures are particularly driven by Fed funds purchased, time and savings deposits, real estate owned, unearned income, and C&I loans.

[2] Shibut et al. (2003) divide FDIC loss by total assets and classify failures with resolution cost below 12 percent of assets as low cost failures.

Estimating an accelerated failure time model with time-varying covariates, we demonstrate that Fed funds purchased, brokered deposits below 100,000 USD, transactions deposits and time and savings deposits shorten time to failure. This result is again robust to controlling for the impact of asset quality, capital structure, earnings and other measures of liquidity. Our finding underscores that uninsured depositors are a source of market discipline. Moreover, the significantly inverse association of brokered deposits below 100,000 with failure time suggests that seriously troubled institutions engage in liability shifting; this is consistent with previous studies that find evidence for the substitution of uninsured liabilities with insured deposits. These results provide a rationale for further strengthening disclosure of the levels of insured and uninsured deposits in financial institutions to enhance depositor discipline.

The plan of the paper is as follows: Section 2 reviews related work and Section 3 presents an overview on the methodology employed. The econometric analysis is provided in Section 4 and Section 5 offers concluding remarks and avenues for future research.

2. Related Work

Our survey of related studies draws from two distinct strands in the literature. We first focus on work regarding the losses in bank failures and then discuss the link between depositor preference laws, depositor discipline and the cost of bank failures.

A number of studies model the loss on assets as a function of the failed banks asset composition, its asset quality and a set of additional variables. Bovenzi and Murton (1988) draw upon a sample of bank failures between 1985 and 1986 in the US and report an average loss rate of 33 percent of assets. Using ordinary least squares regression analysis, they additionally highlight the role of uncollected income, and geographic differences in explaining the loss on assets. Barth et al. (1990) and Blalock et al. (1991) examine resolution costs of thrift failures. Barth et al. (1990) employ a Tobit model for the period 1984 – 1988 and present evidence that tangible net worth, asset quality and core deposits as a proxy for franchise value are significant determinants of the deposit insurer's loss. Similarly, Blalock et al. (1991) confirm that asset mix is a major determinant of resolution costs. James (1991) presents an examination of bank failures during the period 1985 – 1988 and reports an average loss rate of 30 percent of the failed bank's assets. He moreover underscores the relative importance of unrealized losses, the determinants of charter value and type of resolution procedure for the loss rate. Brown and Epstein (1992) extend these studies and disaggregate the loss on assets into different asset categories. Using detailed information on receivership recoveries, they illustrate that the loss on assets varies over different asset categories and over time to reiterate that portfolio composition is a key determinant of the loss rate.[3] Osterberg and Thomson (1994) build on previous work and conclude that the dollar value of resolution costs is not only a function of asset quality. Employing data for US bank failures between 1986 and 1992, they find that loss is furthermore influenced by bank size, fraud and off-balance sheet items, and that brokered deposits tend to decrease loss. Recent work by McDill (2004) drawing upon a large sample of failures between 1984 and 2002 analyses the effect of the business cycle on resolution

[3] Note that Brown and Epstein (1992) draw upon information regarding bank liability structure to predict losses to the insurance fund.

costs. She contemplates that the deposit insurer's loss increases in a sluggish macroeconomic environment. Corroborating the role of asset composition and franchise value highlighted in previous studies, she additionally finds that the pool of potential acquirers of a failed bank is an influential factor for the loss rate. Bennett et al. (2005) study the impact of Federal Home Loan Bank (FHLBank) advances on expected losses to the Bank Insurance Fund (BIF) and point out that subordination of FDIC claims to FHLBank advances increases both probability of default and loss given default.[4]

A related body of literature focuses on the role of depositor preference laws, designed to reduce the cost of failures to the deposit insurer.[5] Hirschhorn and Zervos (1990) put forward that nondeposit creditors might respond with collateralizing their claims when depositor preference laws are enacted. The authors' empirical analysis of thrift institutions in the US subsequently confirms that large proportions of collateralized claims contribute to higher cost of failures, giving rise to unintended outcomes from a deposit insurer's perspective. On the other hand, Osterberg (1996) substantiates that depositor preference laws decrease resolution costs for failures of commercial banks between 1984 and 1992. However, he also discusses offsetting effects arising from collateralization of claims by nondeposit creditors. Marino and Bennett (1999) analyze failures of six large US commercial banks between 1984 and 1992 to investigate if depositor preference law affects large institutions differently due to their greater dependency on nondeposit and foreign liabilities. Given that depositor preference law provides uninsured and unsecured claimants with an incentive to protect themselves from losing money, an ailing bank's liability structure is likely to change as it approaches failure. While the authors do not offer an econometric analysis of the association between liability structure, depositor preference law and FDIC loss, they illustrate that liability structure experiences considerable changes prior to failure, whereby uninsured and foreign deposits decrease substantially.

Considerable effort has gone into the analysis of how depositors discipline financial institutions.[6] Holders of unsecured claims have an incentive to monitor risk-taking behavior of banks and discipline them by demanding appropriate risk premiums, collateral or by withdrawing their funds. Goldberg and Hudgins (1996, 2002) investigate the holdings of uninsured deposits at savings and loan associations over different sampling periods and illustrate that failing institutions experience declines in uninsured deposits. This result is aligned with work by Jordan (2000), who analyses liability structure of failing banks in New England in the early 1990s. Billet et al. (1998) study the impact of ratings downgrades as a proxy for increased risk in financial institutions and report that downgraded banks increasingly raise insured deposits. This not only increases the deposit insurer's exposure but also suggests that market discipline insufficiently polices banks against risk taking behavior since risk based capital standards and risk based deposit insurance both fail to

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[4] Note again that their loss estimates require knowledge of the existing liability structure of the bank under consideration.

[5] The Depositor Preference Act of 1993 was designed to shift the burden of bank failure from taxpayers to uninsured depositors. It gives depositors claims on a failed institution's assets superior to those of general creditors. Several states had depositor preference laws in place prior to 1993. For detailed expositions of depositor preference see Osterberg (1996) and Marino and Bennett (1999).

[6] We constrain our review of related studies to the direct link between depositor discipline and financial institution's response to increases in risk. Some other studies investigate whether investors can discriminate between the risks undertaken by US banks (Flannery and Sorescu, 1996) and how subordinate debt impacts upon risk-taking behavior of financial institutions (Blum, 2002).

consider banks' liability structure. Thus, the evidence that ailing institutions substitute uninsured deposits with insured deposits suggests the undermining of market discipline. Furthermore, this phenomenon is bound to increase the deposit insurer's loss if the troubled bank eventually defaults. Park and Peristiani (1998) focus on the implications of risk for price and quantity of uninsured deposits in a sample of thrifts. Institutions with a higher probability of failure are found to offer higher interest rates on uninsured funds. Due to their increased risk profile, such thrifts however attract smaller amounts of uninsured deposits. These results are consistent with the view that uninsured depositors are a source of market discipline. Recent work by Maechler and McDill (2006) investigates how banks respond to depositor discipline. The study argues that bank behavior and depositors' response is a jointly determined process and provides evidence that depositors constrain bank risk-taking behavior. In contrast to Park and Peristiani (1998), their results indicate that weak banks cannot raise uninsured deposits by increasing the interest rates offered, whereas sound institutions are able to do so. Using individual bank-level data, Davenport and McDill (2006) focus on the behavior of fully insured depositors prior to the failure of Hamilton Bank and uncover that insured depositors are also a source of market discipline. They present evidence that the total balance of insured deposits that exited prior to the failure exceeds the amount of uninsured deposits withdrawn.

3. Data and Methodology

Our initial sample consists of 1,665 failed banks that were resolved by the BIF during the period 1984 – 1996.[7] Since failing institutions have been resolved by the FDIC through various different types of transactions, we follow the FDIC's bank failure database[8] and classify failure as either of the following instances having occurred: assisted merger, purchase and assumption, transfer and assumption of insured deposits, re-privatization, closing and reopening, or depositor payoff. A bank is also classified as having failed if it was subject to the management consignment programme. Missing values for some explanatory variables limit the dataset to 1,227 failed bank observations that we use for our econometric analysis. Bank specific data are taken from the Quarterly Report of Condition and Income (Call Report) prior to failure. In instances where no final report was available, we use the last available call report. Information on the cost incurred by the FDIC was obtained from the FDIC's database on bank failures. This information is an estimate of the FDIC's resolution cost calculated as the difference between net cash outlays and the estimated discounted net recovery on any assets remaining in the receivership's books. In order to account for problems caused by inflation and asset size, we use the loss rate calculated as FDIC resolution costs divided by total deposits. We normalize the loss by total deposits since this denominator is close to the assessment base employed by the FDIC to price deposit insurance.[9] Notice that it is more common in the literature to use loss rates rather

[7] The sampling period is constrained by the Federal Funds variable. This variable is not available on the Quarterly Report of Condition and Income (Call Report) for the period 1997 – 2003 and we therefore sample the failed institutions up to 1996 only.

[8] http://www.fdic.gov/bank/individual/failed/index.html

[9] Several studies normalize loss by total assets (e.g. Shibut et al., 2003; McDill, 2004; Bovenzi and Murton, 1988)

than the absolute dollar value of losses (see e.g. Shibut et al., 2003; McDill, 2004; Bovenzi and Murton).[10]

Explanatory variables are chosen due to their importance in the prediction of the FDIC loss rate found in previous studies and by our aim to establish as to whether certain types of deposits are a key determinant for the loss rate. Explanatory variables utilized in the loss equations are also normalized by total deposits. *Table 1* presents summary statistics for our dataset.

[TABLE 1]

The average loss rate for the full sample is 21.5 percent of total deposits. Our detailed breakdown illustrates a large degree of variation across the quantiles. While the loss rate is 2 percent of total deposits for the .05 quantile, failures at the upper tail of the distribution cost the insurer more than 45 percent of total deposits. The most expensive failure had a loss rate of more than 182 percent of total deposits. This suggests the presence of outliers, a phenomenon that can be better accommodated by quantile regression than by other types of estimators. We consider 'expensive failures' as those failures whose loss rates lie at the 90th quantile and above of the distribution. The sample also shows that the failed banks have a mean of total assets of 96m USD, with the largest failures exceeding well over 9.8bn USD. A few variables stand out: Total assets during the 4 quarters prior to failure decline on average 13.8 percent, indicating that troubled depositories shrink considerably in the year before failure. Unsurprisingly, the failed banks exhibit excessively high degrees of inefficiency, as illustrated by the ratio of cost to operating income above 1. The ratio of real estate owned to total deposits is on average 4 percent. Real estate owned has been found in previous studies to be an appropriate predictor for resolution costs since this category contains properties obtained by foreclosure. Likewise, the ratio of income earned but not collected figured prominently in previous work because of its indicative character for loans that have not been written off. This ratio has a mean of 1.3 percent. In terms of the funding structure, the average ratio of Fed funds purchased to total deposits is .7 percent, whereas the ratios of small and large brokered deposits are .6 and .4 percent of total deposits. Failed banks have on average a ratio of 24 percent of transactions deposits to total deposits. Time and savings deposits represent 84.9 percent of total deposits.[11]

We next turn to a preliminary analysis and examine correlation between the loss rate and our explanatory variables in *Table 2*. The loss rate shows statistically significant correlation with numerous variables: Bank size, measured by the log of total assets, higher levels of capitalization, and the ratio of transaction deposits to total deposits are negatively associated with the insurer's loss rate. Furthermore, the correlation matrix confirms the positive correlation between many variables previously found to be significant drivers for the deposit insurer's loss rate. The ratios of real estate owned, uncollected income from loans, loans past due and C&I loans to total deposits reveal the anticipated positive sign. Moreover, agricultural loans are likewise positively associated with the loss rate. The

[10] It is noteworthy to mention that larger institutions tend to exhibit lower loss rates (Shibut, 2002). Ongoing research will therefore replace the dependent variable with the absolute dollar value of losses as in James (1991). Furthermore, it is intended to normalize the variables by total assets to enable direct comparison of the results obtained in this study with previous work.

[11] We do not include a variable for demand deposits to total deposits as our preliminary tests indicate perfect correlation between time and savings deposits and demand deposits.

variables that capture funding structure also suggest a link between the loss rate and the type of deposits. Time and savings deposits, as well as the two variables that capture brokered deposits are significantly positively correlated with the loss rate. This indicates that it is important to consider such variables in a multivariate analysis of the deposit insurer's loss given default. We turn to this question in Section 4 below.

[TABLE 2]

3.1 Cost of Failure

Our sample consists of different types of banks (community banks, savings banks, commercial banks, etc.) that pursue different types of business activities. Brown and Epstein (1992) point out that a failing bank heavily concentrated in commercial loans is therefore likely to exhibit larger loss rates than an institution that primarily engages in retail lending activities.[12] Moreover, our sample exhibits large variation with respect to bank size. Bank size, as illustrated by Marino and Bennett (1999), in turn, influences bank liability structure, which ultimately affects the dependent variable in our analyses. Thus, numerous factors suggest that the loss rates vary considerably across the distribution and that a regression technique is required that helps gain detailed insights as to whether the factors driving losses differ systematically across the distribution of the loss rate.

We start analyzing the link between the loss rate and a set of explanatory variables using ordinary least squares regression, similar to the approach pursued in previous work. We model the loss rate as

$$y_i = \alpha + \beta x_i + u_i \tag{1}$$

whereby y_i denotes the loss rate for bank i, α is the constant term and, β captures the coefficients to be estimated for the explanatory variables x_i; u_i is the error term. However, since the loss rate is only observed if it is non-negative, the error u_i term would not be normally distributed. This implies that employing an OLS estimator is unsuitable and that the use of a Tobit model that accounts for the censoring is more appropriate (Barth et al., 1990) since bank failures may be resolved at zero cost to the FDIC. We use these initial analyses for comparison with previous studies and as a benchmark for our quantile regressions.

In order to account for the skewed distribution of the loss rate and draw more appropriate inferences about the sensitivity of the loss rate at the tails of the distribution, we use the conditional quantile regression estimator developed by Koenker and Bassett (1978). Given the heterogeneity of our dataset, conditional quantile regression not only permits drawing more precise inferences about the impact of regressors at certain points of the distribution of the loss rate but also offers an estimation procedure more robust to departures from normality because linear estimators would more likely produce inefficient and biased estimates. Since we are not aware of any study in the banking literature employing quantile regression, we review the key characteristics of this technique below. [13]

[12] Brown and Epstein (1992) compute the loss rate as loss divided by total assets.

[13] Quantile regression has been utilized in labor economics, demand analysis, in empirical finance in the literature on value at risk and in ecology and biostatistics. For recent overviews of applications of quantile

While classical linear regression estimates conditional mean functions, quantile regression permits estimating conditional quantile functions, i.e. models in which quantiles of the dependent variable are expressed as functions of a set of explanatory variables (Koenker and Hallock, 2001).[14] Quantile regression is appropriate when a large degree of variation in the data suggests that there may be more than a single slope parameter describing the relationship between the dependent variable and the regressors. Thus, quantile estimation goes beyond linear regression in that it gives a more complete picture of the effect of a set of regressors on the different quantiles of the dependent variable.

Given that the θ th quantile of a conditional distribution of y_i is linear in x_i and assuming (y_i, x_i), $i = 1,...,n$ is drawn from the population of failed institutions whereby x_i is a $K \times 1$ vector of explanatory variables, we write the conditional quantile regression model as

$$y_i = x_i'\beta_\theta + u_{\theta i} \tag{2}$$

$$Quant_\theta(y_i|x_i) \equiv \inf\{y : F_i(y|x)\theta\} = x_i'\beta_\theta \tag{3}$$

$$Quant_\theta(u_{\theta i}|x_i) = 0 \tag{4}$$

where $Quant_\theta(u_{\theta i}|x_i)$ captures the θ th conditional quantile of y_i on the regressor vector x_i. The expression β_θ is the vector of parameters to be estimated for different quantiles θ, lying in the range (0;1). The error term u_θ is assumed to have a continuously differentiable c.d.f. $F_{u\theta}(.|x)$ and a density function $f_{u\theta}(.|x)$. The entire distribution of y conditional on x can be traced by moving along the (0;1) interval of θ. To estimate β_θ we proceed as follows and minimize

$$\min \sum_{i}^{n} \rho_\theta(y_i - x_i'\beta_\theta) \tag{5}$$

whereby $\rho_\theta(u)$ is defined as follows

$$\rho_\theta(u) = \begin{Bmatrix} \theta u & if\ u \geq 0 \\ (\theta - 1)u & if\ u < 0 \end{Bmatrix}. \tag{6}$$

This minimization problem can be solved according to Koenker and Bassett (1978) using linear programming techniques. The covariance matrix of the parameter vector can be obtained using bootstrap methods to calculate standard errors and confidence intervals. We use this quantile estimator to investigate as to whether our assertion of systematic differences of the impact of regressors on the loss rate is correct in Section 4.1. However, this quantile regression estimator does not allow for censoring. Due to the fact that the

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regression we refer the interested reader to the surveys by Koenker and Hallock (2001) and Cade and Noon (2003).

14 Quantiles divide the cumulative distribution function of a random variable into a given number of equally sized segments. Quantiles are the general case of certain other ways of splitting a population into segments. For instance, quartiles divide a population into four segments with equal proportions of the reference population in each segment, and the median divides the population into two equally sized segments (Koenker and Hallock, 2001).

FDIC did not incur losses for some failures, we also utilize a censored least absolute deviations estimator for regression quantiles to adjust for the non-negativity of our dependent variable. [15]

We employ Powell's (1986) estimator for censored regression quantiles, which is an extension of Powell's (1984) censored least absolute deviation estimator that centers on the median of the dependent variable. These two regression techniques are generalizations of Koenker and Bassett's (1978) least absolute deviations estimator. Powell (1986) shows that modifying his median estimator for the censored regression model can yield a consistent and asymptotically normal estimator for censored regression quantiles that includes the median estimator for the censored model as a special case. The general censored regression model can be written as

$$y_i = \max\{0, x_i'\beta_0 + u_i\}, \qquad i = 1,\ldots,N, \tag{7}$$

where we observe the dependent variable y_i and the vector of explanatory variables x_i for each individual i but the parameter vector β_0 and the error term u_i cannot be observed. Powell (1984) shows that his least absolute deviation estimator for the median of the censored regression model minimizes the sum of absolute deviations of y_i from $\max\{0, x_i'\beta_0\}$ over all β in a parameter space B. The estimator, denoted as $\hat{\beta}_i$, minimizes the function

$$S_i(\beta) \equiv (1/N)\sum_{i=1}^{N}\left| y_i - \max\{0, x_i'\beta\} \right| \tag{8}$$

over all β in the parameter space B. The estimator is computed using methods for nonlinear programming. However, since minimizing this function only yields an estimate for the median, the technique needs to be extended to other quantiles for our purpose. To obtain an estimator for censored regression quantiles other than the median, we let θ denote the θth quantile of y_i for $\theta \in (0,1)$. Following again Koenker and Bassett (1978) who show that the θth quantile of a random variable Z minimizes $E[\rho_\theta(Z-b) - \rho_\theta(Z)]$ over b, where

$$\rho_\theta(\lambda) \equiv [\theta - 1(\lambda < 0)]\cdot\lambda, \tag{9}$$

Powell (1986) illustrates that minimizing the function

$$Quant(\beta;\theta) \equiv (1/N)\sum_{i=1}^{N}\rho_\theta(y_i - \max\{0, x_i'\beta\}) \tag{10}$$

over all β in a parameter space $B(\theta)$ yields a consistent estimator for $\beta_0(\theta)$ for the coefficients in the different quantiles θ in the range (0;1).[16]

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[15] Censoring applies to 0.4 percent of the failed banks in our sample.

[16] For a detailed exposition of the proofs for consistency and normality of the censored least absolute deviation (median) estimator and the censored regression quantile estimators see Powell (1984, 1986).

3.2 Timing of failure

To test the effect of funding structure on time to failure, we utilize an accelerated failure time (AFT) model with time-varying covariates. Such models are called 'accelerated failure time models' because the effect of the independent variables is to rescale time, i.e. to accelerate or decelerate time to failure.

We formalize time until failure as a probability density function of time *t*. A convenient way of describing survival of a depository past time *t* is through its survivor function

$$S(t) = P(T \geq t) \tag{11}$$

which equals one minus the cumulative distribution function of *T*. We then can compute the conditional probability of closure within the time interval *t* until *t + h*, given survival until time *t*, as

$$P\{t \leq T \langle t \langle t + h | T \geq t\}. \tag{12}$$

This probability can be divided by *h*, to calculate the instantaneous rate of failure, i. e. the average probability of leaving per unit time period over the interval *t* until *t + h* such that the hazard function can be written as

$$\lambda(t) = \lim_{h \downarrow 0} \frac{P\{t \leq T \langle t \langle t + h | T \geq t\}}{h} = \frac{-d \log S(t)}{dt} = \frac{f(t)}{S(t)}. \tag{13}$$

Accelerated failure time models are written in the form

$$\ln(t_j) = x_j \beta_x + \tau_j \tag{12}$$

where $\ln(t_j)$ is the log of time to failure, x_j denotes our explanatory variables, β_x are the parameters to be estimated and τ_j is a random variable that follows a distribution. Thus, to estimate the model, we need to determine the distribution of τ_j and specify τ_j to follow the log-logistic distribution. This distribution is rather flexible since it permits two inflexion points for the hazard function. The log-logistic distribution was utilized in previous work on bank failures and bank exit (Cole and Gunther, 1995; DeYoung, 2003). The parameters of interest can be obtained using maximum likelihood estimation technique.

The sampling period for this analysis starts in 1983 and we use the same set of 1,227 failed institutions that underlie the estimation of the loss rate. The starting date 1983 is chosen to assert that we have at least four quarterly observations for the banks that fail during the first quarter in 1984. We sample this set of institutions until 1996 when the last bank remaining in the dataset fails. The minimum duration is therefore *t=4* if the bank failed in the first quarter of 1984 and the maximum duration is *t=56* if the institution failed in the last quarter 1996. This approach enables us to draw upon a large sample with 23,986 bank-quarter observations. Our setup of the dataset differs from previous models of time to failure in that we do not include nonfailed depositories in our analysis.[17] This is due to our interest in the question whether dependency on certain types of deposits accelerates or decelerates time to failure of troubled institutions.[18] Our modeling approach is appropriate since the deposit insurer needs to closely monitor the risks arising in particular from ailing depositories to the insurance fund. Including sound institutions would therefore introduce noise into our estimates. Moreover, policy considerations also play a role: knowledge of the factors that impact time to failure of troubled banks helps obtain better estimates of when the losses occur. This enables the insurance fund to adjust its resources more appropriately.

4. Empirical Results

We report the results for the analysis of the effect of funding structure on the loss rate in Section 4.1 and discuss the impact of funding structure on time to failure in Section 4.2.

4.1 Bank funding structure and cost of failure

Table 3 presents the results obtained using ordinary least squares and Tobit models to enable comparison with previous studies. We estimate four setups for the loss equation with an OLS estimator in Specifications (1) – (4) and use the Tobit model in columns (5) – (8). Specifications (1) and (5) draw upon a parsimonious set of variables previously found to be significant determinants of the deposit insurer's loss. All our regressions include year dummies and region dummies to control for the macroeconomic environment.[19] We provide details on the coding of the region dummies in the Data Appendix. Measures for liability structure are introduced in Specification (2) and (6). For instance, we separate small and large brokered deposits since the small brokered deposits are protected by deposit insurance. Additional control variables are used in Specifications (3) and (4), and (7) and (8) to test for possible omitted variable bias. The measure of bank size, log of total assets, is adjusted for inflation using the GDP deflator.

[17] Commonly utilized duration models to predict bank failure often include failed and nonfailed institutions (e.g. Lane et al., 1986; Whalen, 1991). According to Cole and Gunther (1995), these studies suffer from the severe shortcoming in their assumption that all banks in the sample eventually fail. This assumption does not hold in reality and those models therefore cannot distinguish between the factors driving failure and those that drive time to failure.

[18] Oshinsky and Olin (2005) provide an in-depth analysis of the factors that determine whether troubled institutions recover, merge, continue as a problem bank or eventually fail. They report that the Office of the Comptroller of the Currency (OCC) highlights reliance on volatile liabilities as important cause of bank failure. However, Oshinsky and Olin's (2005) empirical analysis suggests that failing banks do not experience increases in volatile liabilities. This result may be due to regulatory reasons. The Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) restricts the use of brokered deposits of critically undercapitalized depositories. Thus, exploring the nexus between liability structure and its implications for the timing of failure of ailing banks is a fruitful avenue for research.

[19] This is due to the fact that McDill (2004) finds evidence for higher loss rates in a sluggish macroeconomic environment. Note that using region and time dummies instead of selecting individual macroeconomic variables is a tough test as regards to the robustness of the effect of the other explanatory variables. This is due to the fact that region dummies soak up any variation arising from regional differences and due to the fact that time dummies account for any changes arising from the economic cycle.

Specification (1) confirms findings by other authors that bank size and higher capitalization tend to decrease FDIC loss, whereas higher ratios of real estate owned, loans past due and income earned but not collected to total deposits feed into the deposit insurer's loss (e.g. Osterberg and Thomson, 1994). All variables are significant at the one percent level. Moreover, total asset growth over the four quarters prior to failure also increases the loss rate and assumes significance at the five percent level. In terms of the magnitude of the coefficients, the proxy for uncollected income dominates the other coefficients, this is consistent with the results obtained by McDill (2004), Osterberg and Thomson (1994) and Bovenzi and Murton (1988).

In Specification (2) the ratio of transactions deposits to total deposits enters with a negative sign and is highly significant. This finding can be explained by the fact that transactions deposits resemble core deposits, often used as a proxy for the franchise value of financial institutions. This result is aligned with Osterberg and Thomson (1994) and James (1991). None of the other four regressors that capture bank funding structure becomes significant in this setup. In particular, we do not find a significant role of brokered deposits, a finding that contrasts with Osterberg and Thomson (1994) who contend that brokered deposits are a source of market discipline. Our result may be due to the longer sampling horizon in the present study: critically undercapitalized institutions face restrictions regarding the use of brokered deposits since FDICIA became effective and therefore may not be able to make excessive use of this type of funding.

Controlling for additional variables in Specification (3) does not change our inferences. We find that C&I loans significantly increase the loss rate at the one percent level, consistent with work by McDill (2004). The final specification (4) includes a dummy variable for the effect of depositor preference law on the loss rate to test whether the law meets its objective of decreasing resolution costs. The dummy takes on the value one if depositor preference law was in place at the time of failure or zero otherwise. This dummy variable takes account of the fact that some states already had depositor preference laws in place prior to the enactment of national depositor preference. Additional details about enactment of depositor preference are given in the Data Appendix. The variable enters with the anticipated negative sign and assumes significance at the ten percent level. This result is indicative for a weakly decreasing effect of the law on the loss rate. Including this additional regressor does not considerably affect magnitude and significance of the other variables. The adjusted R^2 and the Akaike Information Criterion indicate that Specification (4) is the most appropriate setup for the model.

Our Tobit models in Specification (5) – (8) adjust for the left censoring in the loss rate. The Tobit models widely corroborate the results obtained with the OLS procedure. Merely the ratio of brokered deposits below 100,000 USD to total deposits becomes weakly significant with a positive coefficient in Specification (5). However, the effect is rendered insignificant upon controlling for additional variables that capture composition of the loan portfolio. In Specification (7) and (8), the ratio of time and savings deposits to total deposits enters the equations significantly at the five ten and five percent level with a positive sign. This variable captures insured and uninsured deposits, in particular large CDs and money market deposit accounts. This result indicates that it is important to account for the funding structure when modeling loss rates to the deposit insurer. Using the Tobit model does not impact the conclusions obtained with the OLS estimator regarding the other controls variables. We therefore do not discuss these results in greater detail for reasons of brevity.[20]

As alluded to previously, estimates obtained from OLS and Tobit only approximate the central tendency of the distribution and are unsuitable to account for heterogeneous data with outliers. Furthermore, deposit insurers and bank supervisors are particularly concerned about high cost failures and have therefore a vested interest in the factors driving losses for those costly failures. We therefore employ quantile and censored quantile regression models that aim to overcome the limitations of OLS and Tobit to obtain better estimates for the determinants of the factors for high cost failures. We present the results using quantile and censored regression estimators in *Table 4* and *Table 5* respectively.[21]

In order to evaluate the effect of our explanatory variables at different quantiles of the distribution on the loss rate, we estimate quantile regression models to obtain coefficients for the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantile. The estimation is based on the regression setup of Specifications (4) and (8) in *Table 3*. This regression setup includes additional control variables for the composition of the failed banks' loan portfolios and also takes account of depositor preference law. We report the results in *Table 4* and also include the coefficients obtained with the OLS estimator for comparability. Figures 1 a) – 1 p) plot the estimated coefficients of interest obtained with the quantile estimator against the different quantiles as the solid curve. These point estimates can be interpreted as the impact of a one-unit change of the regressor on the loss rate with the other covariates held constant. Thus, the vertical axis indicates the effect of the regressor and the horizontal line represents the quantile θ scale. The gray shaded area shows a 95 percent confidence band based on bootstrapped standard errors for the quantile estimates and the dashed line represents the OLS estimator.

[TABLE 4]

[FIGURE 1 a) – p)]

Table 4 provides an illustration of the differences in magnitude, significance and change in direction of the relationship between the loss rate and our regressors as we move along the distribution. The effect of bank size, measured by the deflated log of total assets, shows that the decreasing effect of size on the loss rate is stronger for more costly failures and remains significant across all quantiles. This result is aligned the findings by Oshinsky (1999) and McDill (2004). These studies report smaller loss rates with increasing bank size. This can

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[20] McDill (2004) highlights that relying on Call Report data creates difficulties when failures are caused by fraud since the Call Report might be not informative. She uses confidential FDIC data and the publicly known fraud cases mentioned in Gup (1995) to adjust her sample accordingly. We therefore perform two additional robustness tests to control for the influence of fraud on bank failure. We use the publicly available information on instances of fraud in Gup (1995) and remove those failures from our dataset, and additionally re-run our analyses with a dummy variable that takes on the value one if the failure is due to fraud or zero otherwise. Both robustness tests do not impact the inferences drawn with either standard econometric techniques or the different quantile regression estimators. Moreover, the dummy variable for fraud remains insignificant across all specifications. The results for the additional tests may be obtained upon request.

[21] We also estimated all models with a dummy variable that takes on the value one if the failure occurred prior to the enactment of the Federal Deposit Insurance Corporation Improvement Act (FDICIA), which was designed to reduce losses to the deposit insurance fund. However, the dummy variable was dropped in these specifications due to collinearity problems.

be explained with differences in liability structure since larger institutions tend to rely less on insured deposits. Figure 1 b) shows a highly nonlinear relationship between the ratio of real estate owned to total deposits and its contribution to the loss rate. Exhibiting significance across all quantiles, the effect is increasing up to the 25th quantile and decreases considerably for the expensive failures, where the impact at the 95th quantile is nearly halved in magnitude in comparison to the 5th quantile. Since real estate owned captures the level of foreclosed real estate owned by failed institutions, this finding indicates that the variable is less important in explaining high cost failures. Such failures may be more strongly influenced by other determinants, e.g. composition of the loan portfolio. The impact of loans past due is not as straightforward as indicated by previous studies that use linear estimators: This regressor has no influence at the tails of the distribution on the loss rate. We record merely between the 25th and the 75th quantile a significant impact at the one and five percent level with the anticipated positive sign on the dependent variable. This finding indicates that the loss rate of low cost failures cannot be sufficiently explained by non-performing loans. Indeed, Shibut et al. (2003) report considerable differences in the levels of non-performing loans between high cost and low cost failures and explain this with marked differences in the level of non-current commercial real estate. They state that the median low cost failure in their sample had no non-current commercial real estate whereas the high cost failures exhibit a median non-current rate of approximately four percent. While significant and positive across all quantiles, compared with the OLS estimate, the effect of the ratio of uncollected income to total deposits is considerably smaller at the lower tail of the distribution of the loss rate as depicted in Figure 1 d). Bovenzi and Murton (1988) argue that growing asset problems can be hidden easily in distressed institutions. While uncollected income can reflect these hidden asset problems, the effect of the variable depends on the extent to which the classification of assets is complete. This factor could explain the lower impact of the variable on low cost failures: classification of non-performing assets may receive less attention in low cost failures than in costly failures since managers of banks that are more likely to cause large losses to the insurance fund might devote more resource to the hiding of growing asset problems. The impact of total equity to total deposits appears to be U-shaped and is highly significant and negative across the quantiles but the 95th quantile. The median loss rate declines by more than .54 with a one-unit increase in capitalization, but the effect is much weaker at the lower and upper tail of the distribution. This may be explained with sale and lease back transactions of many ailing institutions apart from the very expensive and the most expensive failures. Sale and lease back transactions can be used to bolster troubled depositories' equity capital. If the sales price of the asset exceeds its book value, the transaction enables the institution to realize an accounting profit. Figure 1 f) shows that total asset growth exhibits an increasing impact on the loss rate as we move up the distribution. The positive sign for this coefficient is also reported by McDill (2004). The increasing effect over the quantiles may be due to 'gambling for resurrection' by bank managers. The more they gamble and increasingly engage in risky investments, the higher the impact on the loss rate. However, it is only significant at the 75th and 90th quantile, suggesting that reliance on the OLS estimates gives rise to misleading inferences.

In terms of the liability structure, the quantile regressions provide better insights into the role of Fed funds purchased than the estimates obtained with OLS and Tobit procedures. Figure 1 g) highlights that the sign of the coefficient changes from negative to positive between the 25th and 50th quantile. Moreover, while no significant effect can be established with the other techniques, the detailed analysis at different quantiles indicates that the variable significantly increases FDIC loss at the 90th and 95th quantile. This result provides a good illustration of the benefit of quantile regression: had we relied on the estimates from the OLS and Tobit procedures, we would have mistakenly concluded that Fed funds purchased do not affect FDIC loss at all.

However, the quantile estimator highlights that Fed funds purchased matter for the costly failures. Troubled banks that are able to borrow or retain Fed funds prior to failure may be able to hide their difficulties from the regulator and therefore delay closure, thus increasing resolution costs to the FDIC. This may be due to the lack of market discipline: while Fed funds are likely to leave the bank in the run up to failure, certain institutions may not be subject to close scrutiny by the market and can cover up impending difficulties with activities that ultimately increase the loss rate.[22] Similarly to the results obtained with standard estimation procedures, we find that brokered deposits below 100,000 USD to total deposits do not assume significance. The ratio of large brokered deposits to total deposits is however significant and positively signed at the lower tail of the distribution. This finding may be explained with activities that aim to cover up problems in troubled institutions to avoid depositor discipline. Figure 1 j) illustrates a highly nonlinear effect of the ratio of transactions deposits to total deposits on the loss rate. This effect is only significantly negative at the median loss rate and the large confidence band suggests caution has to be exercised when drawing inferences. While transactions deposits resemble core deposits that proxy the franchise value of the institution, our result indicates that the franchise value plays a less important role than indicated by the results obtained with standard econometric methods as the economic impact of the variable does not hold over the entire distribution of the loss rate. Figure 1 k) suggests that the ratio of time and savings deposits to total deposits has a highly nonlinear effect. However, it is only weakly significant and positively signed below the median and at the 90th quantile of the loss rate. This finding indicates that the variable is only of moderate importance for explaining high cost failures.

The ratio C&I loans to total deposits is positive and significant across all quantiles. Figure 1 l) illustrates departure of the quantile estimator from the OLS estimator at the lower and upper tail of the distribution. However, the magnitude of the departures is comparatively small. This result is aligned with the work by Shibut et al. (2003). Their analysis does not suggest considerable differences in the medians of C&I loans between high cost and low cost failures. Family residential mortgages do not have a statistically significant impact on FDIC loss according to both standard and quantile regression estimators. *Table 4* however contrasts the findings regarding loans to individuals: while standard methods do not indicate statistically significant association between this variable and the loss rate, quantile regression not only suggests that the variable changes the sign of the coefficient as we move up the distribution, it also indicates a highly significant and decreasing impact on loss rates for high cost failures. This finding is underpinned by Figure 1 n). We explain this result with portfolio effects: while C&I loans drive expensive failures as illustrated above, loans to individuals help balance the asset portfolio and, moreover, exhibit generally higher

[22] An alternative explanation may be that these Fed funds were borrowed from affiliated banks and therefore did not leave the bank or that the market anticipated that all borrowers would be protected in case of default. Moreover, if a bank is able to borrow short-term Fed funds only, this could be indicative of serious problems that ultimately increase the loss rate.

recovery rates (Brown and Epstein, 1992). Agricultural loans significantly decrease FDIC loss only at the median loss rate and the quantile regression coefficients trace the OLS estimator fairly closely. Given the magnitude of the confidence interval, we believe that the impact of this regressor has to be interpreted with caution. Finally, Figure 1 p) highlights a highly nonlinear effect of depositor preference law on the loss rate. While both the OLS and the Tobit model indicate an independent and decreasing effect of depositor preference law on FDIC loss, our quantile regressions underscore that depositor preference law significantly decreases failure cost only at the upper tail of the distribution. This implies that the law meets the objective of decreasing FDIC loss exclusively for expensive failures. This finding may be affected by the way a failed institution is resolved. In instances where an assisted merger (or purchase and assumption transaction) took place, all depositors may have been treated as if they were insured so that the effect of the law was limited. By contrast, if the FDIC liquidated the failed bank and paid off depositors, the law might have lived up to its expectations.[23]

We re-estimate the models using the estimator for censored regression quantiles presented in Section 3.1 and report the coefficients obtained with the Tobit model in column (1) of *Table 5*. Similar to our comparison of the OLS and Tobit estimators presented above, we find that adjusting for censoring only marginally impacts the magnitude of the coefficients and impacts the level of significance only in a few instances. We therefore refrain from a more detailed discussion of the results obtained with the estimator for censored regression quantiles and only highlight the differences: the ratio of Fed funds purchased to total deposits additionally becomes weakly significant with a negative sign at the 5th quantile. This result indicates that Fed funds decrease loss rates for low cost failures; this result is consistent with Osterberg (1996), who argues that Fed funds are highly liquid and that failing banks able to borrow such funds will have lower resolution costs. The ratio of loans to individuals to total deposits is also weakly significant for the 5th quantile. The variable enters with a positive sign, suggesting that such loans increase cost for low cost failures. This may be explained with the portfolio composition of the low cost failures. Those failures may be more invested in this type of loans.

In summary, our results provide empirical evidence for the impact of certain types of deposits on FDIC loss. This finding is consistent with the assertion by Shibut (2002) that liability structure influences FDIC loss since it determines which claimants have to be compensated in case of bank failure. For instance, Fed funds purchased significantly impact high cost failures, a finding that is corroborated by quantile and censored quantile regression estimators. Moreover, the findings illustrate that reliance on standard econometric techniques to assess the determinants of the deposit insurer's loss rate can give rise to misleading inferences. The observed non-linearities are not surprising: failed depositories exhibit different characteristics regarding bank type, business activities and size that all affect the loss rate. Our presented quantile regression estimators accommodate the

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[23] See Osterberg (1996) for the link between bank resolution and depositor preference law. To further investigate the nexus between depositor preference law and the way a failure is resolved, we estimate the model using an interaction term between the dummy for depositor preference law and a dummy that takes on the value one if the depository was resolved using a depositor payoff or zero otherwise. The interaction term enters the equation significantly at the five and ten percent level with a positive sign at the 90th and 95th quantile respectively. This provides further support to our hypothesis that depositor preference law becomes increasingly important when a failure is resolved by a depositor payoff.

heterogeneity of the data and offer more detailed insights into the factors driving the loss rate across the distribution. This is of particular importance for determining how the explanatory variables influence high cost failures. We find that the ratios of Fed funds purchased, time and savings deposits, real estate owned, uncollected income, and C&I loans to total deposits are significantly positively associated with the FDIC's loss rate for high cost failures during the period 1984 – 1996. Total asset growth also reveals a statistically positive relationship with the loss rate. By contrast, bank size, capitalization, loans to individuals and depositor preference law decrease loss rates for expensive failures.

4.2 Bank funding structure and time to failure

We employ the AFT model in this section to test the effect of bank funding structure on time to failure of the depositories in our sample. While previous studies investigate the price and quantity effects of risk on bank funding structure (e.g. Park and Peristiani, 1998; Maechler and McDill, 2006), the nexus between bank funding structure and time to failure is an alternative way of assessing the role of market discipline. This question has gained increasing prominence with the advent of Basel II. For instance, Maechler and McDill (2006) argue that very risky institutions cannot increase the volume of insured deposits by offering higher interest rates to compensate outflows of uninsured deposits. Thus, troubled banks that rely heavily on uninsured deposits might fail faster due to their inability to substitute such cash outflows with other types of funds. This may be interpreted as a signal for the presence of market discipline and underscores the importance of Pillar 3 in the new Basel Capital Accord.

Table 6 presents the results of our duration analysis whereby we use data for the failed institutions that also underlie the cost equations. The set of explanatory variables includes those regressors that we employ for the cost equations augmented by additional variables to capture the CAMEL[24] variables commonly used by banking supervisors to predict failures of depositories. We use the ratio of operating cost to operating income as a measure of management quality, and introduce the ratio of operating income to total deposits as a proxy for earnings. The variable troubled assets is calculated as the sum of real estate owned and loans past due over total deposits to measure asset quality. We capture the effect of liquidity with the variable securities to total deposits. The models contain region dummies to control for the local economy. The results of the AFT models are to be interpreted as follows: A positive coefficient indicates a decelerating effect of the variable on time to failure whereas a negative coefficient indicates shortened survival time.

Specification (1) in *Table 6* is our canonical model that only uses a parsimonious set of variables based on previous studies of bank failure. All six regressors are significant at the one or five percent level and show the anticipated sign. Unsurprisingly, inefficient institutions as measured by the ratio of cost to operating income, with a large proportion of troubled assets tend to fail faster. The proxies for capitalization, earnings and liquidity enter

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[24] CAMEL is an acronym for components of the regulatory rating system employed to assess soundness of financial institutions: Capital adequacy, Asset quality, Management, Earnings, and Liquidity. The rating system has been augmented in 1997 by adding a component that captures Sensitivity to market risk. The system is therefore now referred to as CAMELS rating system. The ratings assigned to banks range from 1 – 5, whereby 1 denotes a sound institution and banks rated 5 are considered extremely risky and unsound.

the equation with a positive sign, indicating increased survival time. Better capitalized banks with greater profitability are better able to absorb shocks. Similarly, more liquid institutions are in a better position to accommodate sudden cash outflows than less liquid depositories. The positive coefficient of the proxy for bank size indicates that larger banks exhibit increased survival time. This may be due to their ability to reap benefits from diversification of risk.

We introduce variables that capture the ailing institutions' funding structure in Specification (2). This augmented specification not only underscores a considerable impact of funding structure on time to failure, but also highlights the presence of omitted variable bias in Specification (1). The magnitude of our measure for profitability used in the canonical model changes by almost 20 percent upon controlling for liability structure in Specification (2). The ratio of Fed funds purchased to total deposits enters the equation at the one percent level with a negative sign. This result empirically substantiates that banks funded by such deposits tend to fail faster. This is aligned with research on depositor discipline: Fed funds are not insured and holders of uninsured claims tend to withdraw their funds from ailing institutions as documented in several studies (e.g. Goldberg and Hudgins, 1996, 2002; Jordan, 2000; Davenport and McDill, 2006). In this respect, our findings can be interpreted as empirical evidence for the presence of depositor discipline. Cash outflows in seriously troubled banks may not longer be offset by either substituting uninsured deposits or by offering higher interest rates. Indeed, Maechler and McDill (2006) show that very weak banks, i.e. banks with CAMEL ratings 4 or 5, face severe constraints in offsetting declines in uninsured deposits by offering higher interest rates. This indicates a potentially non-linear relationship between bank risk and the cost of uninsured funds. Furthermore, banks obviously trying to circumvent market discipline might attract additional regulatory scrutiny and regulators may be ultimately forced to act and close these institutions faster.

The ratio of brokered deposits below 100,000 USD enters the equation negatively at the five percent level. It is well documented that liability shifting occurs prior to the failure of depositories (e.g. Marino and Bennett, 1999) and that banks in difficulties attempt to replace uninsured with insured deposits (e.g. Goldberg and Hudgins, 1996, 2002). Although FDICIA limits the use of brokered deposits by critically undercapitalized banks, institutions not subject to this classification may nevertheless be able to turn to such insured brokered deposits. These deposits are not priced according to the borrower's default risk. Thus, use of insured brokered deposits can be interpreted as evidence for distress such that the regulator's propensity to close a troubled bank faster increases.

Similarly, time and savings deposits to total deposits and transactions deposits to total deposits adversely impact upon time to failure and assume statistical significance at the one percent level. These variables capture both insured and uninsured deposits. Thus, to the extent they capture uninsured deposits such as jumbo CDs, the results indicate that uninsured depositors withdraw their funds in the run-up to failure. Insured depositors, however also may be unwilling to supply funds to troubled banks if they become aware of the impending failure. For instance, Park and Peristiani (1998) argue that even insured depositors may be reluctant to supply funds to ailing institutions, which, in turn, could accelerate time to failure. They find adverse effects of bank risk on the pricing and growth of insured deposits and underscore that insured depositors may be concerned about the insurer's solvency or try to avoid other indirect costs arising from the delay in deposit redemption after failure. In addition, recent evidence by Davenport and McDill (2006) suggests that the majority of deposits withdrawn in the run-up to a failure are fully insured. Moreover, Jordan (2000) reports that declines in large CDs in failing banks in New England in the 1990s were more than offset by increases in small CDs. Thus, liability shifting from uninsured to insured deposits also plays a crucial role in explaining the inverse relationship between time and savings deposits and time to failure.

The ratio of large brokered deposits to total deposits exhibits a positive sign and is significant at the five percent level suggesting increased survival time for these banks. This may be explained with a signaling effect: the institutions' ability to attract uninsured funds could indicate that they are either better able to hide arising difficulties or that the regulator perceives these banks to be less risky since sophisticated depositors still lend to these institutions. Therefore, the regulatory may not step in and avoids taking remedial action. Additionally, the longer maturity of such deposits can also help explain this finding: large brokered deposits may be time deposits that cannot be withdrawn at short notice and hence increase time to failure. All our control variables remain significant in Specification (2).

To test robustness of these results, we include additional control variables in Specification (3) and (4). We introduce a dummy variable for depositor preference law in Specification (3). However, including this additional regressor does not change our inferences drawn thus far. In Specification (4), we additionally employ several variables that map the loan portfolio in detail. While controlling for additional variables decreases the magnitude of several coefficients, our results regarding the funding structure are robust. Merely the level of significance declines for the ratio of Fed funds purchased to total deposits from one to ten percent in Specification (4). Among the controls, the ratios of C&I loans to total deposits and agricultural loans to total deposits enter with a significant coefficient, suggesting lending in these areas shortens survival time. Depositor preference law increases time to failure significantly; this may be due to depositor's lower propensity to run when such law is in place or, alternatively, the regulator forbears since there are too many junior claims. Both the log likelihood function and the Akaike Information Criterion indicate that Specification (4) is the most appropriate setup for our AFT model.[25]

In sum, the findings from our AFT model provide empirical evidence that controlling for the liability structure when estimating time to failure increases the explanatory power of the presented model. Our results are indicative for the presence of depositor discipline: uninsured liabilities such as Fed funds purchased decrease time to failure. In addition, our findings are suggestive for a substitution effect of uninsured deposits with insured liabilities such as brokered deposits below 100,000. Time and savings, and transactions deposits are similarly found to adversely impact survival time of financial institutions and we believe that this substitution effect is a reasonably good indicator for impending failure.

In terms of policy implications, the findings suggest that liability structure deserves more attention by regulatory bodies. Monitoring of the behavior of certain types of deposits can provide better insights into time to failure of financial institutions. Moreover, applying

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[25] We perform an additional robustness test by examining as to whether the timing of the onset of risk impacts our inferences. This additional test redefines the onset of risk for each institution to be the period when the ratio of total equity capital to total assets falls below eight percent. This analysis corroborates the findings reported in *Table 6* and we therefore do not report them. The additional results may be obtained upon request.

capital charges to liabilities that tend to leave a bank faster might curb depositories' risk-taking behavior. Pillar 3 of Basel II currently neglects disclosure of insured and uninsured deposits.[26] In light of our findings, disclosing the levels of insured and uninsured deposits to the public may further enhance market discipline. Finally, the results indicate that banks funded by Fed funds purchased and brokered deposits below 100,000 ought to be subject to additional measures of prompt corrective action to curb their ability to substitute those types of deposits with insured deposits thereby increasing the FDIC's loss rate when those banks eventually fail.

5. Concluding Remarks

This paper analyses the extent to which bank liability structure impacts on the deposit insurer's loss in case of failure of individual financial institutions and how funding structure affects time to failure of ailing institutions. These questions are pertinent to the estimation of loss given default since depositories' liability structure not only determines which depositors have to be compensated in case of failure but also impacts upon financial institutions' risk-taking behavior.

Using quantile and censored quantile regression analysis that permits taking account of the non-normal distribution of the loss rate, we explore how the deposit insurer's loss varies across the distribution and illustrate its sensitivity towards several explanatory variables across different quantiles. This examination is beneficial for bank regulators, supervisory agencies and deposit insurers as they are particularly concerned about high cost failures. Our analysis extends previous work in that it presents empirical evidence for non-linear relationships between the loss rate and the set of explanatory variables. To that extent, our findings highlight the shortcomings associated with standard econometric techniques due to the better use of the information in the sample distribution. The discovered non-linearities are not surprising: failed depositories exhibit different characteristics regarding bank type, business activities and size that all drive the loss rate.

We show that losses are not homogeneously driven by the same set of determinants. In particular, Fed funds purchased significantly increase loss rates of expensive failures of depositories. This finding is robust to different types of quantile regression estimators. Furthermore, time and savings deposits, real estate owned, uncollected income, and C&I loans to total deposits are significantly positively associated with the FDIC's loss rate for high cost failures during the period 1984 – 1996.

Investigating the nexus between liability structure and time to failure, we offer evidence for the presence of depositor discipline: uninsured liabilities such as Fed funds purchased decrease time to failure. Insured brokered deposits, time and savings, and transactions deposits are also found to adversely impact survival time of financial institutions. To the

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[26] Neither the Consultative Document Pillar 3 (Market Discipline), (Basel Committee on Banking Supervision, 2001a), nor the Working Paper on Pillar 3 – Market discipline, (Basel Committee on Banking Supervision, 2001b) mention disclosure rules with respect to financial institutions' liability/deposit structure regarding their status of deposit insurance. This insufficient consideration of bank liability structure in the context of market discipline in general and deposit insurance in particular is also documented in Pennacchi (2005), who underscores that the Third Consultative Paper on the New Basel Capital Accord (Basel Committee on Banking Supervision, 2003) contains no reference to deposit insurance.

extent to which insured deposits decrease survival time, we assign this finding to liability shifting of troubled banks. These results are robust to controlling for numerous covariates that capture bank asset quality and the composition of the failed institutions' loan portfolio. In addition, the results from our AFT model provide empirical evidence that controlling for the liability structure when estimating time to failure of financial institutions increases the explanatory power of the presented model.

The findings regarding time to failure bear important policy implications. If such banks fail faster, there is a case to make them subject to additional measures of prompt corrective action to limit their ability to substitute uninsured deposits with insured deposits, thereby increasing the loss given default. The monitoring of ailing financial institutions should therefore be extended to their use of certain types of deposits. Moreover, while Pillar 3 in the Basel II framework underscores disclosure as an integral component to enhance market discipline, it widely ignores financial institutions' liability structure. Thus, our findings indicate that disclosure of the levels of insured and uninsured deposits could further strengthen depositor discipline. In addition, capital charges may be appropriate for certain types of liabilities to police institutions against risk taking behavior.

Our analysis focuses on the non-linear effect of certain variables on the deposit insurer's loss rate and on the impact of liability structure on time to failure. Future research could build on these results and examine the link between time to failure and the loss rate and evaluate the implications for the regulatory environment in greater detail.

References

Barth, J. R., Philip F. Bartholomew, and Michael G. Bradley (1990) Determinants of thrift institution resolution costs. Journal of Finance, Vol. 45, pp. 731 - 754

Basel Committee on Banking Supervision (2003) The New Basel Capital Accord. Technical report third consultative paper. Basel: Bank for International Settlements

Basel Committee on Banking Supervision (2001a) Consultative document: Pillar 3 (Market Discipline). Basel: Bank for International Settlements

Basel Committee on Banking Supervision (2001b) Working Paper on Pillar 3 - Market Discipline. Basel: Bank for International Settlements

Bennett, R. L., Mark D. Vaughan and Timothy. J. Yeager (2005) Should the FDIC worry about the FHLB? The impact of Federal Home Loan Board Advances on the Bank Insurance Fund. FDIC CFR Working Paper 2005-10

Billet, M. T., Jon A. Garfinkel and Edward S. O'Neal (1998) The cost of market versus regulatory discipline in banking. Journal of Financial Economics, Vol. 48, pp. 333 - 358

Blalock, J. B., Timothy J. Curry and Peter J. Elmer (1991) Resolution costs of thrift failures. FDIC Banking Review, Vol. 4, pp. 15 -26

Blum, J. (2002) Subordinated debt, market discipline, and banks' risk taking. Journal of Banking and Finance, Vol. 26, pp. 1427 - 1441

Bovenzi, J. F. and Arthur J. Murton (1988) Resolution costs of bank failures. FDIC Banking Review, Vol. 1, pp. 1 - 13

Brown, R. A. and Seth Epstein (1992) Resolution costs of bank failures: An update of the FDIC historical loss model. FDIC Banking Review, Vol. 5, pp. 1 - 16

Cade, B. and Barry R. Noon, (2003) A gentle introduction to quantile regression for ecologists. Frontiers in Ecology and the Environment, Vol. 1, pp. 412 - 420

Cole, R. A. and Jeffery W. Gunther (1995) Separating the Likelihood and Timing of Bank Failure. Journal of Banking and Finance, Vol. 19, pp. 1073 – 1089

Davenport, A. M. and Kathleen M. McDill (2006) The depositor behind the discipline: A micro-level case study of Hamilton Bank. Journal of Financial Services Research, Vol. 30, pp. 93 - 109

DeYoung, R. (2003) The failure of new entrants in commercial banking markets: a split-population duration analysis. Review of Financial Economics, Vol. 12, pp. 7-33

Flannery, M. J. and Sorin M. Sorescu (1996) Evidence of bank market discipline of subordinated debenture yields: 1983 –1991, Journal of Finance, Vol. 51, pp. 1347 - 1377

Goldberg, L. G. and Sylvia C. Hudgins (2002) Depositor discipline and changing strategies for regulating thrift institutions. Journal of Financial Economics, Vol. 63, pp. 263 – 274

Goldberg, L. G. and Sylvia C. Hudgins (1996) Response of uninsured depositors to impending S&L failures: evidence of depositor discipline. Quarterly Review of Economics and Finance, Vol. 36 (3), pp. 311 – 325

Gup, B. E. (1995) Targeting Fraud: Uncovering and deterring fraud in financial institutions. Chicago: Probus

Hirschhorn, E. and David Zervos (1990) Policies to change the priority of claimants: the case of depositor preference laws. Journal of Financial Services Research, Vol. 4, pp. 111 – 125

James, C. (1991) The losses realized in bank failures. Journal of Finance, Vol. 46, pp. 1223 - 1242

Jordan, J. S. (2000) Depositor discipline at failing banks. New England Economic Review, March/April 2000, pp. 15 – 28

King, T. B., Daniel A. Nuxoll, and Timothy J. Yeager (2006) Are the causes of bank distress changing? Can researchers keep up? Federal Reserve Bank of St. Louis Review, January/February 2006, pp. 57 - 80

Koenker, R. and Gilbert Bassett (1978) Regression quantiles. Econometrica, Vol. 46, pp. 33 – 50

Koenker, R. and Kevin F. Hallock (2001) Quantile regression. Journal of Economic Perspectives, Vol. 15, pp. 143 - 156

Lane, W. R., Stephen W. Looney, and James W. Wansley (1986) An Application of the Cox Model to Bank Failure. Journal of Banking and Finance, Vol. 10, pp. 511-531

Maechler, A. M. and Kathleen M. McDill (2006) Dynamic depositor discipline in US banks. Journal of Banking and Finance, Vol. 30, pp. 1871 - 1891

Marino, J. A. and Rosalind L. Bennett (1999) The consequences of national depositor preference. FDIC Banking Review, Vol. 12, pp. 19 - 38

McDill, K. M. (2004) Resolution costs and the business cycle. FDIC Working Paper 2004-01

Oshinsky, R. (1999) Effects of bank consolidation on the bank insurance fund. FDIC Working Paper 1999-03

Oshinsky, R. and Virginia Olin (2005) Troubled banks: Why don't they all fail? FDIC Working Paper 2005-03

Osterberg, W. P. (1996) The impact of depositor preference laws. Federal Reserve Bank of Cleveland Economic Review, Vol. 12, pp. 1 – 12

Osterberg, W. P. and James B. Thomson (1994) Underlying determinants of closed-bank resolution costs. Federal Reserve Bank of Cleveland, Working Paper 9403

Park, S., and Stavros Peristiani (1998) Market discipline by thrift depositors. Journal of Money, Credit, and Banking, Vol. 30, pp. 347 – 364

Pennacchi, G. G. (2005) Risk-based capital standards, deposit insurance, and procyclicality. Journal of Financial Intermediation, Vol. 14, pp. 432 – 465

Powell, J. L. (1986) Censored regression quantiles. Journal of Econometrics, Vol. 32, pp. 143 – 155

Powell, J. L. (1984) Least absolute deviations estimation for the censored regression model. Journal of Econometrics, Vol. 25, pp. 303 – 325

Shibut, L. (2002) Should bank liability structure influence deposit insurance pricing? FDIC Working Paper 2002-01

Shibut, L., Tim Critchfield and Sarah Bohn (2003) Differentiating among critically undercapitalized banks and thrifts. FDIC Banking Review, Vol. 15 (2), pp. 1 – 38

Whalen, G. (1991) A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool. Federal Reserve Bank of Cleveland Economic Review, Vol. 27, pp. 21 - 31

Data Appendix

Region Dummy Variables

Variable	Description
Southeast	1 if the bank is in located in Washington DC, Maryland, Virginia, North Carolina, South Carolina, West Virginia, Alabama, Florida, Georgia, Louisiana, Mississippi, Tennessee or zero otherwise
Midwest	1 if the bank is located in Ohio, Pennsylvania, Kentucky, Iowa, Illinois, Indiana, Michigan, Wisconsin, Missouri, Arkansas or zero otherwise
Southwest	1 if the bank is located in Texas, New Mexico or zero otherwise
Central	1 if the bank is located in Minnesota, Montana, North Dakota, South Dakota, Colorado, Kansas, Nebraska, Oklahoma, Wyoming or zero otherwise
West	1 if the bank is located in Alaska, Arizona, Hawaii, Idaho, Nevada, California, Oregon, Utah, Washington or zero otherwise
North East	1 if the bank is located in Vermont, Massachusetts, New Hampshire, Maine, Rhode Island, Connecticut, New York, New Jersey, Delaware or zero otherwise

Depositor Preference Laws

State	Date effective
Alaska	October 15, 1978
Arizona	September 21, 1991
California	June 27, 1986
Colorado	May 1, 1987
Connecticut	May 22, 1991
Florida	July 3, 1992
Georgia	1974[a]
Hawaii	June 24, 1987
Idaho	1979[b]
Iowa	January 1, 1970
Kansas	July 1, 1985
Louisiana	January 1, 1985
Maine	April 16, 1991
Minnesota	April 24, 1990
Missouri	September 1, 1993
Montana	1927[c]
Nebraska	1909[c]
New Hampshire	June 10, 1991
New Mexico	June 30, 1963
North Dakota	July 1, 1987
Oklahoma	May 26, 1965
Oregon	January 1, 1974
Rhode Island	February 8, 1991
South Dakota	July 1, 1969
Tennessee	1969[c]
Utah	1983[c]
Virginia	July 1, 1983
West Virginia	May 11, 1981

a. Legislation became effective on either January 1 or July 1.
b. Passed by both houses of the state legislature on July 1; enactment date is unclear.
c. Neither the month nor the day of enactment is available.
SOURCE: Osterberg (1996)

Table 1: Descriptive statistics

Variable	N	Mean	S.D.	Min	Max	p5	p10	p25	p50	p75	p90	p95
Cost/Total deposits	1227	0.215	0.140	0.000	1.821	0.020	0.046	0.113	0.201	0.292	0.398	0.455
Total assets	1227	96034.7	383442.9	1712.0	9890866.0	5915.0	8340.0	14704.0	29049.0	67326.0	174996.0	323166.0
Total asset growth, 4 quarters prior to failure	1227	-0.138	0.241	-1.735	0.859	-0.546	-0.401	-0.261	-0.130	0.003	0.129	0.219
Total equity capital/Total deposits	1227	0.016	0.057	-0.419	0.307	-0.075	-0.043	-0.007	0.017	0.053	0.075	0.085
Real estate owned/Total deposits	1227	0.041	0.044	0.000	0.531	0.000	0.001	0.011	0.030	0.056	0.095	0.120
Income earned, not collected on loans/Total deposits	1227	0.013	0.010	0.000	0.083	0.003	0.004	0.006	0.010	0.016	0.026	0.031
Loans past due/Total deposits	1227	0.022	0.031	0.000	0.275	0.000	0.000	0.002	0.011	0.030	0.059	0.085
Fed funds purchased/Total deposits	1227	0.007	0.024	0.000	0.360	0.000	0.000	0.000	0.000	0.000	0.024	0.047
Brokered deposits <100k/Total deposits	1227	0.006	0.025	0.000	0.239	0.000	0.000	0.000	0.000	0.000	0.007	0.045
Brokered deposits >100k/Total deposits	1227	0.004	0.017	0.000	0.236	0.000	0.000	0.000	0.000	0.000	0.000	0.014
Transactions deposits/Total deposits	1227	0.240	0.111	0.000	1.000	0.069	0.114	0.173	0.232	0.293	0.368	0.420
Time and savings deposits/Total deposits	1227	0.849	0.079	0.104	1.000	0.718	0.752	0.813	0.860	0.899	0.932	0.950
C&I Loans/Total deposits	1227	0.184	0.120	0.000	0.704	0.031	0.051	0.094	0.161	0.247	0.352	0.417
Agricultural loans/Total deposits	1227	0.063	0.122	0.000	0.821	0.000	0.000	0.000	0.001	0.062	0.236	0.354
Loans to individuals/Total deposits	1227	0.131	0.139	0.000	3.459	0.020	0.031	0.058	0.104	0.169	0.256	0.318
Mortgages secured by 1-4 family mortgages/Total deposits	1227	0.130	0.163	0.000	4.569	0.015	0.026	0.054	0.102	0.169	0.250	0.335
Operating income/Total deposits	1227	1.117	0.281	-1.194	4.299	0.827	0.876	0.961	1.061	1.212	1.409	1.586
Cost/Operating income	1227	0.072	0.035	-0.041	0.352	0.023	0.026	0.047	0.073	0.091	0.114	0.127
Troubled assets/Total deposits	1227	0.063	0.055	0.000	0.562	0.004	0.010	0.026	0.051	0.086	0.132	0.161
Securities/Total deposits	1227	0.140	0.109	0.000	0.663	0.005	0.012	0.052	0.123	0.204	0.285	0.353
Depositor preference law	1227	0.377	0.485	0.000	1.000	0.000	0.000	0.000	0.000	1.000	1.000	1.000

Table 2: Correlation matrix

	Cost/Total deposits	Total assets (log)	Total asset growth	Fed funds purchased/Total deposits	Brokered deposits <100k/Total deposits	Transactions deposits/Total deposits	Time and savings deposits/Total deposits	Real estate owned/Total deposits	Income earned, not collected on loans/Total deposits	C&I Loans/Total deposits	Agricultural loans/Total deposits	Loans to individuals/Total deposits	Loans past due/Total deposits	Total equity capital/Total deposits	Brokered deposits >100k/Total deposits	Mortgages secured by 1-4 family mortgages/Total deposits	Depositor preference law
Cost/Total deposits	1.000																
Total assets (log)	-0.071***	1.000															
Total asset growth, 4 quarters prior to failure	-0.007	0.022	1.000														
Fed funds purchased/Total deposits	0.019	0.356***	0.017	1.000													
Brokered deposits <100k/Total deposits	0.161***	-0.011	0.027	0.177***	1.000												
Transactions deposits/Total deposits	-0.214***	-0.056***	-0.062*	-0.129***	-0.621**	1.000											
Time and savings deposits/Total deposits	0.103***	-0.092***	0.096***	-0.053**	0.112***	-0.596***	1.000										
Real estate owned/Total deposits	0.194***	0.001	-0.173***	-0.035	0.053**	-0.067**	0.051**	1.000									
Income earned, not collected on loans/Total deposits	0.303***	-0.063*	0.082***	0.023	0.031	-0.026	0.048*	-0.115***	1.000								
C&I Loans/Total deposits	0.277***	0.076***	-0.033	0.083***	0.143***	-0.039	-0.237***	-0.073***	0.134***	1.000							
Agricultural loans/Total deposits	0.097***	-0.069***	0.038	-0.052**	-0.080***	0.074***	0.108***	-0.165***	0.614***	-0.176***	1.000						
Loans to individuals/Total deposits	0.002	-0.046*	0.059**	0.386***	0.131***	-0.087***	-0.033	-0.140***	0.048*	-0.046*	-0.108***	1.000					
Loans past due/Total deposits	0.246***	-0.063**	-0.109***	-0.006	0.120***	-0.095***	-0.001	-0.010	0.433***	0.192***	0.109***	0.067**	1.000				
Total equity capital/Total deposits	-0.152***	0.005	0.504***	0.002	-0.055**	0.078***	-0.001	-0.260***	0.172***	-0.027	0.138***	0.153***	-0.065**	1.000			
Brokered deposits >100k/Total deposits	0.096***	0.070***	0.000	0.063**	0.079***	-0.394***	0.025	-0.010	-0.027	0.036	-0.073***	0.003	0.084***	-0.045*	1.000		
Mortgages secured by 1-4 family mortgages/Total deposits	-0.029	0.034	0.068***	-0.027	0.007	-0.131***	0.191***	0.108***	-0.146***	-0.187***	-0.208***	-0.091***	-0.069***	-0.013	0.020***	1.000	
Depositor preference law	0.039	-0.076***	-0.106***	-0.006	-0.030	0.029	0.030	-0.006	0.142***	0.021	0.203***	-0.053**	0.053**	-0.025	0.022***	0.022***	1.000

Significance levels of 1, 5 and ten percent are indicated by *, **, and ***.

Table 3: Ordinary least squares and Tobit regressions

Cost per dollar of total deposits, quarter prior to failure	Ordinary least squares regression				Tobit Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total assets (log)	-0.0129	-0.0178	-0.0208	-0.0207	-0.0136	-0.0184	-0.0214	-0.0213
	(0.0039)***	(0.0044)***	(0.0044)***	(0.0044)***	(0.0045)***	(0.0046)***	(0.0046)***	(0.0046)***
Real estate owned/Total deposits	0.6742	0.6851	0.6923	0.6971	0.6754	0.6873	0.6956	0.7006
	(0.0909)***	(0.0909)***	(0.0891)***	(0.0895)***	(0.0818)***	(0.0807)***	(0.0798)***	(0.0798)***
Loans past due (90 days+)/Total deposits	0.4515	0.4207	0.3292	0.3194	0.4511	0.4213	0.3294	0.3193
	(0.1236)***	(0.1203)***	(0.1137)***	(0.1134)***	(0.1226)***	(0.1214)***	(0.1202)***	(0.1202)***
Income earned, not collected on loans/Total deposits	4.1055	3.9046	4.0823	4.1162	4.1169	3.9022	4.0688	4.1031
	(0.5590)***	(0.5583)***	(0.7964)***	(0.7864)***	(0.4864)***	(0.4891)***	(0.5878)***	(0.5874)***
Total equity capital/Total deposits	-0.4498	-0.3932	-0.3665	-0.3742	-0.4562	-0.3989	-0.3724	-0.3801
	(0.1015)***	(0.1009)***	(0.0998)***	(0.0999)***	(0.0737)***	(0.0735)***	(0.0725)***	(0.0725)***
Total asset growth, 4 quarters prior to failure	0.0486	0.0406	0.0434	0.0428	0.0496	0.0412	0.0439	0.0432
	(0.0194)**	(0.0182)**	(0.0181)**	(0.0181)**	(0.0177)***	(0.0175)**	(0.0171)**	(0.0171)**
Fed Funds purchased/Total deposits		0.1708	0.1514	0.1568		0.1721	0.1506	0.1562
		(0.2412)	(0.2118)	(0.2136)		(0.1510)	(0.1558)	(0.1556)
Brokered deposits < 100k/Total deposits		0.2397	0.1565	0.1474		0.2451	0.1611	0.1518
		(0.1607)	(0.1536)	(0.1521)		(0.1462)*	(0.1419)	(0.1418)
Brokered deposits > 100k/Total deposits		0.2685	0.2289	0.2271		0.2593	0.2198	0.2179
		(0.2156)	(0.2068)	(0.2039)		(0.2066)	(0.2006)	(0.2004)
Transactions deposits/Total deposits		-0.1573	-0.1065	-0.1032		-0.1585	-0.1080	-0.1049
		(0.0559)***	(0.0558)*	(0.0547)*		(0.0497)***	(0.0486)**	(0.0486)**
Time and savings deposits/Total deposits		-0.0173	0.1167	0.1217		-0.0088	0.1279	0.1335
		(0.0762)	(0.0764)	(0.0751)		(0.0675)	(0.0674)*	(0.0674)**
C&I Loans/Total deposits			0.2422	0.2416			0.2449	0.2444
			(0.0390)***	(0.0389)***			(0.0327)***	(0.0326)***
Mortgages secured by 1-4 family residential mortgages/Total deposits			0.0056	0.0058			0.0055	0.0057
			(0.0181)	(0.0179)			(0.0226)	(0.0226)
Loans to individuals/Total deposits			-0.0202	-0.0207			-0.0192	-0.0197
			(0.0325)	(0.0329)			(0.0272)	(0.0272)
Agricultural loans/Total deposits			-0.0692	-0.0650			-0.0683	-0.0641
			(0.0610)	(0.0607)			(0.0458)	(0.0458)
Depositor preference law				-0.0159				-0.0162
				(0.0093)*				(0.0094)*
Observations	1227	1227	1227	1227	1227	1227	1227	1227
Adjusted R^2	0.2669	0.2840	0.3265	0.3275	n/a	n/a	n/a	n/a
AIC	-1711.745	-1735.638	-1806.896	-1807.823	-1687.618	-1712.213	-1784.275	-1785.271

We estimate OLS regressions in column (1) – (4) and Tobit models in column (5) – (8) for the period 1984 - 1996. The dependent variable is the Cost per dollar of total deposits in the quarter prior to failure. Specifications (1) and (5) are the baseline models that include covariates used in previous studies. Specifications (2) and (6) include variables that capture liability structure. We incorporate additional control variables in Specification (3) and (7) to capture asset composition. Specifications (4) and (8) include a dummy variable that takes on the value one if depositor preference law was in place in the state in which the bank is located or zero otherwise. Robust standard errors are reported in parentheses for OLS regressions and standard errors are reported in parentheses for Tobit regressions. All regressions include region and time dummies. Significance levels of 1, 5 and ten percent are indicated by *, **, and ***.

Table 4: Ordinary least squares and quantile regressions

Cost per dollar of total deposits, quarter prior to failure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS Regression	Quantile Regression						
		.05 Quantile	.10 Quantile	.25 Quantile	.5 Quantile	.75 Quantile	.90 Quantile	.95 Quantile
Total assets (log)	-0.0207	-0.0144	-0.0134	-0.0187	-0.0221	-0.0242	-0.0300	-0.0298
	(0.0044)***	(0.0053)***	(0.0048)***	(0.0044)***	(0.0051)***	(0.0059)***	(0.0082)***	(0.0109)***
Real estate owned/Total deposits	0.6971	0.5822	0.6671	0.7852	0.6677	0.6874	0.5189	0.3004
	(0.0895)***	(0.1218)***	(0.0928)***	(0.0776)***	(0.0851)***	(0.1098)***	(0.1272)***	(0.1751)*
Loans past due (90 days+)/Total deposits	0.3194	0.1653	0.1443	0.4265	0.3413	0.4630	0.2708	0.1968
	(0.1134)***	(0.2208)	(0.2069)	(0.1517)***	(0.1544)**	(0.1584)***	(0.1766)	(0.2232)
Income earned, not collected on loans/Total deposits	4.1162	2.6504	4.7875	4.1445	5.6501	4.5221	5.4375	5.3077
	(0.7864)***	(1.0512)**	(1.0091)***	(0.8234)***	(0.7914)***	(0.8429)***	(1.4162)***	(1.7067)***
Total equity capital/Total deposits	-0.3742	-0.2842	-0.5061	-0.5371	-0.5497	-0.4954	-0.3900	-0.2438
	(0.0999)***	(0.1513)*	(0.1267)***	(0.0898)***	(0.0874)***	(0.0925)***	(0.1275)***	(0.1648)
Total asset growth, 4 quarters prior to failure	0.0428	0.0151	0.0148	0.0173	0.0334	0.0482	0.0702	0.0599
	(0.0181)**	(0.0296)	(0.0257)	(0.0194)	(0.0218)	(0.0271)*	(0.0320)**	(0.0422)
Fed Funds purchased/Total deposits	0.1568	-0.1608	-0.3142	-0.2904	0.1613	0.5710	0.6955	0.7429
	(0.2136)	(0.2377)	(0.2539)	(0.3120)	(0.2770)	(0.3733)	(0.2761)**	(0.3066)**
Brokered deposits <100k/Total deposits	0.1474	0.0184	-0.0309	0.0513	0.2737	0.2835	0.1844	0.0462
	(0.1521)	(0.2142)	(0.2267)	(0.2753)	(0.1750)	(0.1875)	(0.2548)	(0.3281)
Brokered deposits >100k/Total deposits	0.2271	0.4889	0.3587	0.3495	-0.1366	0.2972	0.2645	-0.0603
	(0.2039)	(0.2230)**	(0.2002)*	(0.2169)	(0.3045)	(0.3146)	(0.3334)	(0.3948)
Transactions deposits/Total deposits	-0.1032	-0.0588	-0.0637	-0.0227	-0.1268	-0.0923	-0.0841	-0.0990
	(0.0547)*	(0.0664)	(0.0597)	(0.0611)	(0.0552)**	(0.0866)	(0.0831)	(0.0998)
Time and savings deposits/Total deposits	0.1217	0.1388	0.1638	0.2128	0.0439	0.1343	0.2615	0.1793
	(0.0751)	(0.0901)	(0.0905)*	(0.0856)**	(0.0832)	(0.1024)	(0.1144)**	(0.1446)
C&I Loans/Total deposits	0.2416	0.1907	0.2022	0.3025	0.2454	0.2385	0.2093	0.2566
	(0.0389)***	(0.0435)***	(0.0429)***	(0.0375)***	(0.0401)***	(0.0445)***	(0.0704)***	(0.1042)**
Mortgages secured by family residential mortgages/Total deposits	0.0058	0.0381	0.0174	0.0298	0.0069	0.0151	-0.0642	-0.0343
	(0.0179)	(0.0359)	(0.0371)	(0.0275)	(0.0432)	(0.0527)	(0.0738)	(0.1015)
Loans to individuals/Total deposits	-0.0207	0.0234	0.0376	0.0582	0.0545	-0.0192	-0.1248	-0.1536
	(0.0329)	(0.0406)	(0.0448)	(0.0490)	(0.0493)	(0.0473)	(0.0585)**	(0.0614)**
Agricultural loans/Total deposits	-0.0650	-0.0613	-0.0740	-0.0503	-0.1389	-0.1017	-0.1670	-0.0139
	(0.0607)	(0.0713)	(0.0688)	(0.0692)	(0.0645)**	(0.0698)	(0.1246)	(0.1598)
Depositor preference law	-0.0159	-0.0136	-0.0156	-0.0044	-0.0016	-0.0157	-0.0489	-0.0790
	(0.0093)*	(0.0123)	(0.0114)	(0.0119)	(0.0135)	(0.0135)	(0.0192)**	(0.0248)***
Observations	1227	1227	1227	1227	1227	1227	1227	1227
Adjusted R^2/Pseudo R^2	0.3275	0.2066	0.2367	0.2525	0.2575	0.2544	0.2518	0.2401

We report OLS regressions in column (1) and quantile regression estimates in column (2) – (8) for the period 1984 - 1996. The dependent variable is the Cost per dollar of total deposits in the quarter prior to failure. Robust standard errors are reported in parentheses for OLS regressions and bootstrapped standard errors based on 1000 replications are reported in parentheses for the quantile regressions. Pseudo R^2 reported for quantile regressions. The pseudo R^2 is calculated as 1-(sum of the weighted deviations about estimated quantile/sum of weighted deviations about raw quantile). All regressions include region and time dummies. Significance levels of 1, 5 and ten percent are indicated by *, **, and ***.

Table 5: Tobit and censored quantile regressions

Cost per dollar of total deposits, quarter prior to failure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobit	Censored quantile regression						
	Regression	.05 Quantile	.10 Quantile	.25 Quantile	.5 Quantile	.75 Quantile	.90 Quantile	.95 Quantile
Total assets (log)	-0.0213	-0.0129	-0.0211	-0.0192	-0.0222	-0.0238	-0.0304	-0.0299
	(0.0046)***	(0.0096)	(0.0073)***	(0.0048)***	(0.0054)***	(0.0059)***	(0.0080)***	(0.0110)***
Real estate owned/Total deposits	0.7006	0.8067	0.7948	0.7779	0.6653	0.6897	0.5427	0.3279
	(0.0798)***	(0.1193)***	(0.0974)***	(0.0821)***	(0.0925)***	(0.1105)***	(0.1273)***	(0.1771)*
Loans past due (90 days+)/Total deposits	0.3193	0.0603	0.1478	0.3279	0.3266	0.4908	0.2588	0.0817
	(0.1202)***	(0.2605)	(0.2212)	(0.1629)**	(0.1532)**	(0.1559)***	(0.1770)	(0.2234)
Income earned, not collected on loans/Total deposits	4.1031	3.5993	5.0972	4.3454	5.5976	4.3987	5.3808	5.2495
	(0.5874)***	(1.3918)***	(1.1299)***	(0.9593)***	(0.8095)***	(0.8435)***	(1.4006)***	(1.6975)***
Total equity capital/Total deposits	-0.3801	-0.4636	-0.6246	-0.6690	-0.5816	-0.4822	-0.4066	-0.1857
	(0.0725)***	(0.2094)**	(0.1474)***	(0.0970)***	(0.0902)***	(0.0937)***	(0.1253)***	(0.1678)
Total asset growth, 4 quarters prior to failure	0.0432	0.0220	0.0499	0.0231	0.0396	0.0471	0.0647	0.0343
	(0.0171)**	(0.0487)	(0.0375)	(0.0217)	(0.0227)*	(0.0273)*	(0.0313)**	(0.0426)
Fed Funds purchased/Total deposits	0.1562	-0.9353	-0.2108	-0.4603	0.1369	0.5428	0.7236	0.6193
	(0.1556)	(0.5593)*	(0.4398)	(0.3662)	(0.3096)	(0.3715)	(0.2692)***	(0.3039)**
Brokered deposits <100k/Total deposits	0.1518	-0.1347	0.1671	0.1566	0.2570	0.2908	0.0900	0.1274
	(0.1418)	(0.3888)	(0.3101)	(0.3085)	(0.1712)	(0.1881)	(0.2519)	(0.3274)
Brokered deposits >100k/Total deposits	0.2179	0.5215	0.2997	0.3910	0.1246	0.2926	0.2292	-0.0417
	(0.2004)	(0.2718)*	(0.2465)	(0.2382)	(0.3121)	(0.3097)	(0.3225)	(0.3918)
Transactions deposits/Total deposits	-0.1049	-0.1116	-0.1109	-0.0491	-0.1367	-0.0989	-0.1045	-0.1461
	(0.0486)**	(0.1141)	(0.0902)	(0.0774)	(0.0587)**	(0.0913)	(0.0831)	(0.0995)
Time and savings deposits/Total deposits	0.1335	0.1498	0.1496	0.2491	0.0412	0.1588	0.2769	0.1812
	(0.0674)**	(0.1575)	(0.1239)	(0.1029)**	(0.0899)	(0.1033)	(0.1130)**	(0.1469)
C&I Loans/Total deposits	0.2444	0.2740	0.2721	0.3181	0.2579	0.2422	0.2061	0.2773
	(0.0326)***	(0.0709)***	(0.0547)***	(0.0430)***	(0.0433)***	(0.0453)***	(0.0695)***	(0.1035)***
Mortgages secured by family residential mortgages/Total deposits	0.0057	0.0398	0.0354	0.0279	0.0064	0.0177	-0.0536	-0.0252
	(0.0226)	(0.0573)	(0.0475)	(0.0344)	(0.0492)	(0.0551)	(0.0748)	(0.1019)
Loans to individuals/Total deposits	-0.0197	0.1147	0.0438	0.0798	0.0552	-0.0182	-0.1248	-0.1692
	(0.0272)	(0.0670)*	(0.0616)	(0.0543)	(0.0507)	(0.0478)	(0.0586)**	(0.0616)***
Agricultural loans/Total deposits	-0.0641	-0.0049	-0.1026	-0.0574	-0.1405	-0.0919	-0.1525	-0.0151
	(0.0458)	(0.1031)	(0.0851)	(0.0792)	(0.0660)**	(0.0705)	(0.1229)	(0.1586)
Depositor preference law	-0.0162	-0.0249	-0.0183	-0.0070	-0.0022	-0.0173	-0.0488	-0.0850
	(0.0094)*	(0.0182)	(0.0148)	(0.0125)	(0.0134)	(0.0135)	(0.0190)**	(0.0248)***
Observations	1227	1227	1227	1227	1227	1227	1227	1227

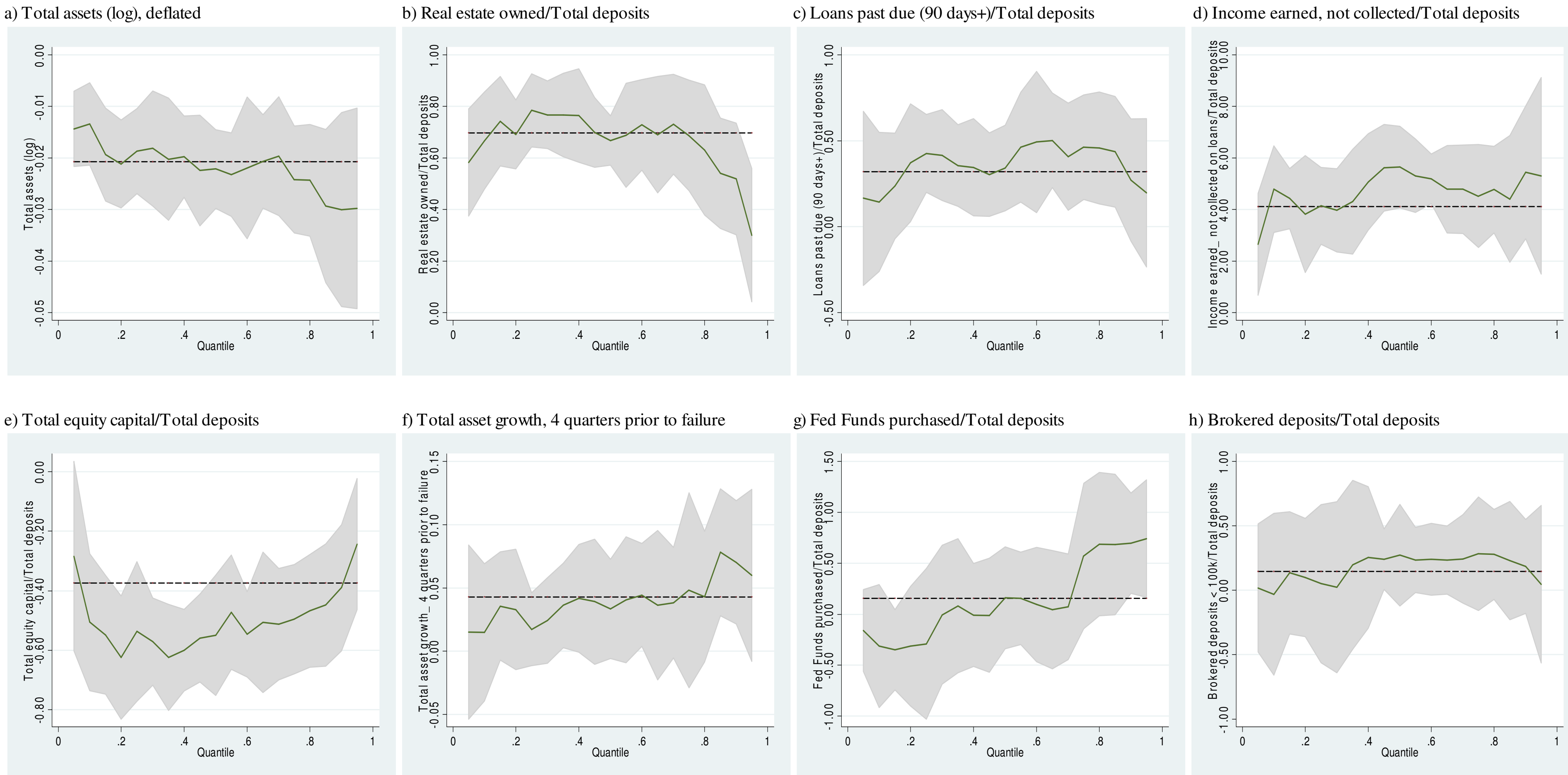
We report Tobit regressions in column (1) and censored quantile regression estimates in column (2) – (8) for the period 1984 - 1996. The dependent variable is the Cost per dollar of total deposits in the quarter prior to failure. Standard errors are reported in parentheses for Tobit regressions and bootstrapped standard errors based on 1000 replications are reported in parentheses for the censored quantile regressions. All regressions include region and time dummies. Significance levels of 1, 5 and ten percent are indicated by *, **, and ***.

Table 6: Duration analysis

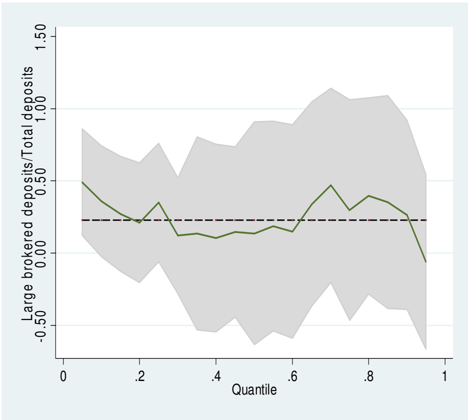
Accelerated failure time model	(1)	(2)	(3)	(4)
Total equity capital/Total deposits	11.7677	11.8665	11.8162	11.5623
	(0.8938)***	(0.8843)***	(0.8849)***	(0.8646)***
Troubled assets/Total deposits	-3.6479	-3.5248	-3.5518	-3.4465
	(0.6972)***	(0.6600)***	(0.6325)***	(0.6507)***
Cost/Operating Income	-0.1581	-0.1614	-0.1612	-0.1615
	(0.0107)***	(0.0106)***	(0.0106)***	(0.0103)***
Operating income/Total deposits	1.0424	1.2377	1.2286	1.5428
	(0.5199)**	(0.5260)**	(0.5223)**	(0.5107)***
Securities/Total deposits	0.7453	0.7365	0.7107	0.6559
	(0.2038)***	(0.1944)***	(0.1924)***	(0.1897)***
Total assets (log)	0.1372	0.1465	0.1454	0.1103
	(0.0174)***	(0.0187)***	(0.0187)***	(0.0223)***
Fed Funds purchased/Total deposits		-0.9239	-0.9086	-0.7401
		(0.2609)***	(0.2611)***	(0.4496)*
Brokered deposits <100k/Total deposits		-1.6403	-1.6391	-1.5977
		(0.6691)**	(0.6397)**	(0.6264)**
Brokered deposits >100k/Total deposits		1.6402	1.6391	1.5976
		(0.6691)**	(0.6397)**	(0.6264)**
Transactions deposits/Total deposits		-1.0405	-1.0474	-1.0621
		(0.2313)***	(0.2318)***	(0.2288)***
Time and savings deposits/Total deposits		-1.3851	-1.4083	-1.2928
		(0.3569)***	(0.3535)***	(0.3559)***
Depositor preference law			0.0846	0.1082
			(0.0542)	(0.0505)**
C&I Loans/Total deposits				-0.3892
				(0.1549)**
Mortgages secured by family mortgages/Total deposits				-0.0164
				(0.1634)
Loans to individuals/Total deposits				-0.4647
				(0.2986)
Agricultural loans/Total deposits				-1.1243
				(0.1921)***
Observations	23986	23986	23986	23986
AIC	482.39582	440.64312	441.2338	397.9312
Log likelihood function	-227.19791	-202.32156	-200.6169	-174.9656

We report log-logistic duration models with time-varying covariates in column (1) - (4) for the period 1983 - 1996. The dependent variable is the log of time to failure. Specification (1) contains variables used in previous studies. Specification (2) includes covariates that capture the funding structure of the failed depositories. We incorporate a dummy variable for depositor preference in Specification (3) that takes the value one if depositor preference law is in place or zero otherwise. Additional control variables are included in Specification (4) to capture composition of the loan portfolio. Robust standard errors are reported in parentheses. All regressions include region dummies. Significance levels of 1, 5 and ten percent are indicated by *, **, and ***.

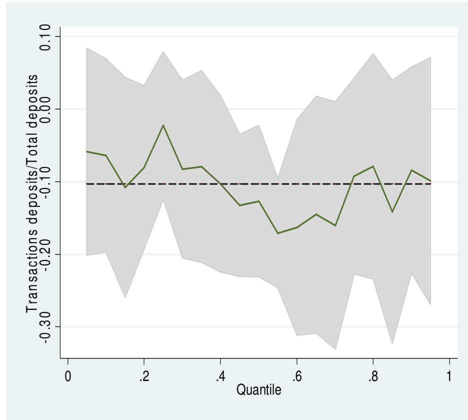
Figure 1: Quantile regression estimators



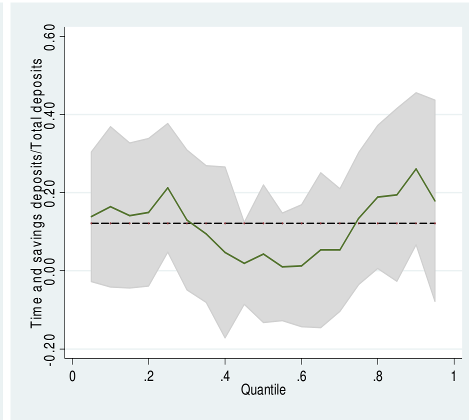
i) Large brokered deposits/Total deposits



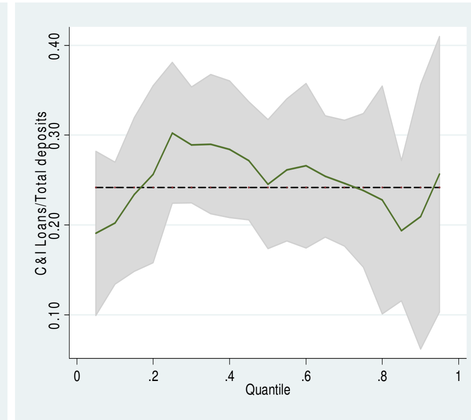
j) Transactions deposits/Total deposits



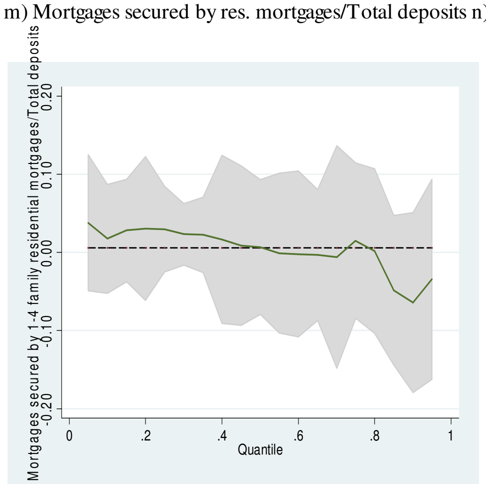
k) Time and savings deposits/Total deposits



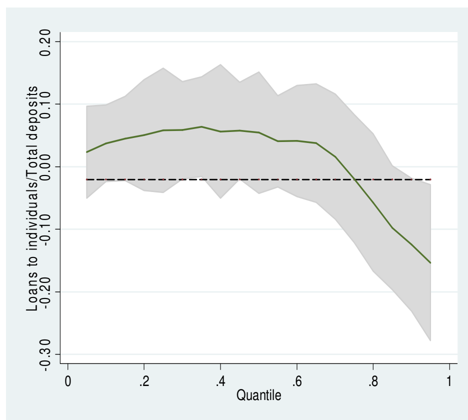
l) C&I Loans/Total deposits



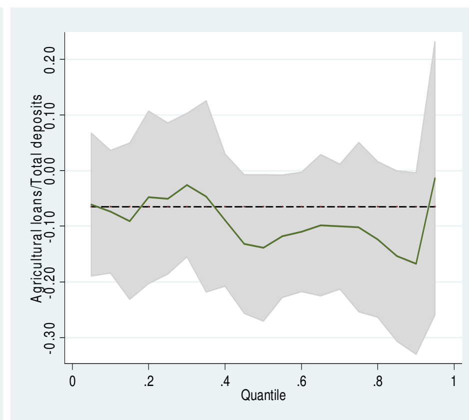
m) Mortgages secured by res. mortgages/Total deposits



n) Loans to individuals/Total deposits



o) Agricultural loans/Total deposits



p) Depositor preference law