The costs of closing failed banks:

A structural estimation of regulatory incentives

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Abstract

We estimate a dynamic model of the decision to close a troubled bank. Regulators trade off an aversion to closing banks against the risk that allowing a bank to continue will raise the eventual costs to the deposit insurance fund. Using a conditional choice probability approach, we estimate the costs associated with closing banks, both in direct costs to the insurance fund and in other costs perceived by regulators, either social or personal. We find that delayed closures were driven by a desire to defer costs, an aversion to closing the largest and smallest troubled banks, and political influence.

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With the advent of deposit insurance in the 1930's, the decision of whether and when a particular bank failed was removed from the perhaps capricious (Diamond and Dybvig, 1983) or perhaps disciplining (Calomiris and Kahn, 1991; Diamond and Rajan, 2001) hands of holders of demand deposits. While deposit insurance largely eliminated the instability that historically plagued the U.S. banking system, regulators understood from the beginning that such insurance could create significant moral hazard and adverse selection problems (Meltzer, 2004). Thus, in place of the discipline of the market for deposits, a system of bank regulation developed where the decision to close a troubled bank resided in the judgment of regulators, and in particular the Federal Deposit Insurance Corporation (FDIC).

This paper examines the motivations of these regulators when choosing whether to close a troubled bank or to permit it to continue to operate. Toward this end, we estimate a structural model of regulatory closure policy, treating the FDIC as a utility maximizing agent who faces a variety of costs when closing an insolvent bank.[1] We focus initially on the first major banking crisis following the introduction of deposit insurance, which spans a period from the early 1980s to the early 1990s. Conventional wisdom and the legislative response to this crisis suggest that the FDIC may have pursued objectives that led to inefficient resolution of failed banks. In particular, excessive regulatory forbearance, where banks were allowed to continue to operate despite being insolvent, may have raised the ultimate costs to taxpayers of resolving the large number of distressed banks operating during this period. We then estimate the model for the recent wave of bank failures following the 2007 financial crisis. We can thus compare parameters governing FDIC behavior during these two episodes.

Such an analysis is necessary because, unlike private debt holders, bank regulators face a myriad of concerns and considerations when choosing which banks to close and which to allow to continue to operate. The FDIC will clearly have some motivation to minimize the direct costs of bank closure to the insurance fund. This concern in and of itself generates an important dynamic tradeoff. Facing a bank in distress, the FDIC can either bear the cost of closing the bank or forebear and allow the bank to continue to operate. The bank may then recover, eliminating the need to ever pay off insured depositors, or it may deteriorate further, raising the eventual closure costs.

At the same time, bank regulators must consider more than just the cost to the insurance fund when closing a bank. Instead, they are likely concerned with the overall state of the banking system and the

[1] In practice, bank closure decisions are made jointly between the FDIC, the relevant chartering agency, and the Federal Reserve, but for expositional simplicity we refer only to the FDIC. See Zisman (2013) for details on the precise allocation of regulatory powers.

availability of banking services in various communities. Regulators may also face pressure from regulated entities (see Stigler, 1971) or politicians to leave certain banks open.[2] Both bank characteristics and the economic environment will influence closure decisions separately from the effect on costs to the insurance fund. We estimate a model that permits us to compare the magnitude of these other considerations and the direct monetary costs associated with bank closure. We can thus uncover the determinants of the implicit, non-monetary closure costs perceived by the regulator as a function of bank characteristics. These costs may represent concern for social welfare and the availability of banking services, or they may come from a desire to protect a regulated entity for its own sake. These estimates allow us to quantify the importance to the FDIC of permitting different types of banks to continue to operate, denominating the non-monetary costs in terms of expected dollars lost to the insurance fund.

Our estimates are obtained through a conditional choice probability (CCP) estimation of a dynamic model of bank closure. In the model, a regulator must decide whether to close a bank. The regulator is averse to closing banks but knows that allowing a distressed bank to continue to operate may raise the eventual resolution costs. Choosing not to close the bank has no immediate cost but may result in closure having to occur in the future. If a troubled bank is allowed to continue indefinitely, it may eventually experience a disorderly failure, which will be particularly costly. Further, regulators may consider the possibility that external pressure will force closures at some point in the future. The regulator's utility can be decomposed into the monetary costs and non-monetary costs discussed above. We also consider the possibility that regulators simply prefer to defer costs into the future due to regulatory myopia. Thus, our analysis can help answer both whether the FDIC waited past the socially optimal point to shut down banks and what considerations led to such waiting.

Our results indicate that during the 1980s and 1990s the FDIC appeared to wait longer to close banks than would have been optimal from the perspective of strictly minimizing the costs to the insurance fund. Our estimates attribute this delay to a mild degree of regulatory myopia, with the FDIC using an annualized discount factor of approximately 0.84, as well as a particular desire to avoid closing both the largest and smallest institutions. We find conflicting evidence regarding the FDIC's non-monetary preferences for closing banks that are in relatively worse condition. Banks with higher net income appear more costly to close from the non-monetary perspective, indicating that the FDIC preferred to wait until a bank faced larger losses

[2] A thorough discussion of the potential motivations of the regulators, both justified and unjustified, can be found in Spong (2000).

even when shutting down the bank earlier would have saved insurance fund capital. This preference could arise from regulatory capture as the FDIC might feel compelled to wait until a bank was more obviously in distress before intervening. Interestingly, another measure of the state of the bank, the non-performing loan ratio, has the opposite effect where banks with higher non-performing loan ratios appear more costly to close from a non-monetary perspective. We also find some evidence that political influence plays a role in the decision to close banks in the 1980s and 1990s. Banks from states with greater representation in leadership positions or banking committees in the House of Representatives tend to be treated as more costly to close. In contrast, during the current period we find little evidence of either myopia or political influence on closure decisions.

The estimates of the determinants of both monetary and non-monetary costs can be used to recover the distribution of both types of costs, providing some insight into their relative importance. For example, in the earlier period of bank failures we estimate that the median monetary cost for closing a potentially distressed bank (defined as a bank with negative net income in a given quarter) is approximately \$1.2 million. The non-monetary cost associated with this median observation is between \$2.8 and \$13 million. For those banks most likely to be closed (i.e. in the top 10% of closure probability), the monetary cost is on average \$21 million, while the non-monetary cost ranges from \$7.8 to \$21 million. These numbers also demonstrate why taking account of the dynamic nature of the choice facing the regulator is crucial. Since the banks most likely to be closed have a much higher monetary closure cost, a static estimation would necessarily conclude that they had a much lower non-monetary closure cost. In fact, we find that those banks that were eventually closed were exactly those that were most costly to close from the non-monetary perspective; the decision to ultimately close these banks was driven by concern that the costs would grow over time.

Since we are able to recover structural parameters, we can perform counterfactual policy analyses in order to evaluate what would have occurred if the FDIC had different preferences for closing banks. We find that the FDIC would have closed banks appreciably more aggressively if they had used a discount rate that implied less regulatory myopia. We also consider an experiment in which the FDIC selects banks for closure based more on monetary considerations than non-monetary considerations. Initially, this policy leads to higher total closure costs since the FDIC chooses to shut down unhealthy banks, but the savings from the policy manifest themselves quickly and lead to an appreciably lower total monetary cost over the course of the banking crisis.

We estimate the model using the Hotz and Miller (1993) technique, which permits identification of structural parameters of dynamic models without solving the dynamic programming problem as is required in methods following Rust (1987). Instead of solving for the potentially highly intractable value function, the researcher acknowledges that the agent has solved the problem in order to choose his optimal behavior, and, therefore, there is an invertible mapping between value functions and empirically observed choice probabilities. This approach leads to an estimator with a much lower computational burden compared to traditional methods, allowing us to consider a richer set of explanatory variables and several different variations of the model. CCP estimation further permits identification of the model parameters without positing details of the costs associated with disorderly failure. This second advantage is essential since we do not observe disorderly bank closures, and in fact are prevented from ever observing such events by the decisions of bank regulators.

Related Literature

Interest in the determinants of bank failure peaked during the 1990's following the unprecedented wave of insured bank failures in the 1980's. Examples include Thomson (1991), Wheelock and Wilson (1995), and Wheelock and Wilson (2000). These papers seek to identify empirical relationships between bank conditions and the probability of closure. Thomson (1989) includes potential constraints on the FDIC's ability to close a bank in the specification for the probability of bank closure, acknowledging that a bank failure is in part a choice by the regulator rather than an event driven solely by the underlying condition of the bank.

None of these papers seek to quantify the direct determinants of the value the FDIC placed on keeping a bank open, nor do they take an explicitly dynamic, forward looking approach to the evolution of bank variables. Cooperstein et al. (1991) analyze deposit insurance in a multiperiod setting and estimate the costs of deposit insurance, but they use a static, reduced-form closure probability function and do not explicitly model the decision making process of the FDIC. James (1991) and Barth et al. (1990) present a reduced-form estimation of bank closure costs for a subset of our sample period but make no attempt to recover the structural determinants of the bank closure decision.

From a methodological perspective, multistage estimation procedures are popular in labor economics and industrial organization,[3] although they have seen little use in finance (Strebulaev and Whited, 2012).

[3] See Arcidiacono and Ellickson (2011) for a recent survey of methods and applications of this class of estimators. We direct the reader here for a more complete literature review, along with a thorough discussion of the costs and benefits of this methodology.

Our approach is similar to Murphy (2010), who examines real estate market dynamics by estimating a dynamic model of the decision to build on a vacant parcel.

Our paper also fits into the growing literature which seeks to apply structural methods to questions in corporate finance. Starting with Hennessy and Whited (2005, 2007) and Strebulaev (2007), a series of papers have used structural methods to estimate magnitudes of variables of interest in capital structure and other areas of corporate finance where dynamics are important. A recent example is Taylor (2010), who estimates the fixed costs associated with CEO firing taking into account imperfect observability of CEO type. In more closely related work, Schroth et al. (2014) use simulated method of moments to estimate a model of runs in the asset backed commercial paper market, where profit maximizing investors, rather than a centralized regulator, effectively choose when a weakened financial intermediary closes.

1 Model

In each period, an FDIC regulator chooses whether to close a bank. If the bank is closed, the regulator must pay a monetary cost. This cost is the direct payout from the insurance fund required to make depositors whole. The FDIC actually can choose between two resolution methods after a bank is closed: depositor payoffs or purchase and assumption. In the second and more common case, the FDIC subsidizes the takeover of the failing bank by another, presumably healthier, institution, thus ensuring that depositors do not suffer losses. For simplicity, we do not model the choice between the two closure methods. In either case the FDIC is simply discharging a liability claim which is greater than the value of the attached assets and must pay the difference between the two in order to do so.

The regulator may have other perceived non-monetary costs. For example, closing a bank through either method may disrupt economic activity within a community (Ashcraft, 2005), lead to contagion within the banking sector, or result in pressure on the regulator from politicians connected to the bank. The total cost to regulators is the sum of both the monetary payout costs and the relative cost of these non-monetary considerations.

The regulator faces a tradeoff between closing a bank in the current period or delaying closure, which may raise closure cost in the future as a bank deteriorates further. If the bank condition deteriorates sufficiently, even deposit guarantees will fail to provide sufficient stability for an insolvent bank and a disorderly failure will occur whether or not the FDIC wants to close the bank. While disorderly failure is actually a hypothetical event in our analysis, a bank could not continue to operate forever in the face of continued large losses and would eventually fail to have enough cash for operations even with FDIC assistance and deposit guarantees. In certain models, we also admit the possibility that external pressures, including but not limited to direct Congressional intervention, might force closure of some banks regardless of the decision made by the FDIC. Appendix A.4 provides a detailed discussion of how we account for this possibility.

We define the state of bank i in period t as x_{it}. This state summarizes the size of the bank and its condition, along with any other factors that would influence the cost of closing the bank. Given x_{it}, the FDIC chooses $d_{it} \in \{0, 1\}$, where $d_{it} = 1$ if the FDIC chooses to close the bank in period t. We define the subset of bank conditions that lead to disorderly failure as Δ.[4] From these definitions, we can write the static payoff to the regulator as:

$$\begin{aligned} u_0(x_{it}) &= -\mathbf{1}_{x_{it}\in\Delta}\tilde{c}(x_{it}) + \varepsilon_{0it} & \text{if } d_{it} = 0 \\ u_1(x_{it}) &= -\mathbf{1}_{x_{it}\in\Delta}\tilde{c}(x_{it}) - (1 - \mathbf{1}_{x_{it}\in\Delta})c(x_{it}) + \varepsilon_{1it} & \text{if } d_{it} = 1 \end{aligned}$$

where $\varepsilon_{it} = \{\varepsilon_{0it}, \varepsilon_{1it}\}$ is the choice specific error term, $c(x_{it})$ is the cost to the FDIC of an orderly bank closure, $\tilde{c}(x_{it})$ is the cost of a disorderly bank failure, and $\mathbf{1}_{x_{it}\in\Delta}$ is an indicator function for being in a disorderly default state.

The regulator is a forward looking decision maker so he not only cares about the current payoff but also the stream of future payoffs. The objective function that the regulator maximizes is therefore

$$(1 - d_{it})u_0(x_{it}) + d_{it}u_1(x_{it}) + \sum_{s=t+1}^{T} \beta^{s-t} E[(1 - d_{is})u_0(x_{is}) + d_{is}u_1(x_{is})|x_{it}, d_{it}] \tag{1}$$

where the expectation is over the uncertain future state and uncertain future choices. Since the FDIC makes an optimal decision in each period, by the Bellman principal the decision problem becomes:

$$V(x_{it}) = \max_{d_{it}\in\{0,1\}} u_{d_{it}}(x_{it}) + \beta E[V(x_{it+1})|x_{it}, d_{it}].$$

Here, the expectation is over future bank states. The future state of the bank, and thus the value of the FDIC's problem going forward, depends on the current state of the bank through the known, random transition process for the state of the bank. Further, the future value depends on whether or not the FDIC closes the

[4] We assume that the bank experiences disorderly failure with probability 1 when entering a state included in Δ; this is without loss of generality in the estimation for reasons that will be discussed later.

bank in the current period. A bank can only be closed once, either in an orderly or disorderly fashion, so we normalize all future payoffs to 0 after the closure event.

2 Model Estimation

2.1 Identification

2.1.1 Identifying Assumptions

We impose three main identifying assumptions. The first permits identification of the costs of orderly closure even though we do not observe disorderly closures. The second allows us to use observed data on the realized bank closure cost to pin down the monetary closure costs, and the third is a standard technical assumption regarding the distribution of choice specific error terms.

Assumption 1. *The probability of entering the disorderly failure state from any state observed in the data is vanishingly small. That is, $P(x_{it+1} \in \Delta | x_{it}) \approx 0$ for all x_{it} observed.*

This assumption is theoretically justified by the FDIC's mission to prevent a catastrophic, uncontrollable run on deposits at all costs. Moreover, this assumption is strongly supported by the data. Within our sample period, no bank, or even a Savings and Loan (S&L), ever experienced a run on their deposits, and the banks in our sample were healthier than the worst S&Ls (Cooper and Ross, 2002).

This assumption allows identification of the monetary and non-monetary costs of an orderly bank closure even though we never observe disorderly failures. This identification is perhaps surprising as the fear of a disorderly closure is the primary reason that banks are closed in an orderly fashion at all. Our partial identification from limited data demonstrates a powerful aspect of the estimation technique applied here. As long as we can obtain estimates of the expected closure cost one period ahead, the probability of closure given each state, and the state transition process, we can identify non-monetary cost parameters and the discount factor without needing either data or assumptions about the costs along choice paths farther into the future. This feature arises because we apply the inversion theorem from Hotz and Miller (1993) to represent value function differences as ratios of choice probabilities, allowing us to account for the dynamics in the decision process of the FDIC without actually calculating the value function directly.

Assumption 2. *The error term on monetary costs is orthogonal to the choice specific error terms.*

This assumption is similar to the assumptions on pre-estimates made in a number of other studies using the methods here. See, for example, Murphy (2010), Ryan (2012), and Gayle and Golan (2012). Under this assumption, we can obtain consistent estimates of the non-monetary cost of closing any bank by pre-estimating the cost function.

Assumption 3. *The choice specific error terms (ε_{0it} and ε_{1it}) are both identically and independently drawn from multivariate extreme value type I distribution with location parameter μ and scale parameter σ. Furthermore, the mean of the choice specific error term is normalized to 0.*[5]

The final identifying assumption simply states that we use the standard type I extreme value distribution for the choice specific error terms. This distribution gives a closed form expression for the mean of the difference between two random variables.

2.2 Estimation Framework

We now describe how to apply the conditional choice probability estimation procedure. A reader only interested in the basic idea behind the derivation of the estimator and the means for identifying relevant parameters may skip directly to section 2.3, which provides a simplified example of the estimator. The key to the estimation approach is expressing the regulator's optimal decision from equation (1) in terms of observable quantities and parameters only. We define the choice specific value functions, V_0 and V_1, as:

$$V_j(x_{it}) = \max_{\{d_{ik}\}_{k=t+1}^{T}} u_j(x_{it}) + \sum_{s=t+1}^{T} \beta^{s-t} E[(1-d_{is})u_0(x_{is}) + d_{is}u_1(x_{is})|x_{it}, d_{it}=j], \quad j \in \{0,1\}.$$

Under equation (1) and Assumption 1, for every state observed in the data we can express the current period payoffs as:

$$\begin{aligned} u_0(x_{it}) &= \varepsilon_{0it} && \text{if } d_{it}=0 \\ u_1(x_{it}) &= -c(x_{it}) + \varepsilon_{1it} && \text{if } d_{it}=1. \end{aligned}$$

By substituting these utility expressions for each decision and applying the Bellman principle we obtain:

$$V_0(x_{it}) = \varepsilon_{0it} + \beta E[p_0^{(1)}(x_{0it})V_0^{(1)}(x_{0it}) + p_1^{(1)}(x_{0it})V_1^{(1)}(x_{0it})] \quad (2)$$

$$V_1(x_{it}) = -c(x_{it}) + \varepsilon_{1it} \quad (3)$$

[5] The assumption that the mean of the choice specific error term is 0 gives the identity $\mu + \gamma\sigma = 0$, where γ is Euler's constant.

where p_1 is the probability that the regulator closes the bank and $p_0(\cdot) = 1 - p_1(\cdot)$. For notational economy, we define a general function $A^{(k)}(x_{jit}) \equiv A(x_{it+k}|d_{it} = j)$ to denote some function A evaluated k periods ahead conditional on choice j having been made in period t. For example, $p_1^{(1)}(x_{0it})$ is the probability that bank i will be closed at $t + 1$ given that the bank is not closed at t.

Note that once $d_{it} = 1$ is chosen, this action cannot be undone and there are no more actions to follow in future periods. Hence, our model features a "terminal action" or "absorbing state" from the dynamic discrete choice literature. We see this by observing that $V_1(x_{it})$ does not include any future payoffs.

Defining the "conditional value function" as $\nu_j(x_{it}) \equiv V_j(x_{it}) - \varepsilon_{jit}$, the difference in the conditional value of each decision can be written in terms of the ratio of the probability of each decision:[6]

$$\nu_0(x_{it}) - \nu_1(x_{it}) = \sigma \ln \frac{p_0(x_{it})}{p_1(x_{it})}. \tag{4}$$

In Appendix A.1 we further show that the difference in the conditional value functions can be expressed as follows:

$$\nu_0(x_{it}) - \nu_1(x_{it}) = \beta E_x[-\sigma \ln p_1^{(1)}(x_{0it}) - c^{(1)}(x_{0it})] + c(x_{it}). \tag{5}$$

Equations (4) and (5) then yield an estimating equation:

$$\sigma \ln \frac{p_0(x_{it})}{p_1(x_{it})} = \beta E_x[-\sigma \ln p_1^{(1)}(x_{0it}) - c^{(1)}(x_{0it})] + c(x_{it}). \tag{6}$$

While the derivation of this estimating equation is somewhat technical, the interpretation is relatively straightforward. Equation (4) is the equivalent of the estimating equation for a logistic regression where the differences in static utilities are replaced by the differences in total discounted expected utility given that optimal decisions will be made in the future. The problem is that the conditional value functions $\nu_0(x_{it})$ and $\nu_1(x_{it})$ cannot be expressed as a closed form function.

The insight that permits identification of the dynamic model is that it is possible to substitute out the terms that cannot be expressed in closed form by replacing them with estimated closure probabilities that can be estimated from the data. This is possible because these closure probabilities are the outcome of the agent solving the dynamic programming problem. As a result, we can obtain an expression that should hold

[6] This expression comes from the fact that $p_0(x_{it}) = Pr(\nu_0(x_{it}) + \varepsilon_{0it} > \nu_1(x_{it}) + \varepsilon_{1it})$ and analogously for p_1. Then, the type I extreme value distribution of the errors implies that $p_d(x_{it}) = \frac{\exp(\nu_d(x_{it})/\sigma)}{\exp(\nu_0(x_{it})/\sigma)+\exp(\nu_1(x_{it})/\sigma)}$.

(equation 6) and which contains only observable data, pre-estimated quantities, and structural parameters.

The total closure cost is parameterized as the sum of a monetary cost, the payout from the FDIC needed to fully resolve a closed bank, and a non-monetary cost which represents the additional utility lost by regulators when forced to close a bank. To allow for this separate estimation, we parameterize the cost function $c(x_{it})$ as follows:

$$c(x_{it}) = MC(x_{it}|\theta_{mc}) + \tilde{x}_{it}'\theta_{nmc} \tag{7}$$

where θ_{mc} (θ_{nmc}) are the parameters determining monetary costs (non-monetary costs) and $\tilde{x}$ is the subset of variables (or functions of variables) that determine non-monetary cost. This non-monetary cost represents the economic, political, and personal concerns that may influence FDIC decisions. The final goal of the estimation is to recover the parameter vector θ_{nmc} which expresses how the $\tilde{x}_{it}$ variables influence the concerns of the regulator relative to the direct dollar denominated resolution cost to the insurance fund.

Estimating the parameters proceeds in steps.

1. Estimate the parameter vector θ_{mc} from the actual monetary payouts by the FDIC. This step permits us to replace the MC term in equation (7) with a numerical estimate for each observation.

2. Estimate the transition process for the x_{it} variables to estimate a predicted period ahead value for each variable.

3. Estimate the probability of closure with a flexible logit as a function of all the x_{it} variables and determinants of the transition process.

4. Through simulation, use the projected period ahead variables to generate an estimate for each observation of the closure costs and closure probabilities one period in the future.

5. Recover the parameter vector θ_{mc} from the estimating equation (6) via continuously updated GMM.

For step 5, we compute the error in the estimating equation as:

$$\upsilon(z_{it}, \pi, \theta_{nmc}, \theta_{mc}) \equiv \sigma \ln \frac{p_0(x_{it})}{p_1(x_{it})} + \beta E_x[\sigma \ln p_1^{(1)}(x_{0it}) + c^{(1)}(x_{0it})] - c(x_{it}) \tag{8}$$

where $z_{it} = \{x_{it}, x_{0it}^{(1)}\}$ and $\pi = \{p_1, p_1^{(1)}\}$.

The moment conditions are then the population counterparts of the normal equations with previously estimated parameters since the error should be orthogonal to all observable data (Altug and Miller, 1998):

$$E[\tilde{z}_{it}\upsilon(z_{it}, \hat{\pi}, \theta_{nmc}, \hat{\theta}_{mc})] = 0, \tag{9}$$

where $\tilde{z}$ is the subset of data used for identification of the non-monetary cost payoffs. More details of the estimation procedure can be found in Appendix A.2.

2.2.1 Separating Monetary and Non-Monetary Costs

Our approach to separating monetary considerations from non-monetary considerations follows the approach taken in discrete choice models such as Murphy (2010), Ryan (2012), Gayle and Golan (2012), and others.[7] Data are used to pre-estimate a monetary component of payoffs, and the discrete decisions then identify the remaining parameters, as our closure decisions identify the non-monetary costs. In Ryan (2012), the decision to enter the cement market depends on anticipated revenue and costs. The pre-estimated demand function determines revenue, and the cost estimation must reconcile the observed choice behavior and the estimates of the anticipated revenue. In Murphy (2010), pre-estimated expected housing prices determine revenue, and construction costs rationalize the observed choice to build.

In our case, we pre-estimate the monetary closure cost, which we can do directly from the data on realized monetary closure costs. We then observe the bank closure decision. Since the FDIC is assumed to behave optimally, the remaining non-monetary costs that cannot be directly observed must rationalize the actual decision to close banks. For example, if two banks have identical estimated monetary closure costs *and* identical expected closure costs in the future, yet one bank is closed and the other is allowed to continue to operate, this would indicate that the non-monetary closure costs are higher for the bank that remained open. Whatever characteristics the bank has that the other does not will then be estimated to lead to higher non-monetary closure costs.

While our paper is methodologically very distinct from Taylor (2010), the identification argument is similar. Taylor (2010) identifies private costs to board members for firing CEOs as the residual cost necessary to rationalize decisions that cannot be rationalized by shareholder wealth maximization. Taylor includes the caveat, which also applies in our case, that perhaps a different model of the "monetary" payoff (in his

[7] See also Arcidiacono and Miller (2011), who use Monte Carlo simulations to compare estimates of entry-exit models when it is or is not possible to pre-estimate the function for the price of output.

case share price response and in our case monetary costs) could rationalize the data with less reliance on the non-monetary aspects.

More formally, the entire choice problem we study is identified from the existence of a terminal state and the natural normalization of payoffs in all periods after closure to zero. This identification is an immediate application of Arcidiacono and Miller (2013, section 4 and particularly section 4.1).[8]

2.2.2 Discount Factor Identification

In contrast to many exercises in structural estimation, we treat the discount factor as a parameter to be estimated. Often, the discount factor is simply set to a level that broadly reflects observed interest rates. Since the discount factor used by the FDIC will play an important role in the timing of closures, we address here why we choose to estimate this parameter and its identification.

In models in industrial organization it is generally reasonable to calibrate the discount factor; the discount factor must to some extent at least be pinned down by real interest rates. In those cases, investing money in fixed income instruments is clearly a viable option and the desire to realize profits now versus in the future should be determined by the rate the decision maker can earn on alternative investments.[9] If, and only if, the FDIC were assumed to be acting exclusively in the interest of taxpayers might this condition be valid for our problem. That is, if the FDIC cares only about the welfare of taxpayers, it would seek to defer losses only when the return that taxpayers could earn on the funds exceeded the rate at which the loss was expected to grow. One of the primary motivations of our study is to learn about the extent to which the FDIC appears to act in the interest of taxpayers, and imposing a discount factor exogenously would effectively shut down one channel where the regulator's interests and taxpayers' interests might not coincide.

Formally, the discount factor is identified in our model, even non-parametrically, because our model exhibits an absorbing state, as demonstrated in Arcidiacono and Miller (2013). This identification result contrasts with the lack of non-parametric identification of the discount factor discussed in Magnac and Thesmar (2002), who show that in many cases an exclusion restriction in which some variables influence how other variables transition without directly influencing payoffs is necessary in order to non-parametrically identify

[8] The limitation of non-parametric identification of the non-stationary model with an absorbing state (a special case of finite state dependence) is that the utility function from the last period sampled cannot be identified. Our Assumption 1 addresses this minor issue. We assume utility function parameters are stable over the sample period and over any state that may be entered into from observations in the sample period. Our two-state payoff setup (regular and disorderly failure) is thus sufficient (but certainly stronger than necessary) to guarantee identification.

[9] The run model in Schroth et al. (2014), for example, fixes the discount rate to the annualized treasury yield since runs are made by investors who could invest in the risk free asset instead of risky asset-backed commercial paper.

the discount factor.

Intuitively, identification of the discount factor hinges on separating two different reasons why the FDIC might wait to close a bank even though the expected monetary closure costs are expected to rise. First, the regulator may have a high non-monetary cost, giving him a strong incentive to wait and hope the bank recovers even though, in expectation, waiting increases the monetary cost. Second, the regulator may discount the future at a high rate, thus preferring to push the realization of monetary and non-monetary costs into the future. The relative importance of these two effects can be identified, in part, from the behavior of the FDIC toward banks that are very likely to be closed. When a bank enters a state in which worsening conditions and eventual failure are practically inevitable, and yet the FDIC waits to close anyway, a high discount rate is the most natural way to rationalize such data. This behavior seems to be present in our data and is consistent with the conventional wisdom regarding the FDIC's behavior during this period. In particular, calls for the FDIC to begin to engage in "prompt corrective action" can be seen as reactions to this type of behavior.

2.3 Numerical Example

At this point, we can consider a simple numerical example that corresponds to our setting to help give an intuitive idea for how relevant quantities are identified. Suppose there are four types of banks, $i \in \{1, 2, 3, 4\}$. The economy starts with an arbitrarily large number of each of the first three bank types and no type 4 banks. In each period, the FDIC decides whether to close each individual bank, where variation in bank closure within bank types is caused by an independently drawn preference shock for each choice from the type I extreme value distribution with mean 0 and scale parameter \$1 million. It is known ex ante that any bank that becomes a type 4 bank must be closed; this bank type corresponds to our "disorderly closure state." Closing a bank brings a monetary cost of $MC(i)$, where i indexes bank types, plus a mean zero idiosyncratic cost component that the the FDIC does not observe before making the closure decision. These costs are, in order of bank type, **\$1 million**, **\$2 million**, **\$7 million**, and \$200 million. The characteristics of the banks and the realized closure cost are observable to the econometrician. For simplicity, we will assume that the FDIC uses a known discount factor of $\beta = 0.9$.

If a bank is not closed then it potentially transitions to being a different type of bank according to the following Markov process:

$$\begin{array}{c c} & \begin{array}{cccc} B_1 & B_2 & B_3 & B_4 \end{array} \\ \begin{array}{c} B_1 \\ B_2 \\ B_3 \\ B_4 \end{array} & \begin{pmatrix} \mathbf{\frac{3}{4}} & \mathbf{\frac{1}{4}} & \mathbf{0} & \mathbf{0} \\ \mathbf{\frac{1}{8}} & \mathbf{\frac{3}{4}} & \mathbf{\frac{1}{8}} & \mathbf{0} \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & 1 \end{pmatrix} \end{array}.$$

The true probability of each bank closing (p_1) is given by $p_1(1) = \mathbf{5\%}$, $p_1(2) = \mathbf{10\%}$, and $p_1(3) = \mathbf{100\%}$. The type 4 closure probability is undefined since there can never be a type 4 bank.

The econometrician can recover from data all numbers in bold above: the cost of closing the first three types of banks, the probability that each of the first three bank types is closed, and the transitions between type 1 and type 2 banks along with the probability that either of these types of banks transitions to being a type 3 or 4 bank. Suppose the econometrician believes that the FDIC is influenced by considerations other than pure cost minimization, and this consideration takes the form of an additional "non-monetary" cost of $NMC(i)$ for closing a bank of type i, where $NMC(i) = \kappa + \zeta i$. The econometrician would like to recover the non-monetary cost for closing each type of bank.

A first pass at this problem could involve a static estimation of the non-monetary closure cost. The fact that type 1 banks are cheapest to close but have the lowest closure probability leads to an estimate of a high non-monetary closure cost for type 1 banks relative to the other banks. A static logit estimator gives the non-monetary closure cost for a bank of type 1 of \$1.9 million and for a bank of type 2 of \$0.2 million, since these values solve:

$$5\% = \frac{\exp\{\$-1\,\mathrm{m} - \mathrm{NMC}_1\}}{1 + \exp\{\$-1\,\mathrm{m} - \mathrm{NMC}_1\}}, \qquad 10\% = \frac{\exp\{\$-2\,\mathrm{m} - \mathrm{NMC}_2\}}{1 + \exp\{\$-2\,\mathrm{m} - \mathrm{NMC}_2\}}.$$

This approach misses two important factors in the bank closure decision. First, the decision to close today instead of waiting may be determined by concerns that the closure cost will increase. This increase provides a reason, other than the relative non-monetary costs, for closing type 2 banks more often than type 1 banks. For example, suppose there are only two periods and all banks are closed in the second period and, for simplicity, that there is a non-monetary cost for closure only in the first period. Considering only type 1 and type 2 banks, we would then estimate the non-monetary closure cost for bank 1 as

$$5\% = \frac{\exp\{\$-1\,\mathrm{m} + \beta\$1\tfrac{1}{4}\,\mathrm{m} - \mathrm{NMC}_1\}}{1+\exp\{\$-1\,\mathrm{m} + \beta\$1\tfrac{1}{4}\,\mathrm{m} - \mathrm{NMC}_1\}}, \qquad 10\% = \frac{\exp\{\$-2\,\mathrm{m} + \beta\$2\tfrac{1}{2}\,\mathrm{m} - \mathrm{NMC}_2\}}{1+\exp\{\$-2\,\mathrm{m} + \beta\$2\tfrac{1}{2}\,\mathrm{m} - \mathrm{NMC}_2\}}$$

which gives $NMC_1 = \$3.1$ million and $NMC_2 = \$2.4$ million for $\beta = 0.9$. The estimation takes into account that closing bank 2 today saves $\$2\frac{1}{2}$ million in expectation the next period, while closing bank 1 saves only $\$1\frac{1}{4}$ million in the next period. These numbers come from calculating the expected closure cost one period ahead for each bank type. In light of this difference, the gap between the non-monetary costs drops since there is a greater dynamic benefit for closing bank 2 now versus waiting and potentially allowing the bank to degrade further.

However, it remains necessary to account for the fact that type 2 banks are closer to entering the "disorderly closure state" and therefore have an additional benefit of closure relative to type 1 banks in the true setting with more than two periods. Thus, we apply the CCP estimator to obtain a correct estimate of the non-monetary costs.

First, we use standard results on the type I extreme value distribution that give the difference between the total value less the idiosyncratic shock of closing and not closing the bank as

$$v_0 - v_1 = \ln\left(\frac{p_0}{p_1}\right)$$

where v_k is the value of taking action k minus the choice specific error term. Since the act of closing the bank is irreversible, we know that $v_1(i)$ is also given by $-MC(i) - NMC(i)$, the static payoff for closing a bank of type i. A key insight from Hotz and Miller (1993) is that $v_0(i)$ also has a simple representation that can be expressed only in terms of simple to estimate quantities and the posited static payoff function of the FDIC. This simple representation comes from the fact that the value of leaving the bank open today is a probability-weighted average of the value tomorrow of leaving the bank open and closing the bank. Rearranging this expression, as shown in Appendix A.2, gives

$$v_0(i) = \beta\left(E[-\ln(p_1^{(1)}(i))] - E[MC^{(1)}(i)] - E[NMC^{(1)}(i)]\right)$$

which then gives for each bank type:

$$\ln\left(\frac{p_0(i)}{p_1(i)}\right) \quad = \quad \beta \sum_{j=1}^{4} P_{ij}\left(-\ln(p_1(j)) - NMC(j) - MC(j)\right) + \left(NMC(i) + MC(i)\right)$$

where the left and right hand side of the equation are two different representations of $v_0(i) - v_1(i)$. For banks of type 1 and 2, this expression gives us the following two equalities:

$$\kappa + \zeta - \beta\left(\kappa + \frac{5}{4}\zeta\right) \quad = \quad \ln\left(\frac{.95}{.05}\right) + \beta\left(\frac{3}{4}\ln(.05) + \frac{1}{4}\ln(.10)\right) + \beta\left(1\frac{1}{4}\right) - 1 \tag{10}$$

$$\kappa + 2\zeta - \beta\left(\kappa + 2\zeta\right) \quad = \quad \ln\left(\frac{.90}{.10}\right) + \beta\left(\frac{1}{8}\ln(.05) + \frac{3}{4}\ln(.10) + \frac{1}{8}\ln(1)\right) + \beta\left(2\frac{1}{2}\right) - 2. \tag{11}$$

It is possible to obtain these expressions because none of the unknown terms associated with banks of type 4 appear in the above expression.

Solving the above system gives the non-monetary costs as a function of the bank type: $NMC(i) = 5.4 + 0.08i$. Note that this implies a smaller gap between the non-monetary closure costs of bank 1 and bank 2 than the previous estimations; in fact, the non-monetary cost of closing bank 2 is now estimated to be higher than that of bank 1. These results arise because the structural estimation allows for the fact that bank 2 is more likely to transition to a state where it risks disorderly failure and thus must be closed. This difference, instead of a direct cost incentive, can explain why banks of type 2 are closed more aggressively than banks of type 1. Crucially, this difference enters the estimation only through the closure probability in state 3, which allows us to recover the correct cost parameters for states 1 and 2 without assuming anything about what goes on for bank 4. In particular, we have no way to estimate the closure costs in state 4, but this quantity never enters into the estimation procedure here. This characteristic of the model highlights the short-panel identification results from Arcidiacono and Miller (2013).

Note also that, while we have not attempted to identify either the discount factor or the scale parameter of the choice specific error term in this example, the only inhibition to such identification in our model is the paucity of bank types. If we introduced another bank type that never transitioned to state 4 into the model, we could obtain a third equation, which would be adequate to separately identify a discount factor. Adding more bank types can then identify the parameters of the error distribution.

3 Pre-Estimation of Monetary Costs and Probabilities

3.1 Data

We combine data on the closure cost obtained directly from the FDIC with call report data for banks. To measure the potential political influence of banks, we collect data on committee assignments from Nelson (2011) and Stewart and Woon (2011). We confine attention to two periods of bank closures, between 1986 and 1992 and between 2008 and 2012. Closure cost estimates are not available prior to 1986. We end at the end of 1992, which corresponds to the effective date of the section of the FDIC Improvement Act that required "prompt corrective action" (PCA).[10] We begin the second period in 2008 since it was the first year since the 1990s with a non-trivial number of bank closures. Figure 1 shows the distribution of bank closures over time, illustrating these two distinct periods of bank closures.

[Figure 1 about here.]

Our estimation samples include all domestically owned state and federally chartered commercial banks administered under the FDIC from the end of 1985 to 1992 and from 2008 to 2012. We require banks to have at least $10 million in assets and to have an equity/asset ratio of less than 30%, which excludes very small banks and entities that may simply be transitional shell companies. We also drop quarters with asset growth exceeding 150% as this generally either represents a scale altering merger or an error in the data. These cutoffs exclude under 0.5% of the raw sample and remove extreme outliers. We also exclude the very largest banks, those with assets above $3 billion. These banks are almost never closed making estimation of the probability of closure difficult, and the very largest banks are likely to be treated in a significantly different manner than other banks.

We use data from 1984 through 1992 and from 2007 through 2012 to estimate the transition processes for bank variables and state level unemployment. State unemployment is taken from the Federal Reserve Economic Data website (FRED) at the St. Louis Federal Reserve. Summary statistics are reported in Table 1 for the early period and Table 2 for the recent period.

[10] The legislation requiring prompt corrective action was passed in 1991 but did not go into effect until 1992. Estimates of choice probabilities are similar if 1992 is excluded. We do not end up seeing the actual effect of PCA because the enactment of the legislation coincided with a period of increasing economic growth and decreasing short-term interest rates and thus most banks returned to a healthy state.

3.2 Monetary Cost

In order to analyze the regulator's closure decision, we must first estimate the expected monetary resolution cost to the FDIC for each bank in any given quarter. The FDIC provides data on the final realized costs of resolution for every bank which was closed and resolved from 1986 onward. Estimating the *expected* closure costs for a bank at each particular point in time comes with a particular set of challenges. The primary challenge is that, since we only observe resolution costs for the sample of banks which actually closed, we necessarily have a sample which has only positive closure costs. At any given point in time, most banks in the system should have a market value of assets which exceeds the market value of their liabilities, and would therefore generate no costs to the FDIC upon closure. For such banks, the FDIC would simply sell the assets and liabilities to another bank at a positive price and would be obligated to remit the difference back to the original equity holders. The bank would have a "negative" shadow cost of resolution and the real cost to the FDIC would be zero.

Since we never observe the negative shadow cost of resolving healthy banks, our cost estimates may be biased upward for most of the unclosed sample. We could pool the non-closed banks with the closed banks and treat their costs as censored at zero, but the sample of unclosed banks would contain banks which would have positive closure costs if they were to be resolved at that time. Indeed, one of the primary purposes of this study is to examine why banks are allowed to remain open even as their expected resolution costs are increasing.

To address this problem, we pool the failed bank observations with a set of banks which we know have a negative shadow closure cost, those that were acquired through an unassisted merger. This approach is similar to Barth et al. (1990). Both groups of banks have a set of observable call report characteristics in the quarter before they disappear. While we do not know the premium paid for these unassisted mergers, we can assume that it represents some latent negative cost value. As long as we assume that FDIC intervention would not have completely wiped out this premium, this corresponds to a zero closure cost observation. We thus treat unassisted mergers as having a cost of zero, with a latent negative shadow cost that accrues to the existing shareholders. We can then estimate this latent cost of resolution using a censored regression model in which the estimated cost over assets is censored at zero.

This pooled sample has distributional characteristics which are much closer to the full sample than the sample of failed banks only. Relative to the failure-only estimates used in most previous studies (e.g. James, 1991; Schaeck, 2008), these estimates are a significant improvement in correcting the obvious bias in the predicted costs. Figure 2 presents box plots of the distribution of the bank specific closure cost determinants for both the failure-only sample and the pooled failure and merger sample against the full estimation sample. Failed banks have significantly lower capitalization and net income ratios and significantly higher nonperforming loan and real estate ownership ratios than the full sample. The pooled sample is far more representative, with the mean and intraquartile range of each variable being quite close to the full sample in most cases. While we recognize that this does not completely solve the problem of conditionality, we believe that our approach provides a good approximation of the likely monetary closure costs.

[Figure 2 about here.]

We rely on a large prior literature to choose the variables which determine the closure cost. Resolution costs depend on bank specific variables: asset size, bank equity ratios, nonperforming loans, real estate owned, net income, and core deposits. In addition to these bank specific variables, we also include a number of aggregate variables. We include state unemployment as a proxy for local economic conditions. Since resolution costs also depend on the availability of bank capital, we include total county level deposits as a proxy for the state of the local banking market, and following Brown and Dinç (2011) we include aggregate U.S. bank capitalization as a proxy for the ability of U.S. banks to absorb closed banks through purchase and assumption transactions. The closure cost is estimated as the final resolution cost divided by the final period assets of the bank. This approach matches the approach of the existing literature, where the estimate predicts the fraction of the bank size (assets) that becomes a cost to the FDIC. We treat closure costs as being paid in the period in which the bank is closed, although operationally the total recovery from the assets acquired by the FDIC may not be immediate.

We estimate this censored regression using several different specifications which are reported in Table 3. Our main estimates use the Tobit model, with left censoring at 0. For each coefficient we also estimate the marginal effect on the predicted total cost ($\frac{\partial E[Cost]}{\partial x}$), in thousands of dollars, evaluated at the median of each variable. In the first two columns, we report the baseline results using only bank specific variables and state level unemployment. Bank size has a slightly negative impact on resolution costs, with smaller banks being slightly more expensive to close relative to their asset base. As expected, banks with lower capitalization, more nonperforming loans, and lower net incomes are also more costly to resolve. Firms with greater real estate owned are also significantly more expensive to resolve, confirming that much of the cost in the earlier period was driven by bad real estate lending. Higher state unemployment increases costs, indicating that the macroeconomic environment influences closure costs in a way that is not directly and immediately picked up in bank condition variables.

In next two columns, we add data on local and national financial conditions to our specifications. We also include core deposits, deposits less than $100,000, because conventional wisdom argues that reliance on brokered deposits over core deposits was a major source of trouble for banks at the time. We do, in fact, find that a higher share of core deposits at a bank leads to lower closure costs.[11] The coefficient on county deposits is negative and significant, suggesting that banks are less costly to resolve in larger banking markets. The coefficient on total U.S. bank equity relative to total bank assets is negative, consistent with the assertion by Brown and Dinç (2011) that bank closures are more costly during periods of low bank capital where outside banks may find acquiring bank assets through purchase and assumption transactions more difficult.[12] Overall, both models perform reasonably well in terms of fit. Moreover, when applied to the entire sample, the fraction of banks which have positive predicted latent closure cost compares well with the percentage of critically undercapitalized banks based on individual bank examinations during the period (FDIC, 1997).

In the final two columns, we report the results of the baseline model for the recent period. Unlike the earlier period, size does not impact the ratio of closure costs to assets, suggesting a near linear relationship between size and costs. Net income and state unemployment are now insignificant. Equity capitalization plays a more important role, which may be due to more stringent capital requirements during the period.

[Figure 3 about here.]

To evaluate how costs evolve over time for troubled banks, Figure 3 shows a box plot of the estimated cost of bank closure in the 8 quarters prior to a bank's actual closure in the base model. Negative values indicate a negative latent closure cost in which the existing shareholders would receive the premium, so the expected cost to regulators is always at least slightly positive. The predicted shutdown cost is increasing for these banks prior to the actual closure decision, indicating that shutting them down earlier would have

[11] Data on core deposits is not available quarterly, and our purpose in including core deposits is to capture cross sectional variation in costs associated with banks that were heavily funded by core deposits and those that were not. Thus, we use the first observation of core deposits available for each bank. Results are very similar when using annual observations, but because of the annual frequency we cannot estimate quarterly transition probabilities in the next estimation step.

[12] Note that while the absolute magnitude of the coefficient is large, the U.S. equity ratio is cross sectionally invariant and the difference only varies in the time series from a low of 0.0595 to a high of 0.0754, so the marginal effect is small.

resulted in a lower cost to the FDIC. However, since the estimates in this sample are conditional on having failed, we cannot directly conclude that this average projected cost increase was expected. In order to determine whether this is true and to calculate the beliefs of the regulator about next period bank conditions, we need to estimate how these bank conditions evolve stochastically over time.

3.3 Transition Probabilities

The transition of variables is modeled parametrically as an autoregressive process where each bank variable is a function of 4 lags of itself and 4 lags of each other bank variable and state level unemployment:

$$x_{it} = \phi_0 + \sum_{s=1}^{4} \phi_s x_{i,t-s} + \sum_{s=1}^{4} \eta_s X'_{i,t-s} + \omega_{it} \tag{12}$$

where X' is a vector of the remaining bank variables and state unemployment and η is a vector of their respective coefficients.

We assume that the macroeconomic state is not directly affected by the condition of any particular bank. State unemployment transitions state-by-state in an AR(4) fashion while aggregate U.S. bank capitalization transitions as AR(2). Finally, since we need to multiply the cost determinants by assets, we also estimate the transition of raw assets (as opposed to log assets) as a simple function of 4 lags of itself.[13] The transition process in equation (12) is estimated through pooled OLS, and the specifications and results are summarized in Table 4.[14]

For tractability purposes, we place one further restriction on our data. We select negative annual net income, summed over the last 4 quarters, as a criteria for being potentially shut down. This restriction is needed in order to shrink the decision set to a region in which closures are at least somewhat probable.[15]

[13] This specification is somewhat nonstandard as assets would clearly not transition independently of log of assets, as these are both measures of the same variable. This is in part a technical simplification to expedite the simulation process (see footnote 18). It is also designed to allow the scale of the bank (i.e. the quantity by which we multiply the estimate of the fraction of the bank that turns into costs for the FDIC) to evolve in a manner that does not reflect changes brought about by distress. If a bank starts to shrink (or grow) its asset base prior to closure, this should not be seen as a change in the fundamental size of the bank, which we try to capture with the raw assets variable. Instead, we posit that there is some general pattern of the evolution of this size variable that captures how size evolves. We also include both log of assets and asset growth in the general transitions, which is somewhat repetitive. Technically, this permits a richer space of non-linear relationships, but we include both variables because it also simplifies the simulations.

[14] We assume that the composition of the relevant Congressional committees transitions deterministically. It would not be possible to estimate quarterly transition probabilities for these variables as committee changes generally occur at specific times. Since the committee changes are effectively predictable one quarter ahead, we can safely treat them as deterministic and fully anticipated by the FDIC.

[15] The unconditional probability of closure if net income is positive is less than 0.01%, and the determinants of closure become effectively impossible to identify for these banks.

For the early period around 40,000 quarterly observations coming from 6,838 unique banks meet these restrictions, while for the later period around 25,000 (from 3,116 unique banks) meet these restrictions. There are 893 closures between 1986 and 1992 and 304 between 2008 and 2012.

[Figure 4 about here.]

The transition estimation models exhibit fairly good fit for each variable with R^2's ranging from .995 to .679. The high R^2 values are unsurprising given that five out of the six variables are levels. More importantly, the Root Mean Squared Error (RMSE) of each regression is small relative to the sample mean and standard deviation of the variables. We also report the contribution of the prediction transition error to the estimated closure cost. We multiply the RMSE for each prediction variable by the associated coefficient in the cost estimation model and report them in the last row of Table 4. This value represents the impact of the prediction errors of each variable on the estimates of monetary cost. These numbers are all quite small in magnitude relative to the closure cost for the banks in the sample. To further illustrate the fit, we plot the period ahead predicted value of each of the six transitioning variables in Figure 4. These graphs show the average fit of the regression prediction for banks which did fail in the 20 quarters up to failure.

Estimation of the transition function allows us to form expectations over the period ahead expected cost as a function of current and past observables. We plot this period-ahead cost over the quarters prior to closure in Figure 5. The graph implies that the projected future cost was increasing prior to closure. This projection is a function of the unconditional estimated transitions and indicates that banks were allowed to remain open over periods where the average cost to taxpayers was expected to increase.

[Figure 5 about here.]

Transition probabilities for the current period are reported in Table 5. Estimates of the transition process are quantitatively similar to the transition process from the earlier period, though the variables exhibit slightly higher persistence relative to the earlier period. Overall fit increases slightly as well, though because the time period is shorter it is difficult to make a direct comparison.

3.4 Conditional Choice Probabilities

It would be ideal to nonparametrically estimate the conditional probability that the regulator closes a bank, for example with a kernel estimator. Our limited data and the large state space render such an approach potentially problematic, so following Murphy (2010) we apply a flexible logit estimator to recover choice probabilities. We apply cubic b-splines within the logit function to permit current state variables to influence the probability of closure in a flexible fashion.

Our estimation equation is:

$$p_1(x_{it}) = \Lambda\left(\{B(b_{is})\}_{s=t,\ldots t-3}, \{m_{is}\}_{s=t,\ldots t-3}\right) \tag{13}$$

where Λ is a logit function and $B(\cdot)$ represents a vector of splines.[16] The conditioning variables, b (bank variables) and m (aggregate or macro variables), are state variables that enter the cost function through the effect on either monetary or non-monetary costs, or affect the transition of state variables. For example, the probability of bank closure depends on the lagged unemployment rates even though these variables do not directly affect the payoff to the FDIC.[17] In some conditional choice probability specifications (Models II and IV below), we include a time trend to account for the possibility that the FDIC anticipated a policy change. See Appendix A.4 for more detail. We obtain future conditional choice probabilities (and future monetary costs) by simulation.[18]

The logit results are included in Tables 6 to 10, corresponding to the five main models we estimate. Models I-IV are for data from the 1980's and 1990's, while Model V is for data from the current period of bank closures. While the coefficients and standard errors on each variable are effectively impossible to interpret in isolation, the pseudo-R^2's (around 0.43 for the data from the early period and around 0.67 for the current period data) indicate that the logit models provide a reasonable fit. To further explore the fit, Table 11 presents the predicted and realized probability of closure for various ranges of the predicted probability. Except for Model V, where the 5 to 10% and, to a lesser extent, the 10 to 15% bins show significant divergence between predicted and realized closure probabilities, the models appear to predict closure probabilities well throughout the range of probabilities. The relatively poor fit for certain bins in the current period is likely driven by the small number of observations available in these bins.

[16] When constructing splines, we use 4 basis functions for each element in b_{it}.

[17] Note that while we restrict our sample of potential closures to banks with negative annual net income, it is possible that such banks will transition to having positive net income in the future. We do allow banks to transition to positive net income, so this requires considering the probability of closure for banks with small but positive net income. If the ratio of real estate owned or non-performing loans transitions below zero we set the value to zero.

[18] For each observation, we first draw errors from the empirical distribution of error terms in the transition processes in equation (12). Then we construct the next period's state variables and predict the future monetary cost and future conditional choice probability using the pre-estimated cost function and the logit function. We repeat this process 5,000 times for each observation. To obtain the expected future values of MC and $\ln p_1$, we take the average of 5,000 simulated values and assign it to the observation.

4 Non-monetary Cost, Discount Factor, and Error Distribution Estimates

Having recovered estimates for monetary costs, choice probabilities, and transitions processes, we can now estimate the remaining structural parameters from the moment conditions derived in Section 2.2. In this section, we present results for four specifications of the model for the 1980s and 1990s (Models I-IV in Table 12); a fifth specification (Model V) covers the recent period and is discussed in Section 6. Models I(a) and I(b) are estimated with a calibrated discount factor and an alternative specification for non-monetary costs, respectively, and are discussed in Section 5.[19] Models I and II, which we refer to as the "parsimonious" models, focus primarily on bank characteristics to determine the monetary and non-monetary closure costs. Monetary costs are estimated using the specification in column (1) of Table 3. Model II includes a time trend in the choice probabilities, as described in Appendix A.4. Results are similar across the specifications with time and without time. Based on the J-test criteria, neither Model I nor Model II is rejected.

Models III and IV (the "full" models) include a richer set of potential determinants of both the monetary and non-monetary closure costs, using the specification in column (2) of Table 3. Model IV includes a time trend in the estimates of the conditional choice probabilities. In addition to the variables included in Models I and II, we include county deposits as a potential determinant of non-monetary costs to capture the possibility that the FDIC cares about the level of banking services available in the area in which the bank operates. Including these variables leads to a rejection of the model based on the J-test, which provides support for focusing on the more parsimonious model.

The results for non-monetary costs are qualitatively similar across all specifications. In particular, no variable that is ever significant changes sign across specifications. Further, the differences are relatively small in the sense that all estimated values fall within the 95% confidence interval of all estimates from the other models. The main difference among the models estimated is that including more variables seems to appreciably decrease the importance of the choice specific error term, with the estimated standard deviation ($\frac{\sigma\pi}{\sqrt{6}}$) falling by more than 75% in the full model relative to Model I.

[Figure 6 about here.]

[19] As we adopt a multi-stage estimation method, pre-estimates can introduce noise in our final estimates of structural parameters. Therefore, we correct for the fact that we are using a pre-estimated cost function and conditional choice probabilities as in Newey and McFadden (1994). When doing so, we assume that the error terms in pre-estimation stages and the final structural estimation are independent of each other (Assumption 2). Given our large number of simulation draws the simulation errors are ignored, based on Stern (1997). To be fully conservative, we should also adjust the standard errors for the estimation of the transition functions. This procedure is not as straightforward as the other corrections and may not be feasible.

Given how we specify the overall cost function of the FDIC, we are able to use the monetary costs to the insurance fund as a unit to measure the non-monetary closure costs. Monetary costs represent the expected loss to the insurance fund from closing a bank in a given period. Non-monetary costs can then be interpreted as the amount the FDIC would be willing to give up from the insurance fund to avoid closing a bank. Figure 6 shows the distribution of monetary and non-monetary costs for Models I and III (the distributions for Models II and IV are very similar).

From these estimates, we can evaluate the relative importance of monetary and non-monetary costs. At first glance, it appears that non-monetary costs dominate monetary costs. The median bank in our sample of potentially distressed banks would have a \$1.2 million monetary cost and a non-monetary cost around \$13 million (for Model I) or around \$3 million (for the full models). These numbers, however, overstate the relative importance of non-monetary costs compared to monetary costs. Many of these banks, despite having negative net income, were in very little danger of getting closed. Focusing on banks in greater danger, the scale of the monetary and non-monetary costs matches more closely. Out of the 10% of bank-quarter observations with the highest likelihood of being closed, the average monetary closure cost was \$21 million and the average non-monetary cost ranges from \$7.8 to \$21 million (Model III and Model II, respectively). This represents all bank quarter pairs with a closure probability greater than 7%. The set of the next most endangered banks, those with closure probability between 7% and 2.3%, have an average monetary closure cost of about \$7.6 million and an average non-monetary closure cost ranging from \$5.9 to \$17 million. This pattern reflects the relationship between the data on monetary costs and the data on closure probabilities. Many banks in the sample have a very low expected monetary closure cost, reflecting the fact that even banks with negative net income may have assets that exceed their liabilities. These banks are not frequently shut down, and therefore there must be a countervailing factor, in this case high non-monetary costs, that stops the FDIC from engaging in such preventative closures.

As a test of how well the model performs, we can compare the expected monetary closure costs that come out of the model with the realized closure costs that were actually observed over the period. To complete this calculation, we simulate a panel of representative banks and weight them using a non-parametric bin estimator.[20] We then forward simulate the model using the estimated transitions and conditional closure probabilities. At a horizon of 7 years, we obtain a total monetary closure cost of \$22 billion, which compares quite well to the actual realized closure costs over the 7 years of our data of \$23 billion. This simulation

[20]We focus here on the simpler monetary cost specification, which provides the best fit in the structural model.

provides the baseline for the policy analysis in Section 7. Appendix A.3 provides additional discussion on the performance of the model.

4.1 Non-Monetary Costs: Bank Quality

A key factor in the closure cost, both monetary and non-monetary, is the condition of the bank. In general, the worse a bank is performing the higher the monetary closure costs are. Poorly performing banks appear to degrade even further if allowed to continue to operate, giving the FDIC a monetary incentive to be more aggressive in closing more troubled banks. Apart from this, regulators may find it more palatable to close a bank that is weaker, even controlling for the monetary costs. For example, a bank that is performing poorly may be less able to lobby against FDIC action. Also, a bank that is performing poorly is more likely to make bad investment decisions due to well-known distortions associated with financial distress.

We investigate this possibility by including in the payoff function of the regulator two variables which relate to the condition of the bank, net income and non-performing loans. Net income has the expected sign; lower net income implies a lower non-monetary closure cost. Perhaps surprisingly, we obtain the opposite result on non-performing loans. This coefficient indicates that a higher level of non-performing loans raises the non-monetary closure cost. These results hold over all four models. The significance of the results, however, depends on the model used. Under Models I and II, the net income effect is significant while the non-performing loan effect is not. Both coefficients are significant under Models III and IV.

The non-monetary closure costs associated with net income highlights a potentially important driver of the choice behavior observed. Figure 7 shows the monetary costs and non-monetary costs as a function of net income. Relatively high levels of net income are associated with high non-monetary closure costs, making the FDIC hesitant to close relatively healthy banks despite the low monetary costs. This is an important source of the high average non-monetary closure costs for banks with a low probability of closure.

As can be seen in the figure, a bank with falling net income becomes more expensive to close from a monetary perspective but less costly from a non-monetary perspective. When net income is not too low, the FDIC waits to close the bank, hoping that the bank will recover and both costs will be avoided. As the bank's condition continues to deteriorate, the non-monetary closure costs drop, reflecting either decreased pressure on the FDIC to keep the bank open or a belief by the FDIC that the bank may now be doing more harm than good in its investment decisions.[21] At some threshold, it becomes worth paying these costs, along

[21] The possibility that the FDIC chooses whether to keep a bank open based on its beliefs about how efficient the bank's invest-

with the monetary costs, to prevent further deterioration. Note that monetary costs are growing as a bank's net income declines. Thus, the decision to wait to attempt to avoid high non-monetary costs will end up raising the eventual monetary closure costs if the bank does not recover. From the perspective of total costs, the non-monetary cost effect is larger than the monetary cost effect, so from a static perspective it becomes more appealing to close banks as they become weaker. As such, the inherent aversion to closing relatively strong banks probably played a significant role in keeping banks open longer than would be socially optimal.

[Figure 7 about here.]

In the full model the results actually suggest a non-monetary *benefit* for closing the worst banks. This result is consistent with the conventional wisdom that poorly performing banks may engage in value destroying risk shifting. Such a concern would make closing a particularly bad bank potentially socially beneficial, even without the benefit of avoiding an acceleration in the monetary closure costs.

Finding a preference for closing more poorly performing banks (as measured by net income) beyond the effect performance has on monetary costs is likely evidence that the FDIC waited too long to close banks. Regulators would likely face less pressure from Congress and the industry when shutting down banks that were obviously in difficulty, suggesting political or industry pressure on regulators. Thus, we interpret a higher non-monetary cost for closing better performing banks as an inefficient tendency to wait too long to close banks, leading to a higher-than-necessary monetary cost. This effect highlights the importance of considering the dynamics of the closure decision; for any bank the expected monetary cost of eventual closure will depend on the preferences of the FDIC since these preferences critically influence the timing of the closure.

The reverse result for non-performing loans suggests a preference for waiting to close banks that have a lot of poorly performing loans still on their books. Waiting until banks have resolved or written off these loans could be beneficial if banks have an advantage over the FDIC in resolving outstanding loans. While higher recovery on such loans would appear in the monetary cost estimates, greater administrative or time costs for the FDIC would appear as non-monetary costs. Further, the borrowers may be better off dealing with the original lender, and the FDIC could be taking the borrowers' welfare into account. Thus, a preference against closing banks with high non-performing loans could represent evidence of the FDIC pursuing non-monetary, but socially legitimate, objectives.

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ment decisions are is explored theoretically in Mailath and Mester (1991).

4.2 Non-Monetary Costs: Size

We admit a somewhat flexible functional form for the non-monetary costs associated with the size of a bank. Specifically we include size and size squared, where size is measured as the log of assets. This functional form permits a non-monotonic relationship between the size of a bank and the non-monetary closure costs, and we in fact detect that both the smallest banks and the largest banks are more costly to close. From a monetary perspective, the total closure costs are increasing in size (even through the fraction of the bank that becomes a cost to the FDIC is shrinking in size), but this increase is not sufficient to undo the non-monotonicity in non-monetary costs. Figure 8 plots the implied relationship between size and non-monetary costs.

Clearly, the largest banks impose the highest non-monetary closure costs, which is consistent with "too-big-to-fail" holding even among banks that are not extremely large. This result may represent concern about systemic spillovers or it may represent the greater political influence of larger banks. The smallest banks also become more costly to close from a non-monetary perspective. This hesitation to close small banks could represent forbearance aimed at small community banks that perhaps provided the only banking services available in an area. Note, however, that we do not detect hesitation to close banks located in counties with relatively low total county deposits, which somewhat contradicts this interpretation.

[Figure 8 about here.]

4.3 Non-monetary Costs: Real Estate Owned

Real estate owned plays a significant role in both monetary and non-monetary costs. In all models, higher real estate owned leads to a higher non-monetary closure cost. This result suggests a hesitation to close those banks whose difficulties arose from exposure to real estate. The FDIC may have viewed dealing with the troubled real estate portfolio as costly beyond the monetary losses as this type of asset might prove more time consuming and difficult to dispose of following a failure. Thus, the FDIC may have preferred to wait to close banks with a lot of real estate taken in forclosure in the hope that the bank would either recover or successfully dispose of the real estate before entering FDIC receivership.

4.4 Non-Monetary Costs: Political Influence

We allow the FDIC to care directly about the potential political influence of a bank, which would not affect the monetary closure costs. We proxy for political influence with the concentration of state Congressmen and Senators on relevant Congressional committees and in leadership positions.[22] Well known examples of pressure from Congress on financial regulators include the pressure applied by Charles Keating to push five Senators, three from the two states in which his businesses operated, to prevent the Federal Home Loan Bank Board (FHLBB) from closing Lincoln Savings and Loan. While the FDIC is generally considered to have operated under less political pressure than the FHLBB, we directly test this question by allowing the costs to vary with the level of influence available to a bank.

Our results detect a small but potentially significant influence of Congressional representation on the non-monetary closure costs. In the parsimonious model, the estimate of the coefficient on House influence indicates that the FDIC treats an additional member of the House of Representatives serving on a relevant committee as costing the equivalent of $849 thousand insurance fund dollars at the time of closure ($829 thousand when time is not included). These coefficients, however, are only marginally statistically significantly different from zero. In contrast, the coefficient is estimated as $299 thousand and $287 thousand with and without time in the full model, but these estimates are significant. We find no effect of Senate Committee membership in any of the four main models. The presence of a House effect and the absence of a Senate effect could indicate that banks are able to exert influence on politicians with a more local, community focus while having less success influencing Senators, who would necessarily take a broader view of the effects of bank closures since they have wider constituencies. Clearly such influence is possible in extreme cases, as discussed above, but it does not appear pervasive with respect to the FDIC.

4.5 County Deposits

In the full model, we include total deposits in the county in which the bank operates in the non-monetary cost as a proxy for the availability of banking services. The idea here is that the FDIC might hesitate to close banks in areas where banking services are sparse out of concern for the effects on competition and on the availability of banking services. We do identify a significant effect of county deposits on the non-monetary closure costs, but surprisingly it is in the opposite direction from what we expected. That is, higher total

[22] We include Banking and Financial Services; Banking, Finance, and Urban Affairs; Government Reform and Oversight; and majority/minority leader or whip.

county deposits leads to a higher non-monetary cost of closing a bank.

There are several possible explanations for this result. Total county deposits will correlate closely with population and the level of economic activity. Banks in urban counties may have greater influence at the FDIC even after controlling for bank size, or the FDIC might be more concerned about contagion within the banking sector when closing banks in areas with more total banking activity.

4.6 Discount Factor

We are able to precisely estimate the quarterly discount factor as 0.96, with standard errors of between 0.005 and 0.012.[23] These quarterly estimates give an annual discount factor of 0.84, which implies a significant but not overwhelming degree of regulatory myopia.[24] Since the average non-monetary closure costs appreciably exceed the monetary closure costs and the discount factor falls well below what would be implied by real interest rates, we find evidence of both forms of regulatory forbearance discussed in Section 2.2.2. This suggests that regulators were motivated both by a desire to preserve institutions under their purview and a desire to delay the realization of costs. Solving such distortions of the incentives of regulators requires different approaches. The high average estimates of the non-monetary costs would imply that regulators should be more insulated from pressure to support and preserve regulated entities, while a desire to defer costs more likely reflects problems with internal incentives within the regulatory body.

The level of regulatory myopia estimated in the model suggests a potentially serious problem, and one that perhaps would have triggered intervention by political leaders. Alternatively, it may appear unrealistic that the FDIC would have deviated so far from prevailing discount factors when making closure decisions. On the second point, we note that "regulatory forbearance" is a common concern particularly in financial regulation. A preference for allowing problem institutions to continue could arise naturally out of a model of regulation capture in the spirit of Stigler (1971), or from career concerns whereby realizing losses might increase the chance of intervention by outsiders in the regulatory sphere.

On the question of whether such myopic behavior would have been stopped by those supervising the regulators, specifically Congress, we note that evidence from the parallel savings and loan crisis suggests the

[23] While the discount factor should be non-parametrically identified in our model, to further aid identification we note that asset growth is excluded from the one period utility function as we do not expect how a bank reaches a certain state to influence the static payoff of closing the bank in that state. See Magnac and Thesmar (2002) for a discussion of the role of such exclusions in identifying discount factors. To verify that this exclusion is justified, at least with respect to monetary costs, we estimate the monetary cost specification including asset growth. As expected, the coefficient is small and insignificant. Asset growth does, however, influence the transitions of state variables.

[24] Bond yields averaged approximately 8% over the period, going as high as 11%, with inflation rates of around 3%.

opposite. As documented in, for example, Calavita (1998), individual legislators frequently intervened to try to prevent actions against depository institutions. Such pressure would appear in our estimates both through the political influence variables and through the discount factor. Beyond this, the legislative interventions in the S&L crisis during the 1980's generally called for continued or increased regulatory forbearance.[25] Finally, we note that Congress eventually did intervene at the end of the period via the FDIC Improvement Act's requirement for "prompt corrective action."

4.7 Variance Estimation

As with the discount factor, the variance of choice specific error terms is often not estimated and is simply set to some level. When the decision maker is an individual maximizing utility, this is potentially harmless and may represent little more than a normalization. In other cases, where payoffs can be interpreted in terms of some objective quantity, the variance of the error term should be estimated. In our case, the choice specific error term is the unobservable, random term in non-monetary closure costs. This value will be denominated in lost insurance fund dollars and thus should be estimated.

Our highest estimate of the scale parameter of the error distribution is $646 thousand (Model II), which corresponds to a standard error of $828 thousand. With an average observable component of non-monetary costs of around $13 million, this seems to be a reasonable scale for the error. Under Model III and Model IV, respectively, the estimates are $149 thousand and $201 thousand. Overall, the magnitude of the choice specific error term does not dominate the monetary or non-monetary costs, which indicates that the characteristics of banks and expected evolution of closure costs are primary determinants of the closure decision.

5 Alternative Specifications

To further investigate the model, we consider two other specifications. In one case, we calibrate the discount factor to explore the role of regulatory myopia in explaining the behavior of the FDIC. We also consider an alternative model of non-monetary costs, where the effect of bank characteristics on the non-monetary costs interacts with the size of the bank.

[25] Specifically, the Garn St. Germain Depository Institutions Act of 1982 and the Competitive Equality Banking Act of 1987 (CEBA) both included formal provisions encouraging regulatory forbearance (see *History of the 80s*, Chapter 2).

5.1 Calibrated Discount factor

We estimate a relatively high degree of regulatory myopia. Since discount factor estimation is generally difficult and often problematic, we also consider a version of the model where we impose a calibrated discount factor consistent with real interest rates. Model I(a), shown in Table 12 presents the results of the model with the discount factor calibrated to an annual rate of 0.95. The results for the remaining parameters are qualitatively unchanged. Two quantitative differences arise. First, the estimate of the variance parameter of the choice specific error term nearly doubles. This increase likely arises in part from the need to rationalize behavior where the FDIC refrains from shutting down a bank that will almost inevitably fail. When the discount factor is estimated, this behavior can be attributed to a desire to postpone costs, even if they will grow. When this channel is shut down the behavior can only be rationalized by having the potential for a large idiosyncratic cost in some periods, which can prevent closure of even such a doomed institution. The fact that shutting down the regulatory myopia channel forces the model to rely more heavily on the idiosyncratic error supports the identification of regulatory myopia from the main estimation. Further, eliminating the myopia channel leads to a poor fit as measured by the J-test.

Another potentially interesting difference is that the magnitude of the House political influence variable increases three-fold. This change suggests that much of the delay of near-inevitable bank closures may occur for politically connected banks, and thus shutting down the possibility that regulators are systematically myopic leads to more apparent importance for political influence. On the other hand, the Senate influence variable, which has the opposite sign of what would be expected is now significant.

5.2 Variable Non-Monetary Costs

Our main estimation allows non-monetary costs to vary with bank size, but the effect of other variables, such as the non-performing loan ratio and return on assets, are treated as fixed components of the cost. That is, an increase in the non-performing loan ratio is modeled as having the same total effect on non-monetary costs for a small bank or a big bank. An alternative model would allow such variables to have a differential impact based on the size of the bank. Absent any a priori reason to prefer one model over the other, the question of which model is better can only be answered by determining which provides a reasonable rationalization of the data. We estimate this alternative model as Model I(b). Here, the effect on non-monetary costs of the equity ratio, non-performing loan ratio, and real estate owned over assets is interacted with bank size.[26]

An advantage of this specification is that the coefficients on the bank variables are more directly comparable with the coefficients in Table 3 that give the effect of the bank characteristics on the monetary costs. For example, a one percentage point increase in the net income ratio leads to a 0.9 percentage point decrease in the percentage of bank size that becomes a monetary cost, while at the same time leading to a 0.2 percentage point increase in the multiplier on bank size for non-monetary costs. Thus, the model predicts a decrease in total costs as net income increases.

This estimation, however, performs poorly relative to our main estimates. Specifically, the variance of the choice specific error term is far too low. Other than this, however, the results are qualitatively similar. This model is also not rejected at the 5% level, though it is rejected at the 10% level. A relatively large fraction of observations (33%, see Appendix A.3), however, imply a *benefit* of closure, which leads us to conclude that this model does not perform as well as the main models that we estimate.

6 Current Period Estimation

Given the above results, it is natural to ask whether the inefficiencies that appear to drive the behavior of the FDIC have been ameliorated through various reforms introduced during the 1990s. Fortuitously, there has been a second wave of bank failures following the recent financial crisis, so we apply our model to this modern era to obtain estimates on the behavior of the FDIC since 2007.

The total number of bank closures during the wave of bank failures following the 2007 financial crisis is appreciable lower than in the 1980s (304 vs 893), which makes estimation of the model on these data more challenging. For this reason, when estimating the behavior of the FDIC in the recent period of bank failures we consider only the simplest specification (Model I), which is also the specification that is not rejected by the test of overidentifying restrictions at any conventional significance level.[27] Even focusing on the simpler model, estimation on the modern period is difficult. Specifically, the estimate for the variance of the choice specific error term is forced to virtually zero.[28] The inability to estimate this value is not particularly

[26]This specification is effectively treating the level of these variables, rather than the ratio, as relevant for the non-monetary costs because we define the bank characteristics as ratios.

[27]The variables that are not considered in this specification, county deposits and core deposits, are arguably less relevant to the new period of bank failures as interstate banking has become the norm and concerns about the local banking environment would have consequently decreased. Further, the inclusion of core deposits was specifically to address the conventional wisdom that reliance on brokered deposits was a major contributor to the banking crisis in the 1980s.

[28]A value of $\sigma \approx 0$ would imply that bank closure decisions are practically deterministic functions of observable variables,

surprising, as many CCP estimation papers end up having to calibrate this value. To address this issue, we calibrate the value of σ to the lowest value from any of the early period models.[29]

The results for non-monetary costs, presented as Model V (without calibration of σ) and V(a) (with σ calibrated) in Table 12, show interesting similarities and differences with the results from the earlier period. In Model V(a), the intercept term, size terms, and net income effect are in the same direction as in the earlier period, while non-performing loans and real estate owned switch signs, with non-performing loans becoming significant. The results are similar if we use the complete estimation with the unreasonable σ estimate. Thus, in the later period, both measures of performance move in the same direction; from the non-monetary perspective it is more costly to shut down better performing banks. This suggests that the FDIC is no longer as concerned about potential difficulties from dealing with non-performing loans on the balance sheet of troubled banks.

The reversal for real estate owned could suggest that the FDIC no longer hesitates to deal with real estate portfolios itself. More generally, it is not surprising that the FDIC's attitude toward bank-owned real estate might change in light of the advent of widespread private label securitization; real estate owned may, in fact, proxy for banks that participate less in securitization, which might be treated systematically differently. Why the FDIC would be more aggressive in closing banks who did not securitize their real estate portfolios is an interesting question but the answer is not obvious.

Perhaps the most interesting result is the marked difference in the estimated discount factor. In the current period, we estimate an annual discount factor of 0.97, suggesting that legislative push for prompt corrective action may have succeeded in reducing regulatory myopia. On the other hand, this result hinges on using the model with calibrated σ; under the complete estimation the decrease in regulatory myopia is much smaller. A further heartening result is that we no longer detect any political influence, although this also comes from using the calibrated model, and the weakening of political influence is less pronounced in the complete estimation. These results should be interpreted with some caution. The model fit as measured by the J-test is poor. Given that the sample is small relative to the previous period and the small sample properties of the J-test are notoriously poor, this result may not be particularly meaningful. Still, it may indicate that factors not considered in our model are influencing current bank closure decisions.

which is not the case in our data. The problem, which is not unique to our setting, is that σ enters the estimation through a number of channels, including but not limited to the extent to which observables explain closure decisions.

[29]While it might be preferable to use the σ from the parsimonious model from the early period, we note that this σ estimate ($640,000) falls outside the confidence interval of the estimate of $\sigma \approx 0$, while the σ we use ($149,000) is within the confidence interval.

7 Policy Experiments

One of the significant advantages of structural estimation is that, once parameter estimates are recovered, it is possible to perform counterfactual policy experiments to determine how the agent in question would have behaved under a different policy regime. In our case, such a different policy regime refers to different incentives facing the regulator. The standard approach to policy analysis for CCP estimation is to recover the parameter estimates, which does not require solving the dynamic programming problem for the agent, and then to solve the program with the estimated parameter values to get a baseline for comparison. Then, the program can be solved again with the posited policy changes given the estimated parameters.

Our setting, where we use a "short panel" (Assumption 1) to estimate the model, does not lend itself to such an analysis.[30] Our approach instead is to consider "temporary" policies, where the parameters change for a few periods. Then, the conditional choice probability representation of the value function captures what happens in the remaining periods after the intervention is lifted. The choice probabilities under the one period policy can be recovered by using these probabilities for the future values in the Bellman equation. These probabilities then represent the value function in the first period of a two period policy intervention, and the analysis can work backward from there to establish behavior under increasingly long duration policies.

While we focus on temporary policy interventions primarily out of necessity, such interventions do not seem out of line with what might actually occur. For example, there may be biases and preferences ingrained in a bureaucratic institution, but that institution would also be susceptible to external pressure from within the government or externally from advocacy groups or the press. Such pressure may not be sustained permanently, and the decision maker within the FDIC is likely to know that the pressure will fade after some time. To analyze policy, we generate a representative sample of 5,832 banks formed on a grid of bank characteristics and weighted based on a non-parametric (bin) estimate of the distribution in the data of these characteristics. We investigate two temporary policies using the estimates from the early period that give the best fit.

The first policy we consider is a one-period change in the discount factor, reflecting a temporary willingness to bear costs early rather than late. Here, we use the modern period (Model V) β as the counterfactual

[30]Specifically, we do not observe the state of disorderly failure and thus cannot estimate the parameters that govern behavior in this state. These parameters are accounted for within the value function, which is mapped to empirical choice probabilities. It is not possible from this, however, to solve the dynamic programming problem facing the FDIC.

discount factor. The decision maker in this case is aware that in the future he will revert to making decisions based on the original estimated discount factor (Model I). Appendix B.1 shows how to obtain the conditional choice probabilities for the period in which β is changed. For this policy we simply report the change in the unconditional probability of closing the bank. Without policy, when quarterly $\beta = 0.96$, the unconditional closure probability from our weighted representative sample is 3.2%. Temporarily increasing β to 0.99 raises this probability to 5.7% for the period in question. Thus, a single period of non-myopic behavior by the FDIC would lead to an economically significant clearing out of troubled banks.

The second policy considers a 4-quarter change in the non-monetary costs of closing banks. Here, we reduce the importance of non-monetary cost differences between banks by reassigning each bank a new non-monetary cost, which is set to $(1 - \alpha)$ times the bank's non-monetary closure cost plus α times the mean non-monetary cost for all banks, where $\alpha \in \{.2, .4, .6, .8\}$. The policy represents a temporary increase in the focus on minimizing monetary costs, relative to other considerations. Appendix B.2 presents the derivations needed to calculate choice probabilities for this temporary policy.

In order to make a reasonable comparison between policy and no-policy treatments, we further adjust the intercept term for the non-monetary costs (i.e. the common, additive non-monetary cost of closing a bank that does not depend on bank characteristics) so that the unconditional probability of bank closure in each quarter of the policy intervention matches the no-policy control. With this adjustment, we can compare the total realized monetary closure costs with and without the policy when the policy affects which banks are closed but not the total number of banks closed. This adjustment is important because, with a temporary policy and a fully forward looking decision maker, simply changing the non-monetary closure costs leads to overly aggressive closure of banks in the last period of the policy since the decision maker takes his last opportunity to shut banks that will, once the policy expires, become appreciably more expensive to close. This effect is not of particular interest, so we shut it down by adjusting the intercept term during the policy period. Adjusting the intercept term for each of the four policy periods must be done simultaneously, as the future costs enter the calculation of the choice probabilities for each policy period, while the composition of banks in a period is determined by past closure costs. To match unconditional closure probabilities between policy and no-policy periods, we adjust the non-monetary costs by α and then simulate the closure decisions resulting from that α and a separate adjustment to the intercept of the non-monetary cost for each policy period. Then we search over the space of these adjustments until the average closure probability over the simulations matches the closure probability from the no-policy control.

In Table 13 we report the effect of the policy on the cumulative monetary closure costs during the policy period ($T = 1$ to 4) and up to 6 years after the policy ends ($T = 28$). As can be seen from the table, while the policy is in place the aggregate monetary closure costs are *higher* as a result of the policy treatment, despite the fact that the FDIC is relatively less concerned with differences between banks based on factors other than the monetary closure costs. This result highlights the importance of a dynamic analysis of closure decisions. Those banks with high non-monetary closure costs (without the policy treatment) turn out to be the banks that have high monetary closure costs but are also expected to become even more costly to close in the future. Thus, once non-monetary costs are evened out among banks, the FDIC proceeds to close the most troubled banks, which will get worse. This effect can be seen from the cumulative monetary costs incurred for the years after the policy expires. By the end of the first year after the policy has expired, the higher costs incurred during the policy period have more than paid for themselves, with the accumulated costs falling well below the level of costs accrued when the policy never takes place. From the table, it is also clear that most of the benefit from reducing the importance of non-monetary cost differences among banks comes from the initial reduction (from $\alpha = 0$ to $\alpha = .2$), so only mild intervention could have led to significant taxpayer savings.

Figure 9 plots the cumulative percent savings for the policy with $\alpha = .2$. The graph starts after the policy has concluded. Up to 15 quarters, the benefits of the better selection of banks to close during the policy leads to an increase in the percent savings over time. After this point, most banks that are being closed are newly distressed banks, and the continued growth in costs for both the policy and no-policy treatment leads to a decrease in the relative gap between the two costs. Thus, most of the value of the temporary policy accrues within the first three years after the policy is concluded.

[Figure 9 about here.]

8 Discussion: Potential for Unobserved Heterogeneity

The CCP estimation procedure we use has the drawback that we cannot account for persistent unobserved heterogeneity. In effect, we must trade off the ability to account for more observed heterogeneity and to identify the model without observing transitions or costs in the disaster states against this limitation. Our concern about unobserved heterogeneity is relatively limited as call report data will include most of the information available to the FDIC about the condition of a bank. This situation contrasts with settings where unobserved heterogeneity is considered of first order importance. For example, in labor market models a major determinant of wage will be labor market productivity, and measures of age, education, and experience will likely miss a large component of productivity that is known to the worker himself. It is of course possible that the FDIC has some soft information about certain banks, but in most cases such soft information will likely be of second order importance relative to the influence of observable quantities, such as bank equity or size. Finally, the main concern with unobserved heterogeneity for us would be that our estimates of monetary costs would be biased if the FDIC tends to close banks based on privately observed information about the monetary closure costs. In our setting it is unclear in what direction this bias would go. From a static perspective, the FDIC would avoid closing banks with a high unobserved closure cost, but the dynamics of the problem could have the reverse effect if a high unobservable closure cost also implies faster expected growth in that closure cost, as would be likely if the unobservable component captured managerial competence or the presence of fraud. Thus, even if unobserved heterogeneity is present, it will have offsetting effects and thus any bias introduced into the estimates will likely be mitigated. Our setting thus contrasts with cases where the direction of the bias is clear and likely of first order importance. For example, Glover (2013) studies bankruptcy costs in a structural model, noting that the realized costs of bankruptcy will be lower than the expected costs since those firms with relatively high bankruptcy costs will avoid leverage and thus seldom enter bankruptcy. In our setting, the deadweight costs of failure are not borne by the bank's depositors but instead by the FDIC, and rational bankers would not take steps to avoid failure simply because it is more costly to the FDIC.

9 Conclusion

Our estimation of the determinants of bank closure suggests that the behavior of the FDIC did not reflect a single-minded purpose of minimizing the direct costs of closing banks. Instead, we find evidence that the FDIC cared directly about a variety of bank characteristics in ways which were unrelated to monetary cost minimization. Among other things, we find some evidence of political influence on the FDIC, and we find that the FDIC tended to prefer to allow the largest and smallest banks to continue to operate even at an expected cost to taxpayers. Our work should illuminate both the specific pressures on and preferences of the FDIC during an important period of bank failures and more generally shed light on the motivations and concerns of regulators.

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A Estimation Details

A.1 Derivation of CCP Estimator

Define $\nu_j(x_{it}) \equiv V_j(x_{it}) - \varepsilon_{jit}$ for $j \in \{0, 1\}$. Then equation (2) can be rewritten as

$$\begin{aligned} V_0(x_{it}) &= \varepsilon_{0it} + \beta E[p_0^{(1)}(x_{0it})(\nu_0^{(1)}(x_{0it}) + \varepsilon_{0it+1}) + p_1^{(1)}(x_{0it})(\nu_1^{(1)}(x_{0it}) + \varepsilon_{1it+1})] \\ &= \varepsilon_{0it} + \beta E[p_0^{(1)}(x_{0it})\varepsilon_{0it+1} + p_1^{(1)}(x_{0it})\varepsilon_{1it+1} \\ &+ p_0^{(1)}(x_{0it})(\nu_0^{(1)}(x_{0it}) - \nu_1^{(1)}(x_{0it})) + \nu_1^{(1)}(x_{0it})] \end{aligned} \quad (14)$$

where the second equality exploits the fact that $p_1^{(1)}(x_{0it}) = 1 - p_0^{(1)}(x_{0it})$.

The next step, which applies Proposition 1 from Hotz and Miller (1993), eliminates the difference between value functions from the previous expression. Specifically, with the extreme value distribution, the difference $\nu_0 - \nu_1$ is equal to $\sigma \ln \frac{p_0}{p_1}$. Intuitively, the value of each choice depends on the current payoff to each choice and the value going forward available following each choice. Only the difference between the values is relevant. Differences in values imply differences in the likelihood of selecting one action over the other. Since there is a one-to-one correspondence between the value function difference and the probabilities of choosing actions, as shown in Proposition 1 in Hotz and Miller (1993), it is possible to replace this value difference with a function of the probabilities of taking one or the other action. The distribution of the choice specific error term makes the expression particularly simple. In principle, it is possible to estimate the model with different error distributions but in practice it is standard, and certainly most convenient, to assume an extreme value distribution. It is also necessary at this stage to exploit the existence of an absorbing state, specifically bank closure. Thus, $\nu_1^{(1)}(x_{0it}) = -c^{(1)}(x_{0it})$; closing the bank generates the value associated with paying the costs to close now, with no further payoffs in the future.[31] Note that this correspondence also exploits Assumption 1, since there is no risk of transitioning into the disorderly closure states.

Thus, equation (14) becomes, applying the law of iterated expectations:

$$\begin{aligned} V_0(x_{it}) &= \varepsilon_{0it} + \beta E[p_0^{(1)}(x_{0it})\varepsilon_{0it+1} + p_1^{(1)}(x_{0it})\varepsilon_{1it+1} + p_0^{(1)}(x_{0it})\sigma \ln \frac{p_0^{(1)}(x_{0it})}{p_1^{(1)}(x_{0it})} - c^{(1)}(x_{0it})] \\ &= \varepsilon_{0it} + \beta E_x E[p_0^{(1)}(x_{0it})\varepsilon_{0it+1} + p_1^{(1)}(x_{0it})\varepsilon_{1it+1} + p_0^{(1)}(x_{0it})\sigma \ln \frac{p_0^{(1)}(x_{0it})}{p_1^{(1)}(x_{0it})} - c^{(1)}(x_{0it})|x_{0it}^{(1)}]. \end{aligned}$$

[31] In fact, there can be a continued stream of payoffs of some form, as long as there are no choices that are relevant for these payoffs that can be taken after the terminal action is chosen. In this case, further payoffs are normalized to 0.

Note that this expression has current and one period ahead components without any other future component even though it is an equivalent expression for the maximum of equation (1), which includes all future payoffs. This is the result of having a terminating action or absorbing state.

Using the assumed distribution of the choice specific errors, it can be shown that $E(\varepsilon_{jit+1}|x_{0it}^{(1)}) = \mu + \sigma\gamma - \sigma \ln p_j^{(1)}(x_{0it})$ for $j \in \{0,1\}$ where γ is Euler constant (≈ 0.577). Therefore, after some algebra, the previous expression becomes

$$V_0(x_{it}) = \varepsilon_{0it} + \beta E_x[\mu + \sigma(\gamma - \ln p_1^{(1)}(x_{0it})) - c^{(1)}(x_{0it})],$$

or

$$\begin{aligned} \nu_0(x_{it}) &= \beta E_x[\mu + \sigma(\gamma - \ln p_1^{(1)}(x_{0it})) - c^{(1)}(x_{0it})] \\ \nu_1(x_{it}) &= -c(x_{it}). \end{aligned}$$

Again applying Proposition 1 from Hotz and Miller (1993) yields

$$\begin{aligned} \sigma \ln \frac{p_0(x_{it})}{p_1(x_{it})} &= \nu_0(x_{it}) - \nu_1(x_{it}) \\ &= \beta E_x[\mu + \sigma\gamma - \sigma \ln p_1^{(1)}(x_{0it}) - c^{(1)}(x_{0it})] + c(x_{it}) \end{aligned}$$

where the second equality provides the moment equation used in the estimation of the model. By the normalization in Assumption 3, $\mu + \gamma\sigma = 0$ since the mean of the choice specific error term is zero. This gives the expression in the text.

A.2 Details on moment condition construction

We choose $\tilde{z}$ to be the variables that enter the payoff function, either as monetary costs or non-monetary costs, and variables that influence transitions. We do not include constructed variables, such as one period ahead expected costs or expected future state variables, and we do not include lags. The parameters to estimate in this stage are the determinants of non-monetary costs, the scale parameter of the choice specific error term, and the discount factor. There is one moment for each variable that influences non-monetary costs, plus one moment for each variable that influences either transitions or monetary costs. Because the transition and monetary cost parameters have been pre-estimated, these moments provide additional sources of identification for the non-monetary cost parameters, scale parameter, and discount factor; any observable variable, not just the variables that determine non-monetary costs, should be orthogonal to the error term. With these moments, the system is overidentified, so we apply continuously updated GMM (CU-GMM). CU-GMM provides asymptotically efficient estimates in the last estimation stage. We choose this method both because it is asymptotically efficient and because it removes the need to arbitrarily specify an initial weighting matrix. There is also some evidence (Hansen et al., 1996) that CU-GMM outperforms two-step GMM in small samples. In our implementation, we compute the (simpler) one-step GMM estimator using $Z'Z$, $Z = \{\tilde{z}_1, \tilde{z}_2, \ldots, \tilde{z}_n\}'$, as the weighting matrix in order to obtain an initial parameter guess for CU-GMM and perform a grid search to verify that the model is identified in the data and that there appears to be only one minimum over the relevant range of parameter values. The one-step estimates, while not numerically equivalent to the CU-GMM estimates, are reasonably close to the final estimates. This provides some reassurance that our estimation procedure is appropriate as one-step GMM and CU-GMM should correspond exactly in large samples.

A.3 Model Fit Discussion

Our model assumes that bank closure is usually costly to the FDIC. Note, however, that our estimation procedure does not directly impose this restriction on our estimates. We can thus investigate whether the estimated total closure cost is consistent with our model of costly bank closure by looking at the frequency with which our estimates indicate that there is a net benefit to closing banks. For the parsimonious model, this happens very rarely. When time is not included in the logit, 92 out of 22,269 observations indicate a benefit of closure (less that 0.1 percent). Including the time variable drops this number to 68. Thus, with very few exceptions our cost estimates line up with the cost minimization assumption of the model.

In the full model, the results are less clear, with 2,971 out of 22,076 total cost estimates being positive (2,061 with time included). These positive numbers, however, are quite small and appear to be driven by imprecision in the estimation of the constant term. Specifically, a 0.076 standard deviation change in the constant term is all that is needed to eliminate all positive observations. Thus, the estimates are generally consistent with the model of cost minimization. Combined with the relatively poor performance of the full model on the test for overidentifying restrictions, however, we conclude that the parsimonious model performs better overall; for this reason, we focus on the parsimonious model when considering policy analysis.

Furthermore, the model where non-monetary cost is scaled by bank size performs poorly by this measure, with 7,395 out of 22,269 observations having a benefit of closure.

A.4 Time Varying Conditional Choice Probabilities

For the primary model we study, and in the exposition of the model, we have assumed that the environment facing the FDIC is time invariant. That is, the state of the bank and the aggregate state of the economy is assumed to be sufficient to describe all current and future payoffs to the FDIC. This assumption is not necessarily valid in our context. Specifically, the FDIC may anticipate that at some point in the future it could completely or partially lose control over the decision to close banks. Here, we have in mind the possibility that Congress would intervene to force closures. In fact, with the passage of the FDIC Improvement Act, Congress would arguably have been prepared to intervene to enforce prompt corrective action. This risk of outside interference provides a secondary rationale for paying the cost to close a bank rather than allowing it to continue to operate. That is, the FDIC may close a bank not because it fears that the bank will descend into disorderly failure but instead because it expects that at some point in the future it may be forced to close the bank by Congress, involuntarily incurring both the monetary and non-monetary costs.

Accommodating this consideration into our estimation framework is surprisingly straightforward. As long as we allow the estimated conditional choice probabilities to depend on time, our estimation can nest this type of model, again assuming that this regime shift does not occur with positive probability in our sample or one period ahead of any realization in our sample period. The reason is simple; any such anticipated regime shift will affect the expected value of the future payoffs associated with leaving a bank open. This difference will be reflected in the value function difference between leaving a bank open and closing a bank. By allowing the conditional choice probabilities to be time specific, we account for the possibility that the value function difference changes over time, which fully accounts for beliefs that the regime change has come closer in time. Ideally, we would like to estimate choice probabilities on a quarter-by-quarter basis, but as we have only a limited number of closures to work with we instead include a time trend in the logit in the specifications in which we account for the possibility of an anticipated regime shift. Even numbered models (II and IV) include the time trend in the choice probability estimation and thus can account for the possibility of an anticipated policy shift.

B Policy Experiment Derivations

B.1 Calculating the effect of temporary change in β

In order to analyze the effect of a temporary policy that causes the FDIC to use a different discount factor for a single period, we must find the counterfactual conditional choice probabilities that would have prevailed during that period. To do this, define $v_0^{\tilde{\beta}}(x_{it})$ as the conditional value function for leaving a bank with characteristics x_{it} open in the period where the policy intervention has changed the discount factor from β to $\tilde{\beta}$. Note that the FDIC anticipates that the discount factor will revert to normal in the following period. Recall that we can write the value function without the policy as:

$$v_0(x_{it}) = \beta E[p_0^{(1)}(v_0^{(1)}(x_{0it}) + \varepsilon_{0it+1}) + p_1^{(1)}(x_{0it})(v_1^{(1)}(x_{0it}) + \varepsilon_{1it+1})]$$

From the perspective of the decision maker in the period where the policy is in force, the continuation decisions (and payoffs) following a decision not to close in that period are identical to the continuation decisions and payoffs anticipated by the decision maker in the absence of the policy. The only difference, then, is the rate at which the payoffs available for this continuation are discounted in the current period. Thus,

$$v_0^{\tilde{\beta}}(x_{it}) = \tilde{\beta} E[p_0^{(1)}(v_0^{(1)}(x_{0it}) + \varepsilon_{0it+1}) + p_1^{(1)}(x_{0it})(v_1^{(1)}(x_{0it}) + \varepsilon_{1it+1})]$$

so

$$v_0^{\tilde{\beta}}(x_{it}) = \frac{\tilde{\beta}}{\beta} v_0(x_{it}).$$

Defining $v_1^{\tilde{\beta}}$ analogously to $v_0^{\tilde{\beta}}$, defining the conditional choice probability of action k under the policy as $p_k^{\tilde{\beta}}(x_{it})$, we have that:

$$v_0^{\tilde{\beta}}(x_{it}) - v_1^{\tilde{\beta}}(x_{it}) = \sigma \ln \frac{p_0^{\tilde{\beta}}(x_{it})}{p_1^{\tilde{\beta}}(x_{it})}$$

by the conventional mapping between value functions and choice probabilities under the assumption of type I extreme value errors; thus, noting that $v_1^{\tilde{\beta}}(x_{it}) = v_1(x_{it})$, we have

$$\sigma \ln \frac{p_0^{\tilde{\beta}}(x_{it})}{p_1^{\tilde{\beta}}(x_{it})} = \frac{\tilde{\beta}}{\beta} v_0(x_{it}) - v_1(x_{it}).$$

Rearranging, we have

$$\sigma \ln \frac{p_0^{\tilde{\beta}}(x_{it})}{p_1^{\tilde{\beta}}(x_{it})} = \frac{\tilde{\beta}}{\beta} \sigma \ln \frac{p_0(x_{it})}{p_1(x_{it})} - \left(\frac{\tilde{\beta} - \beta}{\beta}\right) c(x_{it}).$$

This derivation gives the probability of closure in the policy intervention period ($p_1^{\tilde{\beta}}(x_{it})$) for bank x_{it} as a function of observables (x_{it} and estimated choice probabilities from outside the policy period), estimated parameters (σ, β, and the cost parameters that enter $c(x_{it})$), and the counterfactual policy parameter $\tilde{\beta}$. Thus, counterfactual closure probabilities can be obtained.

B.2 Calculating the effect of reduced variance of non-monetary costs

For the purpose of policy analysis, we will superscript functions with p_k, where k is the number of periods remaining for the policy. For example, superscript p_1 is the last period of the policy, and p_2 is the second to last period of the policy. Since $c^{p_k}(x_{it}) = c^{p_j}(x_{it})$ for all $k, j > 0$ we define $c^p(x_{it}) \equiv c^{p_k}(x_{it})$ for all k. Values for leaving the bank open and closure probabilities, however, will depend on the number of periods remaining on the policy. Note that p_0 denotes the period after the policy has expired; since the functions and values for this period are simply those from the estimation we can suppress this notation when needed.

Suppose there are T periods left of the policy. We can write

$$\begin{aligned} V_0^{p_T}(x_{it}) - V_1^{p_T}(x_{it}) &= v_0^{p_{T-1}}(x_{it}) - v_1^{p_{T-1}}(x_{it}) + \varepsilon_{0it} - \varepsilon_{1it} \\ &+ (V_0^{p_T}(x_{it}) - V_0^{p_{T-1}}(x_{it})) \\ &- (V_1^{p_T}(x_{it}) - V_1^{p_{T-1}}(x_{it})). \end{aligned}$$

Note that the values $V^{p_{T-1}}$ here are not one period ahead values given the state x_{it}. They are counterfactual values, i.e. what the value with $T-1$ periods left in the policy would be, given the state x_{it}. Note also that we will assume that the realization of the choice specific error term is invariant to the policy regime. Moving the choice specific error terms to the left and substituting probabilities for conditional value functions on the right gives:

$$\begin{aligned} v_0^{p_T}(x_{it}) - v_1^{p_T}(x_{it}) = \sigma \ln \frac{p_0^{p_{T-1}}(x_{it})}{p_1^{p_{T-1}}(x_{it})} &+ (V_0^{p_T}(x_{it}) - V_0^{p_{T-1}}(x_{it})) \\ &- (V_1^{p_T}(x_{it}) - V_1^{p_{T-1}}(x_{it})). \end{aligned}$$

Again replacing the conditional value function differences with choice probabilities and observing that $V_0^{p_T}(x_{it})-V_0^{p_{T-1}}(x_{it})=0$ if $T=1$ (i.e., for the last period of the policy), while $V_1^{p_T}(x_{it})-V_1^{p_{T-1}}(x_{it})=0$ if $T\neq 1$, we have

$$\sigma \ln \frac{p_0^{p_T}(x_{it})}{p_1^{p_T}(x_{it})} = \sigma \ln \frac{p_0^{p_{T-1}}(x_{it})}{p_1^{p_{T-1}}(x_{it})} + \begin{cases} c^p(x_{it}) - c(x_{it}) & \text{if } T = 1 \\ v_0^{p_T}(x_{it}) - v_0^{p_{T-1}}(x_{it}) & \text{if } T \neq 1 \end{cases}$$

Note that we can move to conditional value functions (lower case v instead of upper case V) because the choice specific error term is added and substracted. Rearranging, this expression gives the counterfactual closure probability for the period where the policy will remain in effect for T more periods:

$$p_1^{p_T}(x_{it}) = \frac{1}{1 + \frac{p_0^{p_{T-1}}(x_{it})}{p_1^{p_{T-1}}(x_{it})} \exp \left\{ \begin{array}{ll} \frac{c^p(x_{it})-c(x_{it})}{\sigma} & \text{if } T = 1 \\ \frac{v_0^{p_T}(x_{it})-v_0^{p_{T-1}}(x_{it})}{\sigma} & \text{if } T \neq 1 \end{array} \right\}}. \tag{15}$$

From the above expression, the counterfactual probabilities for a one-period policy can be recovered directly from data on choice probabilities (since $p_1^{p_0}(x_{it}) = p_1(x_{it})$, the choice probability in data), estimated cost functions, and the counterfactual cost function posited under the policy.

For a two- or more-period policy, we can rewrite

$$\begin{aligned} v_0^{p_T}(x_{it}) - v_0^{p_{T-1}}(x_{it}) &= (v_0^{p_T}(x_{it}) - v_1^{p_T}(x_{it})) - (v_0^{p_{T-1}}(x_{it}) - v_1^{p_T}(x_{it})) \\ &= (v_0^{p_T}(x_{it}) - v_1^{p_T}(x_{it})) - (v_0^{p_{T-1}}(x_{it}) - v_1^{p_{T-1}}(x_{it})) \\ &= (v_0^{p_T}(x_{it}) - v_1^{p_T}(x_{it})) - \sigma \ln \frac{p_0^{T-1}(x_{it})}{p_1^{p_{T-1}}(x_{it})} \end{aligned} \tag{16}$$

Above, we use the fact that the conditional value for closing is simply the static payoff for closing, which is the same under any period in which the policy is in effect. Finally, we replace the value function difference in equation (17) with the standard derived expression using one period ahead choice probabilities and expected costs, and substitute the resulting expression into equation (15) to obtain

$$p_1^{p_T}(x_{it}) = \frac{1}{1 + \exp\left\{\frac{1}{\sigma}\left(c^p(x_{it}) - \beta E[c^{(1)p}(x_{it})]\right) - \beta E[\ln p_1^{(1)p_{T-1}}(x_{it})]\right\}}. \tag{17}$$

These counterfactual probabilities can now be calculated for any x_{it} from estimated parameters (β and σ), the counterfactual cost function, estimated transitions (which are invariant to policy changes by assumption), and closure probabilities when there are one fewer periods of the policy remaining. Thus, if we start by analyzing a one-period policy, we can then analyze a two-period policy by using the probabilities calculated for the one-period policy to calculate the expected closure probability in the next period when two periods of the policy remain.[32] We can then continue to solve backwards for closure probabilities for increasingly long policies.

[32]Note that by using the appropriate cost functions and choice probabilities, we could use equation (17) to calculate choice probabilities in the last period as well. The calculation will not, in general, be numerically equivalent to that obtained by directly using equation (15) in finite samples. The difference arises from the fact that we are using two different sides of the equality that generates the moment condition. By construction, then, the difference between the two approaches is minimal, which we confirm. We use the approach from equation (15) because it does not require simulating the forward path of the variables, which should reduce the total error in the policy calculation.

Tables

Table 1: Summary Statistics: 1985-1992

This table presents summary statistics for the sample data from the 1985-1992 period. Panel A reports summary statistics from the quarterly call report data from 1985 to 1992. Panel B reports data on the realized resolution costs from the FDIC for banks which were resolved and counts of failures and unassisted mergers over the period. Assets are Call Report item rcfd2170. Equity is item rcfd3210. Nonperforming Loans is item rcfd1403 + item rcfd1407. Real Estate Owned is item rcfd2150. Net Income is item riad4340, adjusted to reflect current quarter income, and summed over the last 4 quarters. Core Deposits are item rcfd2200 - rcon2343 - rcon2710 or rconf051. County deposits are reported in the FIDC's summary of deposits. U.S. Equity is aggregated from item rcfd3210. Resolution Costs and Cost/Assets in Panel B are reported independently by the FDIC's list of failed banks. The number of unassisted mergers is reported, though no information is available from the FDIC on the value of each merger.

Panel A: Quarterly Call Report Data

	mean	sd	5%	median	95%
Assets ($M)	130	250	16	54	531
Equity/Assets	0.064	0.038	0.010	0.064	0.120
Nonperforming Loans/Assets	0.035	0.032	0.002	0.027	0.095
Real Estate Owned/Assets	0.021	0.027	0.000	0.012	0.070
Net Income/Assets	-0.016	0.021	-0.054	-0.010	-0.001
Core Deposits/Assets	0.235	0.064	0.110	0.247	0.314
State Unemployment	6.921	1.776	4.300	6.700	9.800
County Deposits ($M)	5,734	13,287	58	563	33,598
U.S. Equity/Assets	0.064	0.003	0.061	0.064	0.072
N	39,756				
Unique Banks	6,838				

Panel B: FDIC Failure and Merger Data

	N	mean	sd	5%	median	95%
Failures						
Resolution Cost ($M)	893	25.644	48.254	0.645	9.409	118.249
Cost/Assets	893	0.219	0.137	0.047	0.206	0.464
Mergers	2,785					

Table 2: Summary Statistics: 2007-2012

This table presents summary statistics for the sample data from the 2007-2012 period. Panel A reports summary statistics from the quarterly call report data from 2007 to 2012. Panel B reports data on the realized resolution costs from the FDIC for banks which were resolved and counts of failures and unassisted mergers over the period. Assets are Call Report item rcfd2170. Equity is item rcfd3210. Nonperforming Loans is item rcfd1403 + item rcfd1407. Real Estate Owned is item rcfd2150. Net Income is item riad4340, adjusted to reflect current quarter income, and summed over the last 4 quarters. Resolution Costs and Cost/Assets in Panel B are reported independently by the FDIC's list of failed banks. The number of unassisted mergers is reported, though no information is available from the FDIC on the value of each merger.

Panel A: Quarterly Call Report Data

	mean	sd	5%	median	95%
Assets ($M)	279	376	30	142	1,063
Equity/Assets	0.099	0.043	0.038	0.092	0.185
Nonperforming Loans/Assets	0.037	0.037	0.000	0.027	0.109
Real Estate Owned/Assets	0.018	0.025	0.000	0.009	0.067
Net Income/Assets	-0.017	0.021	-0.056	-0.010	-0.001
State Unemployment	8.410	2.248	4.500	8.500	11.900
N	24,732				
Unique Banks	3,116				

Panel B: FDIC Failure and Merger Data

	N	mean	sd	5%	median	95%
Failures						
Resolution Cost ($M)	304	109.347	151.542	11.749	58.422	380.231
Cost/Assets	304	0.300	0.124	0.113	0.289	0.500
Mergers	729					

Table 3: Monetary Cost Function Estimation

This table presents the estimation results of three models with the realized closure cost (scaled by assets) as the dependent variable. The model includes banks which were resolved by the FDIC as part of a formal closure process and banks which were part of an unassisted merger in which a premium was paid to the target shareholders. The dependent variables represent the reported value from each bank in the quarter prior to the closure or merger event, except core deposits and county deposits, which are not available quarterly and are reported as of the beginning of the sample. The dependent variable (*Cost/Assets*) is scaled by the reported asset value prior to resolution, and is assumed to be censored at zero in the case of an unassisted merger. All models are estimated using observations from 1985Q4 to 1992Q4 and from 2008Q1 to 2012Q4 as indicated.

	Tobit (1985-1992)		Tobit (1985-1992)		Tobit (2008-2012)	
	Coeff.	$\frac{\partial E[Cost]}{\partial x}$	Coeff.	$\frac{\partial E[Cost]}{\partial x}$	Coeff.	$\frac{\partial E[Cost]}{\partial x}$
log (Assets)	-0.0308^{***}	-822	-0.0264^{***}	-759	0.00055	13
	(0.00388)		(0.00429)		(0.007)	
Equity/Assets	-0.975^{***}	$-26,041$	-0.984^{***}	$-28,284$	-3.351^{***}	$-77,476$
	(0.166)		(0.164)		(0.310)	
NP Loans/Assets	1.614^{***}	43,112	1.524^{***}	43,809	1.229^{***}	28,414
	(0.105)		(0.103)		(0.120)	
RE Owned/Assets	1.377^{***}	36,781	1.372^{***}	39,443	1.178^{***}	27,241
	(0.109)		(0.117)		(0.168)	
Net Income/Assets	-0.922^{***}	$-24,633$	-0.846^{***}	$-24,323$	-0.0818	$-1,892$
	(0.212)		(0.211)		(0.284)	
State Unemployment	0.0139^{***}	371	0.0132^{***}	380	0.00612	1,412
	(0.00248)		(0.00254)		(0.0042)	
Core Deposits/Assets			-0.379^{***}	$-10,894$		
			(0.0760)			
log (County Deposits)			-0.00853^{***}	-245		
			(0.00255)			
Total U.S. Equity/Assets			-4.799^{***}	$-137,963$		
			(1.254)			
Constant	0.0758		0.557^{***}		0.00793	
	(0.0466)		(0.0917)		(0.0900)	
N	3678		3659		1033	
Pseudo-R^2	0.8262		0.8395		1.1139	

Standard errors in parentheses

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 4: Transition Processes - Bank Variables 1985-1992

This table presents the estimation results of each of the bank specific variables as a function of 4 lags of the dependent variable and 4 lags of the other bank specific variables and unemployment. All AR(n) lags are significant for every variable at the 1% level, so significance stars are omitted to preserve space.

	log(Assets)	Equity	NP Loans	RE Owned	Net Income	Asset Growth
AR(1)	0.879	0.940	0.835	0.999	0.731	0.255
	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
AR(2)	0.0407	0.00630	0.0497	0.0422	0.0325	0.00927
	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)	(0.007)
AR(3)	-0.0331	-0.00312	-0.0164	-0.0210	0.0283	-0.0108
	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)	(0.007)
AR(4)	0.111	0.0108	0.0177	-0.0299	-0.157	-0.0218
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.004)
log(Assets)$_{t-1}$	.	0.016	0.004	0.005	-0.001	0.781
log(Assets)$_{t-2}$	.	-0.012	0.001	-0.002	-0.008	0.049
log(Assets)$_{t-3}$	.	0.006	0.007	0.001	0.000	-0.029
log(Assets)$_{t-4}$	.	-0.010	-0.011	-0.004	0.009	-0.802
Equity$_{t-1}$	0.541	.	-0.129	-0.032	0.107	0.503
Equity$_{t-2}$	-0.180	.	0.081	0.008	-0.016	-0.097
Equity$_{t-3}$	0.064	.	0.008	0.014	0.002	0.008
Equity$_{t-4}$	-0.144	.	0.014	0.006	-0.092	-0.148
NP Loans $_{t-1}$	-0.224	-0.120	.	0.064	-0.122	-0.148
NP Loans $_{t-2}$	-0.031	0.015	.	0.010	-0.006	-0.028
NP Loans $_{t-3}$	0.046	-0.006	.	-0.007	0.020	0.038
NP Loans $_{t-4}$	0.046	0.053	.	-0.022	0.022	-0.042
RE Owned$_{t-1}$	-0.146	-0.113	0.065	.	-0.081	-0.008
RE Owned$_{t-2}$	0.025	0.011	0.019	.	0.016	-0.050
RE Owned$_{t-3}$	-0.021	-0.018	-0.027	.	0.001	-0.016
RE Owned$_{t-4}$	0.082	0.060	-0.063	.	0.023	0.002
Net Income $_{t-1}$	0.136	-0.043	-0.099	-0.003	.	-0.083
Net Income $_{t-2}$	-0.030	0.003	0.030	-0.003	.	-0.142
Net Income $_{t-3}$	-0.044	0.005	0.059	0.002	.	-0.075
Net Income $_{t-4}$	-0.141	0.040	0.013	0.006	.	-0.245
Asset Growth$_{t-1}$	0.099	-0.011	-0.007	-0.004	0.000	.
Asset Growth$_{t-2}$	0.012	0.003	0.002	0.001	0.005	.
Asset Growth$_{t-3}$	0.010	-0.005	-0.003	0.001	-0.002	.
Asset Growth$_{t-4}$	-0.015	0.000	0.007	0.001	-0.002	.
Unemployment$_{t-1}$	-0.002	0.000	0.001	0.000	0.000	-0.002
Unemployment$_{t-2}$	0.002	-0.001	-0.001	0.000	0.000	0.002
Unemployment$_{t-3}$	0.004	0.000	-0.001	0.000	0.000	0.004
Unemployment$_{t-4}$	-0.005	0.001	0.000	0.000	0.000	-0.005
Constant	0.000	0.004	-0.006	-0.005	-0.004	-0.003
R^2	0.995	0.824	0.733	0.909	0.679	0.755
$RMSE$	0.070	0.015	0.017	0.008	0.012	0.079
Contribution	-0.002	-0.014	0.027	0.011	-0.011	N/A

Table 5: Transition Processes - Bank Variables 2007-2012

This table presents the estimation results of each of the bank specific variables as a function of 4 lags of the dependent variable and 4 lags of the other bank specific variables and unemployment. All AR(n) lags are significant for every variable at the 1% level, so significance stars are omitted to preserve space.

	log(Assets)	Equity	NP Loans	RE Owned	Net Income	Asset Growth
AR(1)	0.965	0.960	0.970	1.025	0.817	0.294
	(0.011)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)
AR(2)	0.011	-0.036	-0.003	-0.004	0.026	0.003
	(0.013)	(0.011)	(0.010)	(0.011)	(0.011)	(0.009)
AR(3)	-0.057	0.008	-0.034	0.003	-0.024	-0.001
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.008)
AR(4)	0.079	-0.005	-0.010	-0.038	-0.119	-0.014
	(0.010)	(0.008)	(0.009)	(0.008)	(0.008)	(0.005)
log(Assets)$_{t-1}$	.	0.006	0.002	0.003	-0.003	0.814
log(Assets)$_{t-2}$	.	-0.004	0.007	0.000	-0.004	0.012
log(Assets)$_{t-3}$	.	-0.001	0.008	-0.000	-0.004	-0.051
log(Assets)$_{t-4}$	.	-0.001	-0.015	-0.003	0.011	-0.777
Equity$_{t-1}$	0.210	.	-0.049	-0.019	0.078	0.214
Equity$_{t-2}$	-0.013	.	0.024	0.014	-0.019	0.053
Equity$_{t-3}$	-0.016	.	0.010	-0.001	-0.022	-0.150
Equity$_{t-4}$	0.062	.	-0.006	-0.003	-0.064	0.208
NP Loans $_{t-1}$	-0.114	-0.088	.	0.085	-0.088	-0.074
NP Loans $_{t-2}$	-0.120	0.020	.	-0.005	0.006	-0.108
NP Loans $_{t-3}$	0.051	-0.007	.	-0.008	0.006	0.061
NP Loans $_{t-4}$	-0.012	0.038	.	-0.016	0.029	-0.028
RE Owned$_{t-1}$	-0.050	-0.104	0.088	.	-0.074	0.090
RE Owned$_{t-2}$	-0.062	0.029	0.001	.	-0.000	-0.062
RE Owned$_{t-3}$	-0.040	0.016	0.011	.	0.029	-0.046
RE Owned$_{t-4}$	0.159	0.031	-0.094	.	0.028	0.049
NetIncome $_{t-1}$	0.055	-0.011	-0.086	0.002	.	0.001
NetIncome $_{t-2}$	0.156	0.044	0.043	0.001	.	0.073
NetIncome $_{t-3}$	0.038	-0.071	-0.007	-0.001	.	0.112
NetIncome $_{t-4}$	-0.157	0.073	0.045	0.007	.	-0.467
AssetGrowth$_{t-1}$	0.072	-0.006	-0.005	-0.002	0.006	.
AssetGrowth$_{t-2}$	0.003	0.000	-0.002	-0.000	0.002	.
AssetGrowth$_{t-3}$	0.016	0.001	-0.003	0.000	0.001	.
AssetGrowth$_{t-4}$	0.004	-0.002	0.006	0.002	-0.002	.
Unemployment$_{t-1}$	0.004	-0.001	0.002	0.000	-0.001	0.003
Unemployment$_{t-2}$	-0.000	0.002	-0.002	-0.001	0.001	-0.001
Unemployment$_{t-3}$	-0.002	-0.001	-0.000	0.001	-0.000	-0.006
Unemployment$_{t-4}$	-0.001	0.001	-0.000	-0.001	0.000	0.002
Constant	0.053	0.004	0.004	0.001	-0.004	-0.006
R^2	0.997	0.878	0.830	0.928	0.737	0.844
$RMSE$	0.059	0.013	0.015	0.007	0.010	0.070

Table 6: Coefficient estimates for flexible logit: Model I

This table shows the coefficient estimates for the logit model, with standard errors in parentheses. Each variable and three lags are included, and each variable and lagged variable is represented by 3 spline terms. The reported pseudo-R^2 is McFadden's.

	Current			Lag 1			Lag 2			Lag 3		
Variable	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3
Equity/Assets	38.23	32.47	65.61	29.16	-18.28	10.13	131.34	-47.46	90.66	-112.62	43.14	-46.50
	(6.83)	(3.00)	(8.91)	(29.35)	(11.01)	(19.90)	(60.45)	(22.07)	(29.38)	(71.73)	(25.20)	(23.50)
NP Loans/Assets	-3.55	-1.65	-2.79	-2.03	-1.36	-2.98	11.38	10.77	14.78	-0.79	-1.61	-0.03
	(2.35)	(2.00)	(3.54)	(3.88)	(3.51)	(5.45)	(7.62)	(6.81)	(10.53)	(6.30)	(5.61)	(8.85)
log(Assets)	12.35	1.47	0.17	5.80	10.32	2.92	-20.33	-16.29	-9.44	4.18	3.22	8.56
	(6.63)	(5.99)	(6.37)	(8.95)	(8.59)	(10.59)	(8.86)	(8.24)	(10.72)	(6.65)	(5.84)	(6.83)
RE Owned/Assets	-5.02	-6.15	-5.39	-13.81	-9.52	-13.95	37.83	36.91	39.83	-20.68	-20.46	-23.21
	(10.73)	(10.34)	(13.78)	(14.86)	(14.63)	(18.30)	(46.76)	(45.35)	(57.15)	(33.00)	(32.24)	(39.65)
Net Income/Assets	6.30	-9.86	2.21	-7.75	-0.10	2.16	0.70	2.19	-4.42	3.01	2.49	0.82
	(3.40)	(2.53)	(1.06)	(6.34)	(3.72)	(1.38)	(4.14)	(3.15)	(1.33)	(3.40)	(2.92)	(1.06)
Asset Growth	-3.69	-3.84	-7.14	5.65	0.46	13.05	1.10	0.13	-0.48	-4.88	3.37	-4.45
	(3.03)	(2.24)	(3.97)	(4.87)	(3.26)	(6.86)	(3.77)	(2.80)	(4.99)	(3.28)	(2.04)	(4.25)
State Unemployment	0.09			-0.08			-0.18			0.08		
	(0.08)			(0.11)			(0.11)			(0.08)		
	House	Senate	Cons									
Static Variables	0.02	-0.19	-64.82									
	(0.02)	(0.08)	(12.59)									
pseudo-R^2	0.43											

Table 7: Coefficient estimates for flexible logit: Model II

This table shows the coefficient estimates for the logit model, with standard errors in parentheses. Each variable and three lags are included, and each variable and lagged variable is represented by 3 spline terms. The three lags provide the needed AR terms to capture the FDIC's prediction about one-period ahead variable values, while the spline terms permit a non-linear relationship between variables and the latent variable in the logit. The reported pseudo-R^2 is McFadden's.

	Current			Lag 1			Lag 2			Lag 3		
Variable	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3
Equity/Assets	38.26	32.24	65.19	25.22	-17.02	7.30	133.62	-48.48	90.85	-110.47	41.71	-45.62
	(6.85)	(3.01)	(8.92)	(29.49)	(11.06)	(19.99)	(60.17)	(21.98)	(29.23)	(73.18)	(25.73)	(24.12)
NP Loans/Assets	-3.89	-1.79	-3.13	-2.23	-1.55	-3.14	11.42	10.99	14.68	-0.90	-1.59	-0.15
	(2.40)	(2.04)	(3.60)	(3.98)	(3.60)	(5.60)	(7.70)	(6.88)	(10.65)	(6.43)	(5.74)	(9.02)
log(Assets)	12.83	1.74	1.30	6.17	10.55	2.62	-20.78	-16.90	-9.66	4.08	3.58	8.09
	(6.61)	(5.99)	(6.38)	(9.03)	(8.68)	(10.76)	(8.97)	(8.34)	(10.94)	(6.69)	(5.88)	(6.88)
RE Owned/Assets	-3.39	-4.64	-3.44	-13.75	-9.70	-13.64	31.03	30.29	31.89	-15.17	-15.41	-16.29
	(10.41)	(10.05)	(13.35)	(14.61)	(14.40)	(17.97)	(45.34)	(43.97)	(55.41)	(32.01)	(31.27)	(38.50)
Net Income/Assets	6.31	-10.08	2.44	-7.58	-0.30	2.34	0.80	2.13	-4.44	2.95	2.58	0.86
	(3.42)	(2.54)	(1.07)	(6.42)	(3.73)	(1.39)	(4.14)	(3.16)	(1.33)	(3.50)	(2.94)	(1.06)
Asset Growth	-3.67	-4.06	-7.02	5.84	0.50	13.34	1.05	0.11	-0.50	-4.44	3.07	-3.99
	(2.99)	(2.21)	(3.96)	(4.78)	(3.26)	(6.82)	(3.76)	(2.80)	(5.04)	(3.38)	(2.06)	(4.41)
State Unemployment	0.04			-0.04			-0.20			0.15		
	(0.08)			(0.11)			(0.11)			(0.08)		
	House	Senate	T	Cons								
Static Variables	0.02	-0.20	0.03	-64.58								
	(0.02)	(0.08)	(0.01)	(12.59)								
pseudo-R^2	0.44											

Table 8: Coefficient estimates for flexible logit: Model III

This table shows the coefficient estimates for the logit model, with standard errors in parentheses. Each variable and three lags are included, and each variable and lagged variable is represented by 3 spline terms. The three lags provide the needed AR terms to capture the FDIC's prediction about one-period ahead variable values, while the spline terms permit a non-linear relationship between variables and the latent variable in the logit. The reported pseudo-R^2 is McFadden's.

	Current			Lag 1			Lag 2			Lag 3		
Variable	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3
Equity/Assets	38.79	32.97	65.52	28.39	-17.08	11.13	128.61	-47.65	88.48	-112.87	43.20	-48.07
	(6.90)	(3.04)	(9.02)	(29.69)	(11.15)	(20.11)	(61.56)	(22.47)	(29.72)	(72.16)	(25.27)	(23.24)
NP Loans/Assets	-3.77	-1.65	-2.98	-2.61	-2.05	-3.56	10.87	10.43	13.77	-0.06	-1.02	0.80
	(2.42)	(2.06)	(3.64)	(4.08)	(3.68)	(5.73)	(7.81)	(6.97)	(10.80)	(6.53)	(5.82)	(9.14)
log(Assets)	12.32	1.11	1.65	6.15	10.63	2.53	-20.07	-15.98	-9.25	3.63	3.07	7.49
	(6.71)	(6.03)	(6.49)	(9.14)	(8.76)	(10.94)	(9.12)	(8.47)	(11.07)	(6.77)	(5.93)	(6.89)
RE Owned/Assets	-5.28	-6.21	-5.48	-14.28	-9.83	-14.67	37.91	36.99	40.38	-19.35	-19.68	-21.79
	(10.89)	(10.47)	(14.00)	(14.98)	(14.74)	(18.46)	(47.41)	(45.96)	(57.98)	(33.48)	(32.69)	(40.24)
Net Income/Assets	6.77	-10.26	2.47	-8.73	-0.10	2.11	0.95	1.84	-4.17	3.26	2.94	0.84
	(3.43)	(2.56)	(1.07)	(6.46)	(3.74)	(1.39)	(4.19)	(3.17)	(1.34)	(3.54)	(2.96)	(1.07)
Asset Growth	-3.11	-4.16	-6.37	5.86	0.42	13.31	0.89	-0.59	-0.29	-3.67	3.63	-3.11
	(3.08)	(2.24)	(4.08)	(4.75)	(3.26)	(6.80)	(3.72)	(2.82)	(4.99)	(3.56)	(2.13)	(4.69)
State Unemployment	0.02			-0.07			-0.22			0.20		
	(0.09)			(0.12)			(0.11)			(0.08)		
	House	Senate	T	Closure	US Equity	Core Dep	Cons					
Static Variables	0.04	-0.18	49.22	58.22	0.89	-0.07	-71.07					
	(0.02)	(0.08)	(34.90)	(40.66)	(0.84)	(0.03)	(12.89)					
pseudo-R^2	0.44											

Table 9: Coefficient estimates for flexible logit: Model IV

This table shows the coefficient estimates for the logit model, with standard errors in parentheses. Each variable and three lags are included, and each variable and lagged variable is represented by 3 spline terms. The three lags provide the needed AR terms to capture the FDIC's prediction about one-period ahead variable values, while the spline terms permit a non-linear relationship between variables and the latent variable in the logit. The reported pseudo-R^2 is McFadden's.

	Current			Lag 1			Lag 2			Lag 3		
Variable	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3
Equity/Assets	38.48	32.68	65.00	26.53	-16.42	9.85	130.81	-48.50	89.01	-112.61	42.85	-47.66
	(6.91)	(3.05)	(9.02)	(29.72)	(11.16)	(20.15)	(61.26)	(22.37)	(29.60)	(72.56)	(25.43)	(23.47)
NP Loans/Assets	-3.96	-1.78	-3.22	-2.66	-2.10	-3.58	11.11	10.71	14.06	-0.16	-1.05	0.68
	(2.43)	(2.07)	(3.65)	(4.10)	(3.70)	(5.77)	(7.83)	(6.99)	(10.83)	(6.60)	(5.89)	(9.24)
log(Assets)	12.60	1.38	1.79	6.10	10.64	2.44	-20.08	-16.08	-9.09	3.49	2.95	7.33
	(6.71)	(6.04)	(6.51)	(9.16)	(8.78)	(10.98)	(9.15)	(8.50)	(11.11)	(6.78)	(5.95)	(6.90)
RE Owned/Assets	-4.53	-5.53	-4.68	-14.21	-9.85	-14.53	35.12	34.28	37.15	-17.29	-17.72	-19.12
	(10.76)	(10.36)	(13.82)	(14.88)	(14.65)	(18.34)	(46.83)	(45.40)	(57.27)	(33.07)	(32.29)	(39.77)
Net Income/Assets	6.77	-10.26	2.53	-8.57	-0.27	2.18	0.96	1.90	-4.20	3.24	3.01	0.83
	(3.44)	(2.56)	(1.08)	(6.48)	(3.74)	(1.39)	(4.20)	(3.17)	(1.34)	(3.58)	(2.96)	(1.07)
Asset Growth	-3.19	-4.37	-6.46	6.22	0.53	13.79	0.87	-0.61	-0.29	-3.60	3.58	-3.04
	(3.07)	(2.24)	(4.08)	(4.76)	(3.27)	(6.82)	(3.75)	(2.83)	(5.03)	(3.59)	(2.14)	(4.73)
State Unemployment	0.03			-0.06			-0.22			0.20		
	(0.09)			(0.12)			(0.11)			(0.08)		
	House	Senate	T	Closure	US Equity	Core Dep	County Dep	Cons				
Static Variables	0.04	-0.19	26.84	43.82	0.95	-0.08	0.02	-68.75				
	(0.02)	(0.08)	(38.16)	(42.00)	(0.84)	(0.03)	(0.01)	(12.98)				
pseudo-R^2	0.44											

Table 10: Coefficient estimates for flexible logit: Model V

This table shows the coefficient estimates for the logit model, with standard errors in parentheses. Each variable and three lags are included, and each variable and lagged variable is represented by 3 spline terms. The three lags provide the needed AR terms to capture the FDIC's prediction about one-period ahead variable values, while the spline terms permit a non-linear relationship between variables and the latent variable in the logit. The reported pseudo-R^2 is McFadden's.

	Current			Lag 1			Lag 2			Lag 3		
Variable	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3	Spline 1	Spline 2	Spline3
Equity/Assets	18.53	38.01	-14.57	25.28	-58.99	-7.90	-37.19	42.37	-23.89	22.68	-20.36	27.92
	(19.75)	(15.45)	(27.49)	(23.83)	(14.28)	(30.07)	(25.43)	(14.85)	(26.26)	(36.79)	(10.51)	(38.13)
NP Loans/Assets	-2.35	0.41	0.66	4.39	2.52	5.67	-7.47	-2.85	-15.01	0.08	-2.39	2.68
	(3.39)	(2.87)	(4.88)	(7.88)	(6.54)	(11.10)	(14.73)	(12.45)	(20.59)	(13.24)	(11.54)	(18.31)
log(Assets)	14.70	-1.82	6.40	-11.96	6.47	-16.84	-7.99	-9.16	17.77	7.01	4.58	-4.05
	(22.60)	(15.34)	(22.05)	(28.07)	(21.72)	(28.78)	(25.83)	(21.70)	(23.25)	(19.80)	(15.22)	(16.67)
RE Owned/Assets	-5.08	-1.99	-5.70	1.62	0.98	-0.25	3.34	2.16	9.39	-0.68	-1.54	-1.27
	(4.18)	(3.80)	(6.14)	(5.48)	(5.33)	(7.71)	(7.21)	(7.13)	(10.06)	(6.38)	(6.14)	(8.98)
Net Income/Assets	-14.88	-0.20	-3.92	5.51	-1.99	8.87	28.94	-13.44	2.99	-19.89	7.75	0.08
	(7.46)	(4.07)	(2.58)	(13.41)	(6.76)	(3.48)	(15.71)	(7.42)	(3.22)	(14.06)	(6.01)	(2.35)
Asset Growth	28.10	12.37	36.38	-14.17	7.68	-24.58	15.12	-9.38	23.47	-6.56	7.50	-5.13
	(50.33)	(37.08)	(68.63)	(17.61)	(13.66)	(24.07)	(15.55)	(9.40)	(21.09)	(7.03)	(5.51)	(8.51)
State Unemployment	0.85			-1.06			0.45			-0.35		
	(0.31)			(0.57)			(0.56)			(0.28)		
	House	Senate	Cons									
Static Variables	0.09	-0.19	-25.13									
	(0.03)	(0.12)	(44.97)									
pseudo-R^2	0.67											

Table 11: Predicted versus realized closure probabilities

This table shows the empirical probability (as a percentage) of closure and the model predicted probability of closure for various bins of bank observation by predicted probability of closure. Results are presented for each choice probability estimation; note that the alternative models (Models I(a), I(b), and V(a)) use the same choice probability estimation as the associated main model. The column N gives the number of bank-quarter observations within that bin. Observations with effectively zero probability of closure are dropped.

	Model I			Model II			Model III			Model IV			Model V		
Prob.range	Model	Data	N	Model	Data	N	Model	Data	N	Model	Data	N	Model	Data	N
$0 < p \leq 0.5\%$	0.13	0.10	13493	0.13	0.10	13564	0.13	0.10	13545	0.13	0.10	13554	0.02	0.03	12367
$0.5\% < p \leq 1\%$	0.71	0.41	2173	0.71	0.55	2201	0.71	0.52	2117	0.72	0.57	2118	0.72	0.65	309
$1\% < p \leq 5\%$	2.32	2.13	3799	2.33	2.11	3695	2.34	1.98	3629	2.33	1.99	3611	2.38	1.71	586
$5\% < p \leq 10\%$	7.14	7.09	1114	7.10	7.26	1115	7.06	7.53	1102	7.09	7.70	1130	7.08	2.70	185
$10\% < p \leq 15\%$	12.2	13.7	467	12.2	14.1	489	12.2	13.7	489	12.3	12.6	470	12.6	16.8	95
$15\% < p \leq 30\%$	21.2	25.9	590	21.0	23.2	555	21.0	24.9	550	21.1	24.8	553	21.9	22.8	171
$30\% < p \leq 50\%$	38.8	40.5	321	38.7	42.3	338	38.6	39.0	328	39.0	40.5	333	39.5	37.8	111
$50\% < p \leq 100\%$	66.1	59.0	312	66.5	60.3	312	66.4	61.7	316	67.0	62.2	307	76.5	80.4	184

Table 12: Structural Parameters: Non-Monetary Costs

This table presents the coefficients on each of the structural parameters in the non-monetary cost function. Each of the bank specific variables, log(Assets), NPL, Net Income, and real estate owned, are measured as the current reported value in their respective call report. The Senate variable represents the number of senators from the bank's home state who are on one of the following committees: Banking and Financial Services, Banking, Finance, and Urban Affairs, Government Reform and Oversight, or hold the position of majority/minority leader or majority/minority whip. The House variable represents the number of representatives from the bank's home state who are on one of the following committees: Finance, Banking, Finance, and Urban Affairs, Government Affairs, or hold the position of majority/minority leader or majority/minority whip. Standard errors are corrected via GMM to account for noise in the estimates of the monetary cost function and choice probabilities.

Parameter	Model I 85-92	Model I(a) 85-92	Model I(b) 85-92	Model II 85-92	Model III 85-92	Model IV 85-92	Model V 08-12	Model V(a) 08-12
Intercept	507,336***	648,864***	356,052***	507,025***	390,168***	392,574***	579,760**	641,436
	(82,629)	(190,116)	(71,004)	(83,595)	(66,096)	(66,185)	(251,395)	(484,084)
log(Assets)	-93,663***	-138,830***	-64,147***	-93,753***	-72,395***	-73,013***	-102,169**	-110,252
	(15,714)	(29,469)	(12,828)	(15,998)	(12,172)	(12,221)	(42,903)	(80,892)
(log (Assets)^2)	4,321***	7,254***	2,861***	4,334***	3,244***	3,274***	4,498**	4,916
	(762)	(1,203)	(585)	(782)	(541)	(544)	(1,822)	(3,401)
NP Loans/Assets	54,122	178,311***	0.13	56,343	30,934**	32,592**	-49,063*	-151,393***
	(35,619)	(52,268)	(0.10)	(37,543)	(14,211)	(14,542)	(29,763)	(45,796)
Net Income/Assets	48,967**	50,545*	0.23*	48,087**	24,330**	27,104**	9,400	113,754***
	(22,812)	(26,504)	(0.13)	(22,202)	(11,761)	(12,423)	(27,179)	(32,869)
RE Owned/Assets	183,796**	444,163***	0.60***	188,034**	64,552**	71,013**	-128,539***	-236,833***
	(90,199)	(130,800)	(0.18)	(94,043)	(30,904)	(32,206)	(40,514)	(55,665)
House	829*	2590***	209***	849*	287***	299***	165**	-7
	(438)	(520)	(54)	(458)	(73)	(77)	(72)	(97)
Senate	-210	-954***	-148***	-207	60	68	4	305
	(155)	(339)	(63)	(156)	(71)	(73)	(170)	(213)
log(Local Deposits)					796***	903***		
					(282)	(327)		
β	0.96	0.99	0.93	0.96	0.96	0.96	0.97	0.99
	(0.01)	X	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
σ	640	1191	2	646	149	201	0	149
	(426)	(255)	(154)	(430)	(121)	(140)	(107)	X
J-test p-value	0.27	<0.01	0.06	0.26	<0.01	<0.01	<0.01	<0.01

Standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < .05$, $^{***}\ p < .01$

Table 13: Policy Experiment: Monetary Costs

This table presents the results of the policy experiment where the variance of non-monetary costs are reduced for 4 quarters. The table gives the cumulative monetary costs under the no policy regime and the policy regime for four values of the weight (α) used for the bank's own fitted non-monetary cost. Monetary Costs are in Billion Dollars, Changes refer to the percentage change between the no policy case and the policy case. The costs come from an experiment with 5,832 representative banks, each receiving a weight determined by a non-parametric (bin) estimator of the distribution of the actual bank condition data. In each policy quarter, a fixed non-monetary cost adjustment is added to the non-monetary closure cost under the policy to make the unconditional bank closure probability identical in the policy and no-policy periods. The four needed adjustment are simultaneously determined.

	$T = 4$		$T = 8$		$T = 12$		$T = 16$		$T = 20$		$T = 24$		$T = 28$	
	Costs	Change	Costs	Changes	Costs	Change	Costs	Change	Costs	Changes	Costs	Change	Costs	Change
No policy	2.97	-	8.08	-	12.8	-	16.3	-	18.9	-	20.7	-	22.0	-
$\alpha = 80\%$	3.37	13.4%	7.38	-8.6%	11.3	-11.4%	14.4	-11.6%	16.7	-11.4%	18.4	-11.1%	19.6	-10.7%
$\alpha = 60\%$	3.61	21.7%	7.26	-10.2%	10.9	-14.8%	13.8	-15.3%	16.0	-15.1%	17.6	-14.7%	18.8	-14.3%
$\alpha = 40\%$	3.67	23.6%	7.16	-11.3%	10.6	-16.9%	13.5	-17.6%	15.6	-17.4%	17.2	-17.0%	18.3	-16.6%
$\alpha = 20\%$	3.68	23.9%	7.11	-12.0%	10.5	-18.1%	13.2	-19.1%	15.3	-19.0%	16.8	-18.5%	18.0	-18.0%

List of Figures

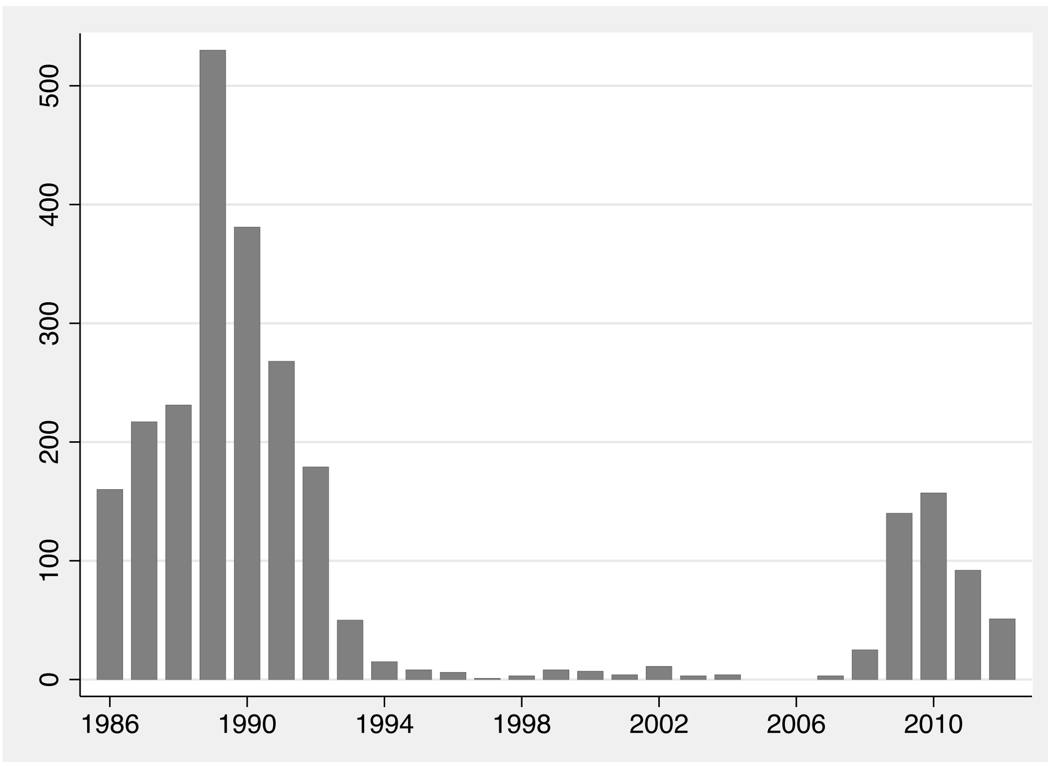
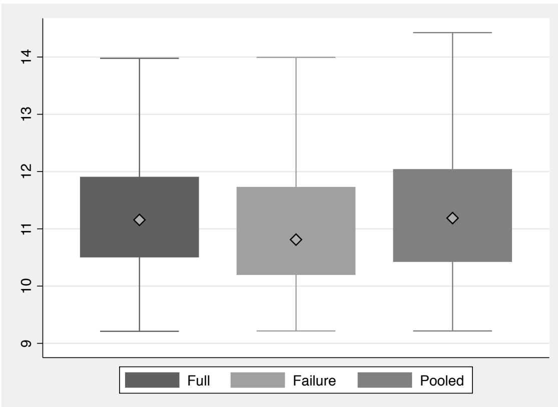
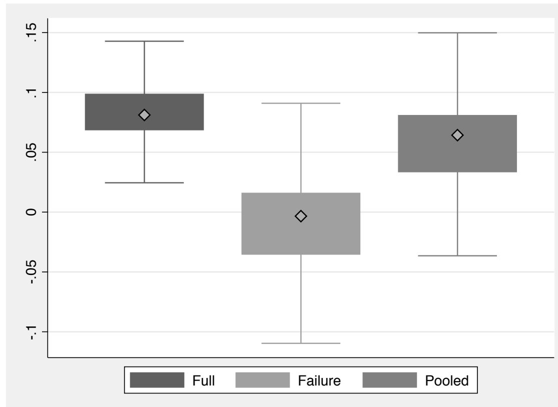


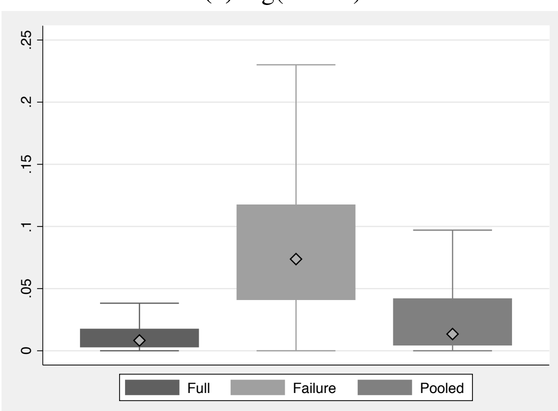
Figure 1: Number of bank closures per year from 1986 to 2012



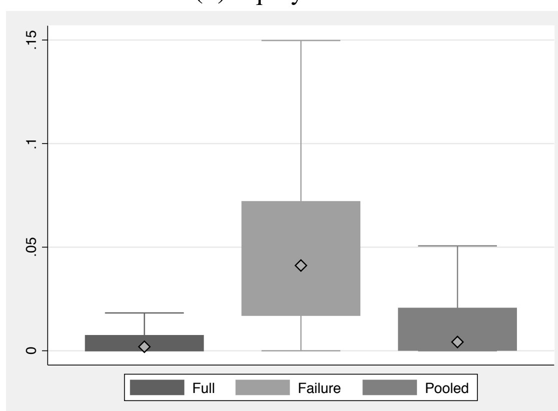
(a) log(Assets)



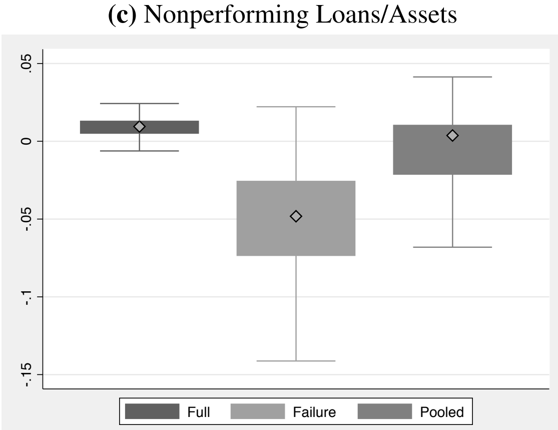
(b) Equity/Assets



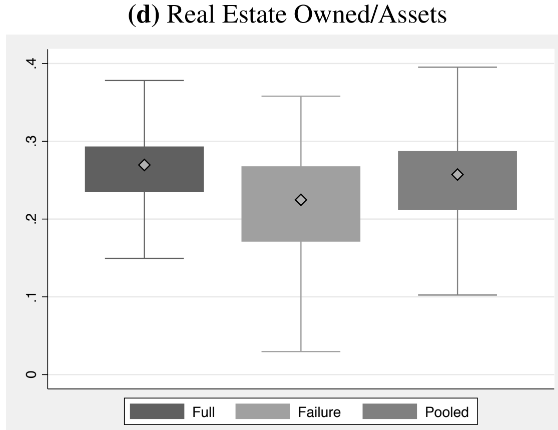
(c) Nonperforming Loans/Assets



(d) Real Estate Owned/Assets



(e) Net Income/Assets



(f) Core Deposits/Assets

Figure 2: Distributional box plots of the major cost determinants for the full estimation sample, the "failure" sample and the pooled sample of mergers and failures for the 1980s and 1990s. The full sample represents all observations used in the quarter ahead prediction sample for the full model. The "failure" sample represents only the observations for banks which failed and resolved the quarter of their failure. The pooled sample represents observations of both failures and unassisted mergers.

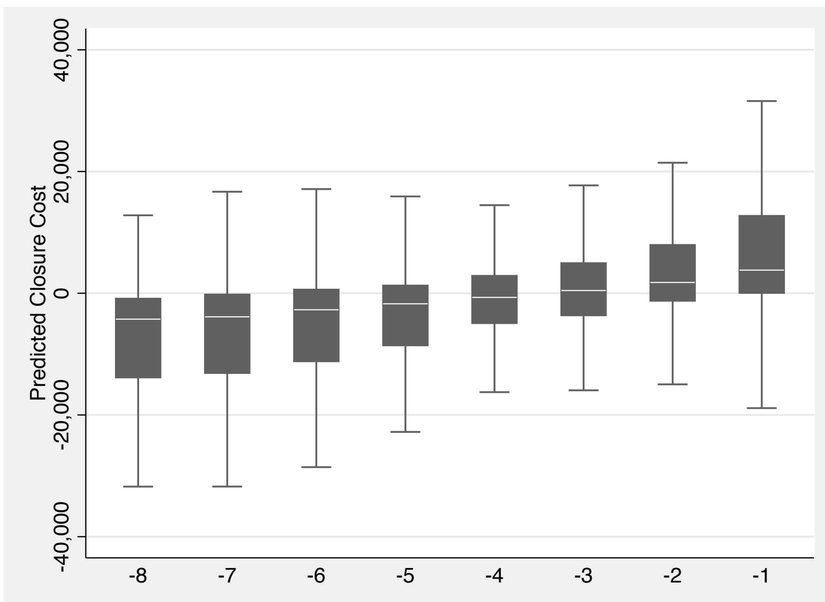
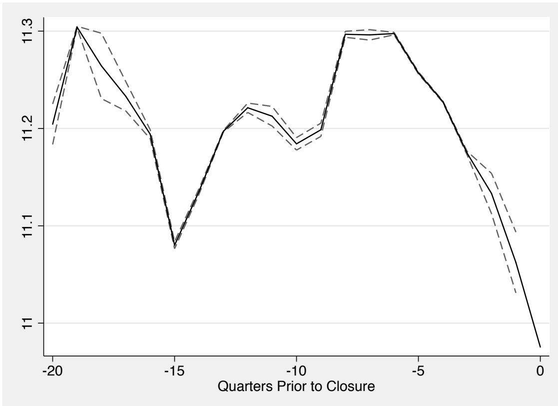
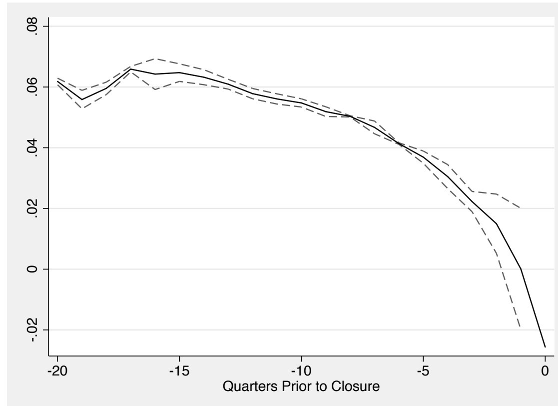


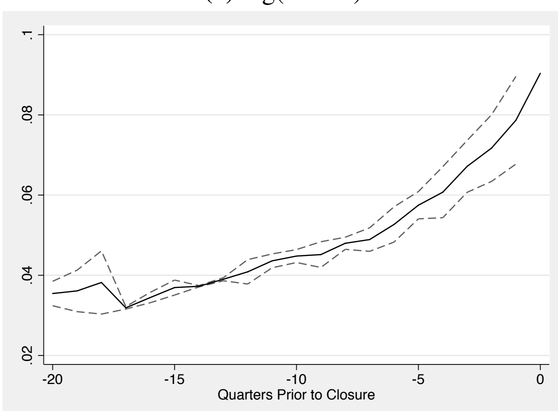
Figure 3: Predicted unconditional cost of resolution of banks over 8 quarters prior to closure (actual path) in thousands of dollars for the 1980s and 1990s.



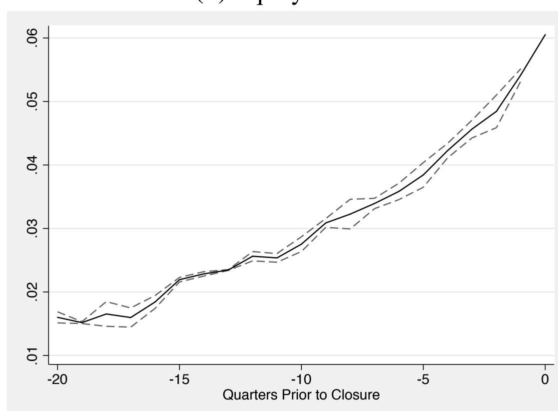
(a) log(Assets)



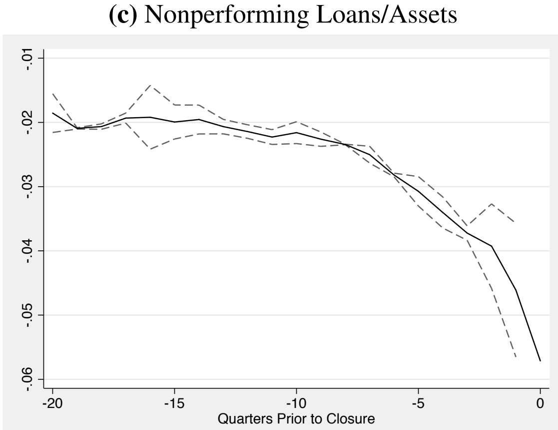
(b) Equity/Assets



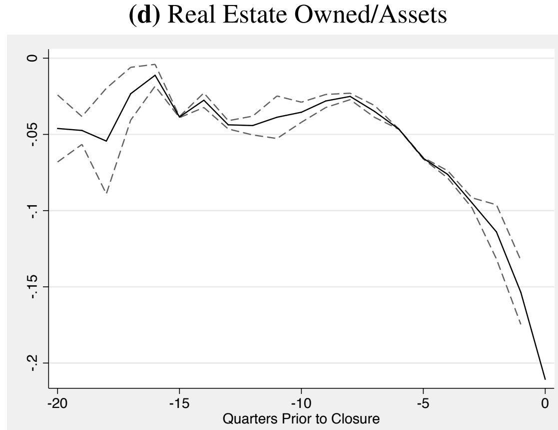
(c) Nonperforming Loans/Assets



(d) Real Estate Owned/Assets



(e) Net Income/Assets



(f) Asset Growth

Figure 4: This figure shows the mean quarter ahead predicted values of the transition variables for the sample of banks which were eventually closed by the FDIC in the 1980s and 1990s. The solid line represents the predicted value and the dashed line represents the range around the estimate given by the Root Mean Squared Error. Note that since the final quarter ahead prediction is unrealized, the error cannot be calculated and there is no error band for the final observation.

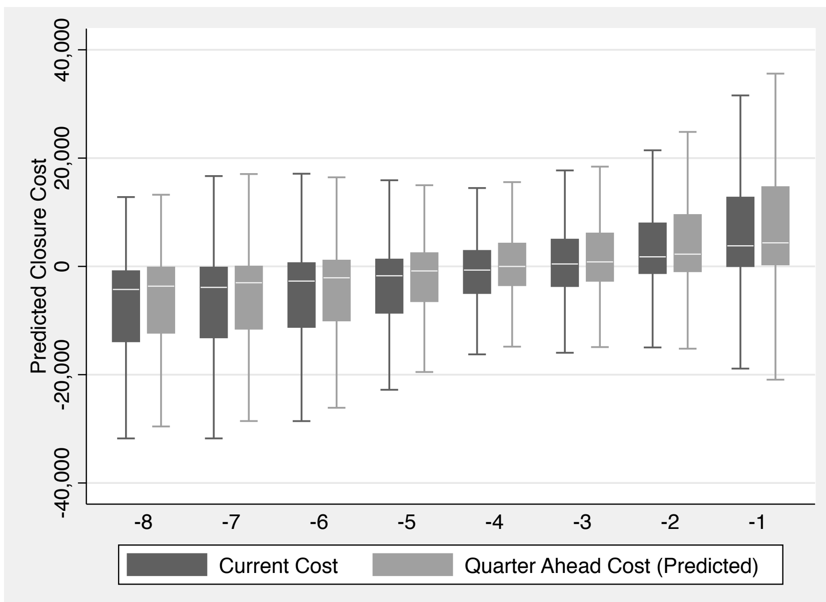


Figure 5: Predicted unconditional closure cost of banks over 8 quarters prior to closure (current and projected quarter ahead path) for the 1980s and 1990s.

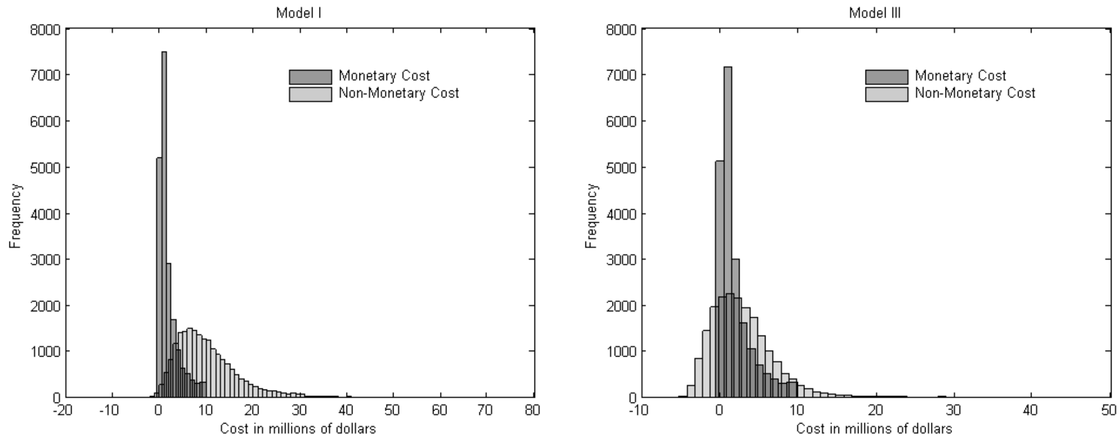


Figure 6: Distribution of Closure Costs

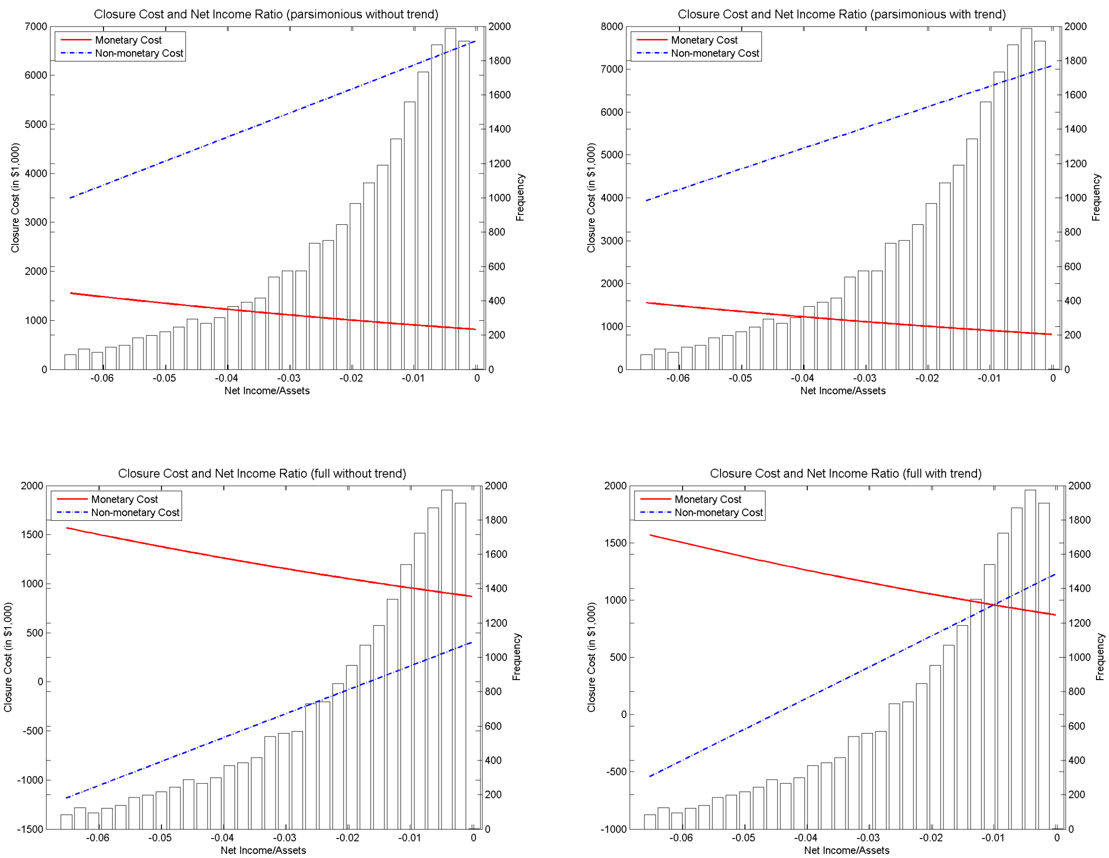


Figure 7: Effect of net income on monetary and non-monetary closure cost, superimposed on distribution of bank size in the data on negative net income banks. The top shows the effect for the parsimonious model and the bottom for the full model. The right column of figures includes the time trend in the conditional choice probabilities.

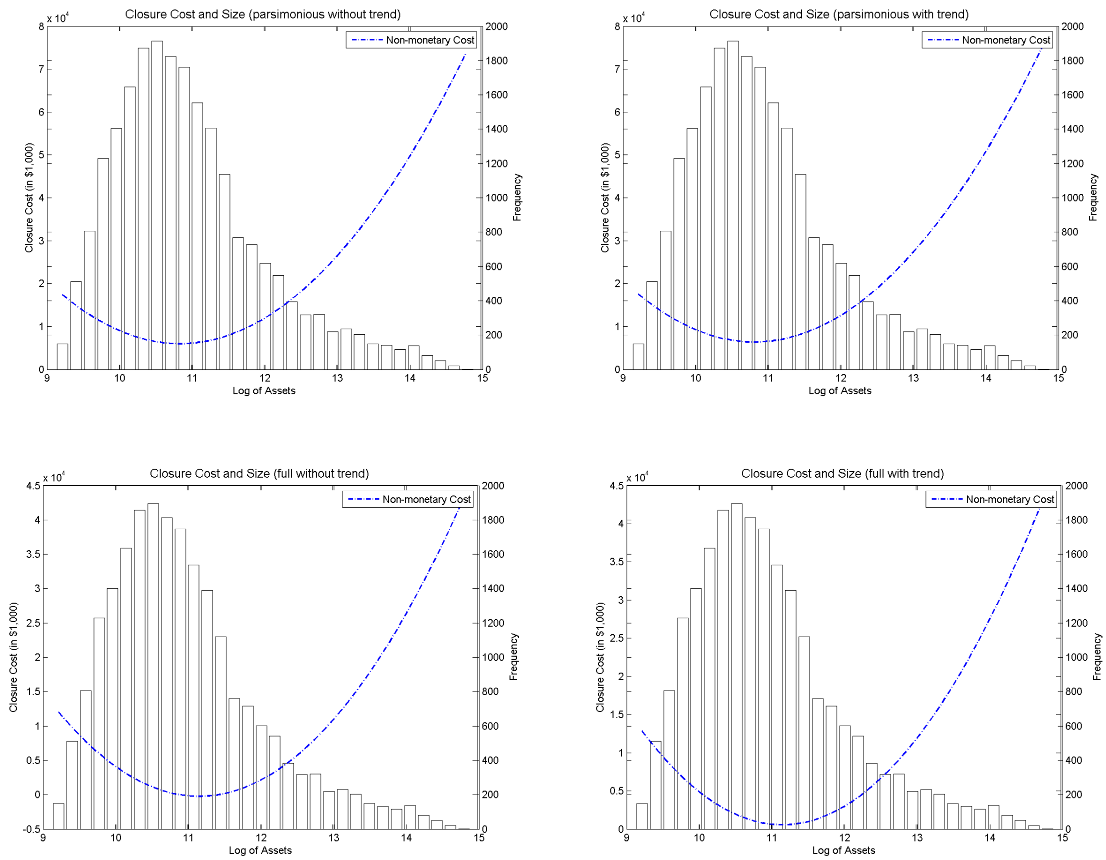


Figure 8: Effect of size on non-monetary closure cost, superimposed on distribution of bank size in the data on negative net income banks. The top shows the effect for the parsimonious model and the bottom for the full model. The right column of figures includes the time trend in the conditional choice probabilities.

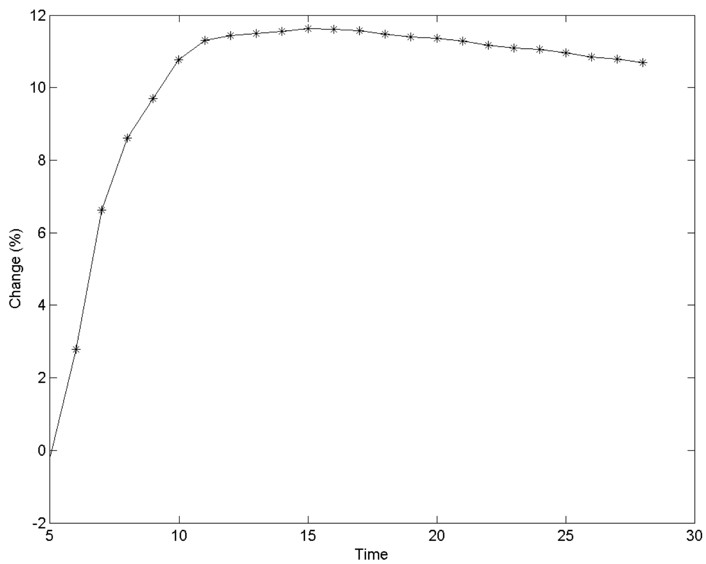


Figure 9: Cumulative percent difference between monetary costs under the $\alpha = .2$ policy versus no policy.