Bank Bailouts and Moral Hazard? Evidence from Banks' Investment and Financing Decisions

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ABSTRACT

The goal of this paper is to estimate a dynamic model of a bank to explain how bank bailouts exacerbate moral hazard. In the model, a bank makes an endogenous choice of the risks of its investments and can finance these investments by deposits and risky debt. I estimate nine model parameters that characterize a bank's behavior. For the full sample of U.S. banks, I estimate the expected bailout probability, conditional on bankruptcy, to be 52%. The estimated conditional bailout probabilities for small and large banks are 36% and 76%, respectively. The model predicts that rescue funding constitutes 4.2% of total assets, which is very close to the actual capital injection, 4.4% of total assets, made by the U.S. government under the 2008 Troubled Asset Relief Program (TARP). The simulation results show that a bank with a higher bailout belief takes more risks, especially when it is very close to bankruptcy.

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1 Introduction

This paper examines the effects of U.S. government bailout policies on bank moral hazard. Because widespread financial institution failure is generally considered to have serious negative real effects, the U.S. government has repeatedly intervened in financial markets. However, bank rescues in the recent financial crisis have been blamed for inadvertently increasing direct costs to taxpayers, as well as increasing incentives for banks to behave in a more risky manner. Intuitively, a bank that expects government protection takes on excessively risky projects and generally acts less responsibly than it would if it had to bear the full burden of its behavior.

The incentive effects of banks' perceptions of bailout probabilities are thus an interesting question, yet measuring and identifying these effects is challenging, largely because of data limitations. First, excessive risk-taking behavior is inherently unobservable because one cannot observe the *optimal* amount of risk-taking. Existing proxies, such as profit volatility, debt-to-asset ratios, nonperforming loan ratios, and market capital-to-asset ratios, are ridden with measurement error, and there are no good instruments for this errors-in-variables problem. Second, banks' ex ante beliefs about bailout probabilities are therefore first unobservable, but this second problem is worse, because a bailout probability is a latent variable with no obvious proxies.

To confront these issues, I use simulated method of moments (SMM) to estimate the parameters of a dynamic model of a bank in order to infer bailout probabilities and the ensuing effects on bank incentives. Structural estimation is particularly useful for addressing the data limitation problems that accompany this inquiry. An additional advantage of this approach is that I am able to quantify ex ante beliefs about bailouts, as well as the causal effects of these beliefs on banks' risk-taking.

The estimation results for the sample period 1994–2007 show that on average banks believe that the probability of a government bailout is 52.44%. To understand whether banks of different sizes have different ex ante bailout beliefs, I split my sample of banks by size, finding that expected bailout probabilities perceived by small banks and large banks are 35.69% and 76.20%, respectively, for the same sample period. These findings confirm that the widespread notion that large banks perceive themselves as "too-big-to-fail."

It is well-known that financial institutions are different from other non-financial firms in that their capital structure and profit-making mechanisms are unique. Bank leverage is on average much higher than that of non-financial firms. Also, most banks' creditors are depositors, which implies that banks have little control over this source of financing. Moreover, a bank makes profits not by producing goods but by borrowing money at a low interest rate and lending money at a high interest rate. Accordingly, I construct a model that captures these distinctive properties of banks. The model features a bank that maximizes shareholder value by determining the optimal allocation of investments and by adjusting financing decisions. On the asset side, the bank holds cash reserves and two types of investments: one-period risk-free bonds and risky loans. The bank's liabilities consist of fully insured deposits and risky debt. Debt is risky because banks have the option to default on this debt. However, there is a possibility that in the event of default, the bank's shareholders will be bailed out, where the bailout consists of a cash transfer from the government sufficient to preserve the bank's solvency.

By estimating the parameters of this model, not only am I able to infer bailout probabilities, but I am also able to characterize the differences between large and small banks. Large banks have riskier loan investments, shorter loan maturities, lower fire-sale prices for their assets, lower rates of return on loans, and smaller costs of adjusting their loan portfolio than small banks. These findings are consistent with the fact that large banks have more commercial and industrial loans and fewer personal loans.

Interestingly, the parameter that quantifies the probability of a government bailout appears crucial in allowing the model to fit the data well. I find that the moments used in my model estimation are not well matched if the bailout belief parameter is set equal to zero but that they are well matched if I allow this parameter to be positive. When I constrain the bailout probability to be equal to zero and re-estimate the model, the parameter estimates suggest that distressed banks be able to sell their loans at minimal discount. This result is inconsistent with the evidence from Shleifer and Vishny (1992) and Allen and Gale (1994) that fire-sale prices of troubled banks' assets are well below one.

With the estimates, I also conduct counterfactual exercises. As banks move closer to bankruptcy, they decrease their risky investments and holdings of risky debt. Banks with beliefs of a higher bailout probability take relatively more risks on both sides of the balance sheet, especially when they are very close to bankruptcy. That is, banks with a strong belief decrease their risks as they approach bankruptcy but not as much as their counterparts. The model can also assess the counterfactual effects of reserve requirements. I find that banks invest less in loans if the reserve requirement ratio increases. Intuitively, the banks have less money available to lend due to the larger amount of reserve requirements.

Finally, I show that the model delivers realistic out-of-sample predictions. I estimate the model using a sample of pre-crisis data, but my simulation results show that the model predicts surprisingly well the actual amount of rescue funds allocated by the Troubled Asset Relief Program (TARP) of 2008. Under TARP, the Treasury injected capital into 736 financial institutions. These rescue funds amounted on average to 4.39% of total bank assets. I compare this figure with the prediction from the model. In the simulated data, the expected amount of the government's rescue funds is about 4.21% of total assets. This prediction is surprisingly close to what actually happened, given that I do not use the amount of bailout funds to estimate the model. Thus, this out-of-sample test lets the model have more credibility.

Three separate literatures are relevant to this paper: bank failure, government intervention, and risk-taking. Whereas most papers look at each issue individually, this paper focuses on all three simultaneously. The literature on bank failure, such as Diamond and Dybvig (1983), Chan-Lau and Chen (2002), Caballero and Simsek (2009), He and Xiong (2009), and Calvo (2012), identifies factors that trigger a bank-run or a financial crisis, but ignores the government intervention or bank risk-taking.

There is a rich body of literature on government intervention. Schneider and Tornell (2004), Stern and Feldman (2004), Congleton (2009), and Basu (2011) examine how government policies affect economic conditions, yet do not consider risk-taking behavior. Wilson and Wu (2010) and Bernardo et al. (2011) attempt to find an optimal government bailout policy. In contrast, the the main goal of this paper is to quantify the consequences of the government's existing bailout policy.

This paper also falls into the literature on bank risk-taking. For example, Saunders et al. (1990), Mailath and Mester (1994), Boyd and De Nicolo (2005), and Laeven and Levine (2009) investigate circumstances in which a bank's risk-taking behavior occurs. Saunders et al. (1990) and Laeven and Levine (2009) study the relationship between risk-taking behavior and ownership structure. Boyd and De Nicolo (2005) investigate a relationship between risk-taking behavior and competition in the banking industry. Mailath and Mester (1994) relate regulators' policy on bank closure and the banks' level of risks. There exists an empirical literature on measuring risks of banks, such as Shrieves and Dahl (1992) and Lepetit et al. (2008). A drawback of these studies, however, is that they employ risk proxy measures that are only indirectly related to the risk-taking of a bank.

Only a few papers try to integrate these areas. The most closely related papers are Cordella and Yeyati (2003), Cheng and Milbradt (2012), and Dam and Koetter (2012). They all attempt to examine the relationship between government bailouts and moral hazard. Cordella and Yeyati (2003) construct a model to explain the effects of a bailout policy on risk-taking, but their analysis does not involve real data or a dynamic model. Cheng and Milbradt (2012) mainly focus on the maturity mismatch between long-term investment and short-term debt (as in He and Xiong (2009)). However, my focus is to explain how government bailouts exacerbate moral hazard. In contrast to my approach of structural estimation, Dam and Koetter (2012) adopt a reduced-form approach. Their approach requires data on risk-taking and expected probability of bailouts, both of which are not directly observable. As an alternative, they run a two-stage regression model with proxy measure of risk-taking and political factors as instrumental variables; my approach requires neither any proxy measure of risk-taking nor expected probability of bailouts. The structural estimation adopted in this paper also allows me to estimate the expected probability of bailouts and to explore counterfactuals.

The paper is organized as follows. Section 2 describes the model. Section 3 describes the data and the estimation procedure. Section 4 presents the estimation results. In Section 5, I present the counterfactuals. Section 6 contains the out-of-sample test. In Section 7, I investigate the ex ante belief about bailout probabilities. Section 8 concludes. The Appendix contains details concerning the model solution.

2 Model

Banks differ from non-financial firms in their capital structures and profit-making mechanisms. Commercial banks borrow money on a short-term basis in the form of consumer deposits, which can be withdrawn at any time. The major assets for most banks are mortgages (real estate loans), credit card loans, auto loan receivables, and business loans, all of which are illiquid and have long maturities. Banks make profits by borrowing money at a low interest rate and lending money at a high interest rate. Banks adjust their assets and liabilities to generate profits. Figure 1 shows a typical U.S. commercial bank's balance sheet with assets on the left side, and liabilities and net worth on the right side. The percentages in parentheses are the actual averages of each category for commercial banks in the U.S. from 1987 to 2008. The sample is from the Reports of Condition and Income, Bank Regulatory Database.

[Insert Figure 1]

A bank has four main categories of assets: loans, securities, cash reserves, and physical assets. More than half of a bank's assets are loans, which are the primary source of interest revenue. Types of loans include loans to consumers (home loans, personal loans, auto loans, credit card loans) and businesses (real estate development loans, capital investment loans). About 30% of a bank's assets are investment securities. Investment securities include U.S. Treasury securities and federal funds. Securities are safer than loans, but they do not pay as much interest as loans do. Securities are not as safe as cash reserves, but they pay more interest than cash reserves. Cash reserves represent about 10% of a bank's assets, and they include vault cash and Federal Reserve deposits, which typically constitute reserve requirements. In the U.S., the Board of Governors of the Federal Reserve System sets reserve requirements, which apply to some deposits held at depository institutions, such as commercial banks, savings and loan associations, savings banks, and credit unions. Last, physical assets include buildings, land, and equipment owned by the bank. This category is relatively small for most banks.

On the other side of the balance sheet are net worth and liabilities. The average leverage of commercial banks is 90%, which is extremely high compared to non-financial firms. The liabilities mostly consist of deposits, suggesting that banks have little control over the liability side. There are two ways to consider the types of deposits. The first way is by the length or accessibility of deposits: demand deposits (or transaction deposits) and time and savings deposits. Demand deposits include all deposits in depository institutions that can be withdrawn without prior notice, and savings deposits are locked up for a certain length of time. The second classification divides deposits into insured and uninsured deposits. Between 1980 and 2008, the Federal Deposit Insurance Corporation (FDIC) insured a depositor's accounts up to $100,000 for each deposit ownership category in each insured bank; the deposit insurance limit was increased to $250,000 on October 3, 2008. The remaining 10% on the balance sheet is net worth, or what the bank owes the equity holders. A negative net worth would put the bank in default.

A bank can therefore be characterized by its balance sheet. The key features of the model proposed in this paper are summarized as follows: (i) on the asset side, there are cash reserves and two types of investments: a one-period risk-free bond, b_t, and a portfolio of risky loans, l_t; (ii) on the liability side, there are fully-insured, exogenously-given deposits, d_t, and fairly-priced risky debt, q_t; (iii) a bank goes bankrupt if its net worth w_t is less than 0, but it believes the government would bail it out with probability η; (iv) a bank maximizes shareholder value by choosing the investment (b_t and l_t) and financing decisions (q_t); (v) shareholders are risk-neutral; and (vi) time is discrete and the horizon is infinite. In addition, the bank's balance sheet should be balanced:

$$l_t + b_t = w_t + d_t + p_t q_t, \tag{1}$$

where p_t is the price of the risky debt q_t. In each period of time, a bank with an infinite horizon optimizes over three decision variables $\{q', l', b'\}$ given six state variables $\{q, l, b, d, d', z\}$, where variables with primes denote the next period's values. The following subsections describe how the model is constructed to resemble the properties of a generic balance sheet of a bank.

2.1 Asset Side

On the asset side, a bank invests in a risk-free bond, b, which yields a risk-free rate of return, r_f. The bank also invests in a portfolio of risky loans, l, which yields a rate of return, r_l. A fraction of the loans, δ, is due in each period; $\delta < 1$ indicates that the average loan maturity is longer than one year. There is a risk that the loans can default; z denotes the survival rate of loans, implying that $1 - z$ of loans default in each period. Defaulting is independent from maturing. Thus, the income from loans consists of two components: a stochastic survival rate, z, and a deterministic profitability rate, r_l. Investing an amount of l in a portfolio of loans yields $(r_l + \delta)zl$ in the following period. The remainder, $(1 - \delta)zl$, is rolled over to the next period. The law of motion of l is therefore given by:

$$l' = (1-\delta)zl + i, \tag{2}$$

where i is the amount of new loans that are invested at time t for the next period. The survival rate z of loans has a truncated-normal distribution (see Appendix B for details):

$$z \overset{iid}{\sim} N(\mu_z, \sigma_z^2),\ \ z \in [0,1]. \tag{3}$$

The bank also holds cash reserves as required by the Board of Governors of the Federal Reserve System. The reserve requirement is denoted by α. The cash reserves are automatically determined by the deposits. The available capital for investments at time t is $A_t - \alpha d_t$, where A_t is total assets and d_t is deposits held by the bank.

2.2 Liability Side

On the liability side, a bank borrows money from depositors, called "deposits," d. The deposits are random in each period; the bank cannot choose how much it wants to borrow from depositors. The deposits, d, follow an AR(1) process:

$$d' = \mu_d + \rho_d d + \epsilon_d, \tag{4}$$

where $\epsilon_d \sim N(0, \sigma_d^2)$. All deposits are fully insured. d corresponds to the insured deposits in Figure 1 and is referred to as deposits instead of insured deposits hereafter. The depositors require a fixed per-period interest rate, r_d, which is lower than the risk-free rate (i.e., $r_d < r_f$), as in De Nicolò, Gamba, and Lucchetta (2011). The difference between the two rates includes costs of the intermediary's service, as well as costs of the insurance.

The bank can also issue debt, q', which is risky, because the bank can default on the debt. The bank's cash balance at the beginning of the next period is given by:

$$c' = (r_l + \delta)z'l' + (1 + r_f)b' - (1 + r_d)d' - q' + \alpha d'. \tag{5}$$

The first two terms in Equation (5) are the incomes from risky loans and risk-free bond investments. The next two terms are the payments to the depositors and debt holders. The last term is the cash reserves determined by deposits held at the bank.

The bank is financially distressed if its cash balance, c, is less than zero after the credit shock, z, is realized but before the new deposits, d', are given. A financially distressed bank does not necessarily exit the market. Financial distress (cash default) occurs when a bank does not have enough cash to pay back outstanding debt. When a bank has insufficient cash, it sells its existing loans at a fire-sale price, ξ, to meet its debt obligations. The distressed bank needs to sell only $\frac{c}{\xi}$ of its loans. After the fire-sales, the net worth becomes:

$$w = (1 - \delta)zl + \frac{c}{\xi}, \tag{6}$$

if any. If w is negative, the bank files for bankruptcy. At this point, the bank is reorganized through Chapter 11 bankruptcy protection, in which the reorganization process imposes costs on shareholders.

The distress threshold can be represented by a function of the survival rate, z, as in Gilchrist, Sim, and Zakrajsek (2010). The bank is in financial distress when $z < z_d$, where:

$$z_d(b', q', l'; d') \equiv \frac{(1 + r_d)d' + q' - \alpha d' - (1 + r_f)b'}{(r_l + \delta)l'}. \tag{7}$$

In the event of financial distress, the recovery of the debt holders, $R(\cdot)$, is:

$$R(b', q', l'; d', z') = \max\Big\{ \min\big\{(r_l{+}\delta)z'l'{+}\xi(1{-}\delta)z'l'{+}(1{+}r_f)b'{-}(1{+}r_d)d'{+}\alpha d', q'\big\}, 0\Big\}, \tag{8}$$

where ξ is a fire-sale price of outstanding loans. Since loans are illiquid, the sale price of the loans is less than 1. Thus, the debt-pricing formula, $p(\cdot)$, is given by:

$$p(b', q', l'; d') = \frac{1}{1 + r_d}\left(1 + \int_{\underline{z}}^{z_d} \left[\frac{R(b', q', l'; d', z')}{q'} - 1\right] d\Phi(z')\right). \tag{9}$$

This equation implies that debt holders' and depositors have the same expected profits as in Hennessy and Whited (2007) and Gilchrist, Sim, and Zakrajsek (2010).

2.3 Bankruptcy and Government Intervention

In the event of bankruptcy, the government can intervene and rescue the troubled bank. I assume that the bailout decision is random and constant from a bank's perspective. The bank has ex ante belief η about the probability of government intervention conditional on bankruptcy. If the government rescues a bank, it injects capital, τ, into the bank to prevent the bank from having to sell its loans at fire-sale prices.

In the real world, the capital injection in a bailout can take several forms, such as loans, stocks, bonds, or cash. During the recent financial crisis, the Treasury bought troubled assets – especially mortgage-backed securities – of domestic financial institutions, and it also bought equity positions in the largest banks in the U.S. using taxpayer funds. In addition to purchasing troubled assets or stocks, another type of bailout occurs in the form of regulatory mergers, which are very common in financial markets but often ignored.

When federal bank regulators get involved with an insolvent bank or financial institution, they can take two types of action. First, the FDIC can become the receiver of a failed bank and enters a liquidation process like a bankruptcy trustee. In such a case, the FDIC closes down the bank, pays off depositors up to the insurance limit ($250,000 since 2008), and sells off the assets. Shareholders of the failed bank can expect to suffer losses. Second, and more commonly, the FDIC finds a healthy bank to merge with or buy the failed bank. The regulators often entice the acquiring bank with subsidies or relaxed capital requirements.

Thus, a merger between two banks arranged by financial regulators can be thought of as a bailout or government help.

Table I contains the number of FDIC-approved bank mergers every year between 2000 and 2010. There are four categories of bank mergers: regular merger, corporate reorganization merger, interim merger, and probable failure or emergency merger. Unfortunately, the data on the regulatory mergers are not available. The table also includes the total number of banks as well as the number of failed banks. The total number of banks comes from the Bank Regulatory Database. Table I shows that there have been a number of mergers over the last decade. On average, about 4% of banks are acquired by another bank each year. Only a few banks have actually failed.

[Insert Table I]

2.4 Bank Problems

Figure 2 summarizes a bank's problems from time t to time $t+1$. The bank has chosen the risk-free bond b, loans l, and risky debt q during the previous period, $t-1$. At the beginning of time t, the bank observes its deposits d and the loan survival rate, z. These shocks determine whether or not the bank becomes financially distressed. If the bank's cash balance is positive, the bank can continue by choosing a new financing decision, q', and new investment decisions, b' and l', given the new deposit level, d'. If the cash balance is negative and thus the bank is in cash default, then the bank sells its loans to fulfill its debt obligations. If it is not feasible to pay back the outstanding debt even after the bank sells all its existing loans, the bank files for bankruptcy. Once a bank files for bankruptcy, the government intervenes and bails it out with probability η. Otherwise, the bank is reorganized, and associated costs are levied on shareholders.

[Insert Figure 2]

There are asymmetric adjustment costs for loans. Increasing the loan amount could be costly for a bank due to monitoring. The adjustment costs, Λ^j, for each case $j \in \{C \equiv \text{Continuation}, D \equiv \text{Distress}, B \equiv \text{Bailout}\}$ are given by:

$$\Lambda^j = \lambda(x - l')^2 \mathbb{1}\{l' > x\}, \quad j \in \{C, D, B\}, \tag{10}$$

where λ is a coefficient of the adjustment cost function of loans and x is the remaining loan amount after fire-sales, if necessary. Cash flows to shareholders are reduced by the loan adjustment costs.

Let e^j be cash flows to shareholders after choosing the next-period financing and investment decisions in each case $j \in \{C, D, B\}$. When cash balance c is positive, the bank continues by choosing the new financing and investment decisions, and cash flows to shareholders are given by:

$$e^C = c + (1 - \delta)zl + (1 - \alpha)d' - l' - b' - \Lambda^C + p(b', q', l'; d')q'. \tag{11}$$

In such a case, the remaining loans, x, are $(1 - \delta)zl$, since the bank does not need to sell any of its existing loans. The bank first realizes its cash balance plus remaining loans plus new deposits. The bank has to maintain some of its deposits as cash reserves. The bank then chooses new investments in risky loans and a risk-free bond, and it pays adjustment costs if it increases its loan investments. Finally, the bank can raise money by issuing debt at a price $p(\cdot)$.

When cash balance c is negative, the bank sells its outstanding loans at a fire-sale price, ξ, until it can meet its debt obligations. If $c + \xi(1 - \delta)zl$ is positive, the bank does not need to sell all its loans. In this case, the bank needs to sell just enough of its existing loans, $|\frac{c}{\xi}|$, to meet its debt obligations. The cash flows to shareholders in this case are given by:

$$e^D = \frac{c}{\xi} + (1 - \delta)zl + (1 - \alpha)d' - l' - b' - \Lambda^D + p(b', q', l'; d')q'. \tag{12}$$

After the fire-sales, the bank is left with $x = \frac{c}{\xi} + (1-\delta)zl$ of loans.

A bank may still be unable to meet its debt obligations even after selling all of its loans. In that case, the bank files for bankruptcy and the debtors enter a reorganization process. The debtors have all ex post bargaining power and extract all bilateral surplus. All reorganization costs are passed along to shareholders, therefore the cash flows to shareholders are the same as in Equation (12). In the event of bankruptcy, however, the government may intervene and bail out the troubled bank with probability η. Once the government decides to rescue the troubled bank, it injects cash τ and cash flows to shareholder are:

$$e^B = \frac{c+\tau}{\xi} + (1-\delta)zl + (1-\alpha)d' - l' - b' - \Lambda^B + p(b', q', l'; d')q'. \tag{13}$$

The government essentially cancels out the negative cash balance c with τ.

Therefore, at each time t, a bank chooses q_{t+1}, b_{t+1} and l_{t+1} that maximize discounted lifetime expected equity value given the set of states, $\{q_t, b_t, l_t, d_t, d_{t+1}, z_t\}$. The objective function of the bank's shareholders is given by:

$$\max_{\{q_{h+1}, b_{h+1}, l_{h+1}, h=t,\cdots,\infty\}} \mathbb{E}_t\Big[\sum_{k=t}^{\infty} \beta^{k-t} e_t^j\Big], \quad j \in \{C, D, B\}, \tag{14}$$

where β is a discount factor. As six state variables create computational complications, simplifying assumptions are made in the following section.

2.5 Model Simplification

I assume that a bank chooses the investment decisions, l' (or i) and b', and the financing decision, q', after observing the income from loans (the credit shock z), but *before* the next-period deposits d' are realized. The bank thus makes financing and investment decisions based on the expected value of next-period deposits. According to the AR(1) process of deposits, the expected value of d' conditional on d is given by:

$$\mathbb{E}[d'|d] = \mu_d + \rho_d d, \tag{15}$$

which is a function of the current level of deposits. The debt pricing formula in Equation (9) then becomes

$$p(b', q', l'; d) = \frac{1}{1+r_d}\left(1 + \mathbb{E}\left[\int_{\underline{z}}^{z_d}\left[\frac{R(b', q', l', d', z')}{q'} - 1\right] d\Phi(z') \middle| d\right]\right). \tag{16}$$

There are two advantages of this assumption. First, the number of state variables is reduced by 1; the state variables are now $\{q, l, b, d, z\}$, which simplifies the computations. Second, the assumption introduces uncertainty about the level of deposits, which can be interpreted as rollover risk.

I further assume that the total assets, A, are fixed at 1. The fixed total capital assumption can be justified, because risk-taking is not determined by the total size of investment but by the allocation between the risky loans and the risk-free bond. As discussed in Section 2.1, the available assets for investment are $A - \alpha d$ per the reserve requirements. Choosing the amount invested in loans automatically determines the amount that should be invested in the risk-free bond, and vice versa (i.e., $b = A - \alpha d - l$). This assumption eliminates one state variable and one choice variable. Therefore, there are two decision variables $\{q', l'\}$ and four state variables $\{q, l, d, z\}$.

The last assumption is not related to computation but to empirical identification of the parameters. I assume that the cash injection made by the government τ is equal to $|c|$, the amount of money that the troubled bank lacks. When the net worth after the fire-sale of loans, $w = \frac{c}{\xi} + (1-\delta)zl$, is negative, the bank files for bankruptcy. With the government's cash injections of $\tau = |c|$, sufficient to supplement the existing loan amount of $(1-\delta)zl$, preventing the bank from entering a fire sale. These cash injections allow creditors to recoup their money from the bank, or, more accurately, from the government. This simplifying assumption is necessary, because the government bailout probability parameter η and the cash injection parameter τ cannot be identified simultaneously. From a bank's point of view, the model is solved based on its expectation about a bailout, which is the product of η and τ.

In sum, the Bellman equations in each case are given by:

$$V^j(q,l,d,z) = \max_{\{q',l'\}} \left\{ e^j + \beta \mathbb{E}[V(q',l',d',z')|d] \right\}, \quad j \in \{C,D,B\}. \tag{17}$$

In each period, a bank chooses its investment decision, l, and financing decision, q, given deposits, d, and credit shock, z. There are four possible outcomes: the bank continues, the bank is financially distressed, or the bank files for bankruptcy, in which case it may or may not get bailed out. For each case, the value function is defined as follows:

$$V(q,l,d,z) = \begin{cases} V^C(q,l,d,z) & \text{if } c \geq 0, \\ V^D(q,l,d,z) & \text{if } c < 0 \text{ and } w \geq 0, \\ \eta V^B(q,l,d,z) + (1-\eta) V^D(q,l,d,z) & \text{if } c < 0 \text{ and } w < 0, \end{cases} \tag{18}$$

where c is the bank's cash balance and w is its net worth after fire-sales if necessary. The model solutions are described in Appendix A in detail.

3 Estimation

3.1 Estimation Outside of the Model

Table II reports all of the model parameters. Most of the parameters in the model are estimated using simulated method of moments (SMM). However, some of the parameters are estimated separately. The risk-free rate r_f is the annualized one-month Treasury-bill return and is set equal to 3%.[1] The market discount factor β is then equal to $\frac{1}{1+r_f}$. The rate of return on deposits, r_d, is set to 1%. The sources for r_d are the national one-year CD rate,

[1]The source for Treasury-bill returns can be found at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/.

the national money market accounts rate, and the checking account interest rate during the sample period. The default rate of loans, $1-\mu_z$, is the average of the sum of charge-off rates and delinquency rates on loans and leases of all commercial banks in the U.S. provided by the Board of Governors of the Federal Reserve System, and it is 4% over the sample period.

The Federal Reserve currently sets the depository institution's reserve requirements at 10% of net transaction accounts if the net transaction accounts exceed \$79.5 million. If net transaction accounts are between \$12.4 million and \$79.5 million, the reserve requirement ratio is 3%, and if net transaction accounts are less than \$12.4 million, there is no reserve requirement. Since data on net transaction accounts are not available, I assume that cash reserves are determined by insured deposits, d, instead of net transaction accounts in the model. As shown in Figure 1, U.S. commercial banks hold 10% of their insured deposits as cash reserves, and thus α is set at 10%. Panels A and B of Table II summarize the set of parameter values estimated outside of the model.

[Insert Table II]

3.2 Estimation by SMM

There are nine model parameters: the drift and serial correlation of the deposits process, μ_d and ρ_d; the standard deviation of the shock to deposit process, σ_d; the conditional belief of the probability of government bailout, η; the standard deviation of the loan survival rate, σ_z; the fire-sale price of existing loans, ξ; the percentage of loans that mature in each period, δ; the rate of return on loans, r_l; and the loan adjustment cost coefficient, λ. These model parameters are estimated using simulated method of moments (SMM), which chooses parameters so that the distance between the moments of the real data and the moments of the simulated data is as small as possible. The data used for the SMM are described in the following section.

The deposit process can be estimated separately from the model. In contrast, I follow the two-step procedure, proposed by Cooper and Haltiwanger (2006), in which the parameters are split into two sets. The first set includes the three parameters generating the deposit process ($\Theta_1 \equiv \{\mu_d, \rho_d, \sigma_d\}$) and the second set contains the other six parameters ($\Theta_2 \equiv \{\eta, \sigma_z, \xi, \delta, r_l, \lambda\}$). Given initial values for the second set of parameters, Θ_2^0, the three parameters related to deposits in Θ_1^1 are estimated by matching three moments: the average, serial correlation, and standard deviation of deposits. Using the estimates of the deposit process, the second set of six parameters is estimated and denoted by Θ_2^1. To identify this set of parameters, nine moments are chosen to be matched. The moments and the details for the identification strategies are described in Section 3.4. When the nine moments are matched, the three moments related to deposits are then re-calculated using the six parameters that have been found so far. If these moments are sufficiently close to the moments in the first step, the procedure stops. If the given moments are not close enough, the first set of parameters is re-estimated, given Θ_2^1, and denoted by Θ_1^2. The process is repeated until the moments related to deposits are matched. Since deposits are exogenously given and they, in turn, are independent from other parameters, one iteration is sufficient to estimate all the parameters.

The hypothetical banks generated by the model are heterogeneous only in terms of their shocks. The SMM's function is to estimate the parameters of an average bank. The real bank data, however, are heterogeneous across many dimensions. Thus, when using the SMM, it is critical to eliminate as much heterogeneity from the data as possible. Firm fixed effects are used in the estimates of variance. In addition, the double-differencing method of Han and Phillips (2010) is used to determine the AR(1) coefficients. Further, the sample is split into two subsamples – small and large banks – and the model is estimated for each subsample. Another reason to estimate the subsamples by size is to see whether large banks have a stronger belief than small banks that the government will bail them out, in other words, that they are "too-big-to-fail". This point will be examined later in this paper. Figure 3 plots the yearly cross-sectional averages of several variables for banks in a sample of commercial banks between 1994 and 2007. Panel A plots the total liabilities, insured deposits, loans, and operating income for the full sample. Panels B and C plot the variables for small banks and large banks, respectively. The figures show that small banks and large banks are different.

[INSERT FIGURE 3]

When minimizing the objective function, a weighting matrix with firm fixed effects is used. The standard errors are calculated using a clustered weighting matrix. According to Erickson and Whited (2000), the weighting matrix is the inverse of the sample variance-covariance matrix of the moments, which is the inner product of stacked influence functions of the moments. More details about how to implement SMM are described in Appendix C.

3.3 Data

The data are from the Reports of Condition and Income (Call Reports), Bank Regulatory Database of the Federal Reserve Bank of Chicago, which provides quarterly accounting data for commercial banks. The sample period is from 1994 to 2007. The sample ends in 2007 because the database provides the amount of deposits greater than $100,000, while the deposit insurance limit has been increased to $250,000 since October 3, 2008. Data variables are defined as follows: total assets is *RCFD2170*; debt is *RCFD2950*; operating income is *RIAD4000*; distributions to shareholders is *RIAD4460 (common stock)* plus *RIAD4470 (preferred stock)* minus negative *RIAD4346 (net sale of stock)*; and insured deposits is *RCFD2200 (total deposits)* minus *RCON2710* or *RCONF051 (deposits greater than $100,000).*

Observations in which total assets are less than $1 million or operating income or deposits are non-positive are deleted from the sample. As some variables are only available on an annual basis, the quarterly data are annualized. Flow variables are accumulated from the first quarter to the fourth quarter of each fiscal year. Stock variables are the fourth quarter's values. If there is a missing value in any quarter, the bank-year observation is dropped. All variables are deflated by the annual total assets. Observations are included only when at least three consecutive years of data are available. Winsorizing the top and bottom 1% of the variables produces an unbalanced panel of banks from 1994 to 2007, with between 7,597 and 10,948 observations per year, and 123,159 bank-year observations. The data reveal that the number of banks in the market monotonically decreases over time.

The bankruptcy frequency is calculated by dividing the number of banks that are delisted from the FDIC database for a given year by the total number of banks that are listed in the FDIC database in the previous year:

$$\text{Bankruptcy Frequency} = \frac{(\#\text{ of banks in } t) - (\#\text{ of banks in } t-1)}{(\#\text{ of banks in } t-1)}. \tag{19}$$

Note that (# of banks in t) does not take into account newly entering banks in year t.

3.4 Identification

The objective of the SMM procedure is to determine the values of the model parameters that minimize the distance between the simulated moments and the actual moments. Since model identification is critical in this procedure, it is necessary to choose the moments carefully; the mean, variance, and autocorrelation of all possible variables are computed and reveal the moments that are most sensitive to variation in parameter values. The three parameters related to the deposit process, $\{\mu_d, \rho_d, \sigma_d\}$, are identified by the three moments of the actual deposit process. The other six parameters, $\{\eta, \sigma_z, \xi, \delta, r_l, \lambda\}$, that characterize a bank's behavior are determined by matching nine moments: the first moment of leverage, the autocorrelation of leverage, the standard deviation of the shock to leverage, the first moment of operating income, the first moment of dividends, the first and second moments of charge-offs, the ratio of insured deposits to total liabilities, and the frequency of bankruptcy.

Identifying the expectation about government bailout probability, η, is crucial for this study. The most informative moments for this parameter are the ratio of insured deposits to total liabilities and the bankruptcy frequency. In the model, the deposits are exogenously given, but banks can choose additional borrowing by paying an appropriate price. In addition, as shown by Figure 3, insured deposits decrease monotonically over time, but total liabilities are stable, forming around 90% of total assets. This trend implies that banks are borrowing more risky debt in order to maintain the high level of leverage, which leads a higher level of risks. The bailout belief parameter can thus be identified by the ratio of insured deposits to total liabilities. The bankruptcy frequency is also of great use for identifying the parameter η. Intuitively, more banks would go bankrupt if they believe that government bailouts are more likely, since the higher belief in bailouts induces banks to take more risks.

The other parameters are standard. The first moments of operating income and dividends help establish the rate of return on loans, r_l. As the rate of return on loans increases, banks become more profitable. When banks profit from high rates of return of loans, they can then pay out higher dividends. Choosing the appropriate moments of leverage helps identify the average maturity, δ. If the maturity of loans were too short, the leverage would be unstable. The adjustment cost coefficient affects the charge-offs as well as bank income. If banks have difficulty adjusting their loan investments, the loan amounts will not change frequently or promptly. The standard deviation of the charge-offs is directly affected by the standard deviation of the survival rate of the loans, σ_z. The fire-sale price, ξ, affects the bankruptcy frequency. Even if a bank cannot meet its debt obligations, and if it can sell existing loans at a higher price, it might be able to alleviate its financial distress. Panel C of Table II contains the parameters to be estimated using SMM with most informative moments.

4 Estimation Results

4.1 Full Sample

Table III contains estimation results for the full sample. Panel A reports both the actual moments and the simulated moments with t-statistics that accompany the difference between the actual and simulated moments. The three moments related to the deposit process are almost perfectly matched to the data moments. Fewer than half of the simulated moments are statistically significantly different from their real-data counterparts. The model fits the average of leverage, the average of income, the average of charge-offs, the deposit ratio, and the bankruptcy frequency particularly well. The model fails to match the first moment of dividends because the model does not include taxes.

[Insert Table III]

Panel B of Table III reports the parameter estimates with clustered standard errors in parentheses. The belief in the bailout probability conditional on bankruptcy is estimated to be 52.44%, which is lower than Dam and Koetter's (2012) estimate of 69%. Recall that Dam and Koetter (2012) run a two-stage regression. In contrast to the structural estimation used in this paper, their methodology requires a proxy for risk-taking and instrumental variables for the latent variable, the expected bailout probability. The structural estimation adopted in this paper also allows me to explore counterfactuals. The estimated fire-sale price is 46.42%, which is lower than that of non-financial firms (e.g. Hennessy and Whited (2005) estimate it at 59.2%). This estimate suggests that investments in loans are generally illiquid. On average, 69% of loans mature in each period. One period in the model is equal to one year, and therefore the average maturity of loans is about 525 days. The estimated value of the average maturity is close to the weighted-average maturity for commercial and industrial (C&I) loans of all U.S. commercial banks in the same period, which is about 469 days. The rate of return on loans is about 11%, which is consistent with the actual data. The rate r_l serves as a required rate of return on a portfolio of loans in order to account for multiple types of loans. For instance, over the same period, the average 30-year fixed mortgage rate is 7%; the finance rate on consumer installment loans at commercial banks is 8%; the finance rate on personal loans at commercial banks is 13%; and the interest rate on credit card plans of commercial banks is 14%. Thus, the rate of return on commercial bank loans should be close to the weighted average of these rates.

4.2 Subsamples

In the model, a bank believes that the government will bail it out in case of failure. The model and its parameters explain an average bank's behavior. On the other hand, the U.S. government's rescue programs appear to have been applied on an ad hoc basis with varying degrees of taxpayer support. For instance, in the recent financial crisis, the U.S. government rescued Bear Stearns by subsidizing its merger with JPMorgan Chase & Co. The U.S. Treasury took over Fannie Mae and Freddie Mac. The Federal Reserve injected capital directly into American International Group, Inc. At the same time, the government declined to help Lehman Brothers Holdings Inc., and the company eventually filed for Chapter 11 bankruptcy protection (Ayotte and Skeel Jr. (2010)).

Despite the varying degrees of assistance offered to financial institutions by the U.S. government, the likelihood of a government bailout seems to increase in the size of a bank; large banks are deemed too big to fail. Since a big bank is connected to many financial and non-financial firms, the failure of the big bank may have a domino effect, potentially affecting both the national and global economies (Aharony and Swary (1983)).

To investigate the idea that some banks are too big to fail, the sample is split by size (small vs. large banks), and the expectation of bailout probability is estimated for each subsample. Tables IV and V show the estimation results for small and large banks. "Bank size" is defined as total assets: small (large) banks are in the lower (higher) third of the distribution of total assets in each year. The estimation method is identical to that described in Section 4.1. The moments related to the deposits are different for each subsample. As shown in Figure 3, the mean ratio of insured deposits to total liabilities is higher for large banks (64.97%) than for small banks (53.10%). Thus, the parameters related to the deposit process are re-estimated for each subsample. The estimation results show that the drift and serial correlation of the deposit process for small banks are slightly higher than those for large banks. Additionally, the standard deviation of shocks to the deposit process is higher for large banks than for small banks.

[Insert Table IV]

[Insert Table V]

Panel B in Tables IV and V refers to the parameters governing a bank's behavior. When comparing small and large banks, several notable differences in parameter estimates emerge. The first is the ex ante bailout probability. This probability is estimated as 76.20% for large banks and 35.69% for small banks. Compared to small banks, large banks believe more strongly that the government will bail them out if they are in trouble, which implies that large banks perceive themselves too big to fail. Second, the fire-sale prices indicate that small banks can sell their existing loans at a higher price than large banks. At the same time, according to the adjustment cost coefficient, large banks can increase loan holdings more easily than small banks. Third, the average maturity of loans is slightly longer for small banks (568 days) than for large banks (515 days). The average maturity of C&I loans is shorter than that of personal loans, and therefore these estimates of maturity reflect the fact that large banks hold more C&I loans and fewer personal loans than do small banks. Finally, the rate of return on loans for large banks is lower than for small banks, but the standard deviation of the loan survival rate is slightly higher for large banks than for small banks. If large banks believe that they are more likely to benefit from a bailout, then they may be more likely to invest in riskier or less profitable loans.

5 Counterfactuals

In this section, two counterfactual exercises are conducted by simulating the model, with the parameter values estimated for the full sample by SMM. The first exercise analyzes how the sensitivity of a bank's behavior to the bailout belief parameter η depends on the bank's health. The second exercise shows how a bank reacts to changes in the reserve requirement rate. Let $\hat{\eta}$ denote the estimated value of the government bailout belief parameter η from Table III, hereafter referred to as "the original belief."

5.1 Distance from Bankruptcy

A bank's behavior depends not only on its belief about government bailouts but also on its health. First, the expectations of future government bailouts may affect a bank's decision making. For example, a stronger belief about the possibility of a government bailout may induce the bank to behave irresponsibly. Second, the bank's behavior may also depend on the bank's health. Health, in this context, refers to the bank's distance from bankruptcy. If a bank is far from bankruptcy, then it has relatively few incentives to take excessive risk even if it believes the conditional probability of bailout is high. Reckless behavior could result in a bad outcome and, in turn, lead the bank closer to bankruptcy. Therefore, the increase in risk-taking behavior due to a stronger bailout belief is more prominent when the bank is close to bankruptcy.

I simulate the model twice and generate 10,000 hypothetical banks in each iteration. One simulation uses the estimated value of the bailout belief for the full sample, $\hat{\eta}$, and the other uses a belief that is 1% higher than $\hat{\eta}$. The simulated banks are then ranked by their distance to bankruptcy. The distance to bankruptcy is captured by w in Equation (6), which is the cash balance plus the remaining loans after possible fire-sales. This is a natural way to measure the distance from bankruptcy because a bank with negative w is forced to file for bankruptcy. Then, I split the simulated banks into five groups, by distance from bankruptcy. Banks in the first (fifth) quintile are the closest to (farthest from) bankruptcy. The averages of variables related to risk-taking are computed for each quintile and plotted in Figure 4. A blue solid line represents the behavior under the original bailout belief, $\hat{\eta}$, and a red solid line represents the 1% higher bailout belief than $\hat{\eta}$.

[Insert figure 4]

Panels A and B of Figure 4 plot the averages of the two decision variables – the risky loans l and debt q – for each quintile. Because the 1% increase in bailout belief affects the decision variables regardless of the bank's distance from bankruptcy, I first re-scale each variable by the average of all banks that do not go bankrupt, and then calculate the average of the variables for each quintile. These calculations reveal the relative magnitude of the variables depending on how close a bank is to bankruptcy.

As a bank moves closer to bankruptcy, it takes fewer risks by decreasing both its debt and risky investments, regardless of its beliefs about bailout probabilities; this information is observable in the upward slope as the bank moves away from bankruptcy. This risk-reducing reaction happens because, for most institutions, going bankrupt is worse than remaining in business. Although a bank is trying to reduce its risks as it moves toward the bankruptcy threshold, it still has to pay higher interest on its debt borrowing as shown in Panel C of Figure 4. Debt holders require higher interest rates when they lend money to risky banks.

The rate of adjustment with respect to the distance to bankruptcy is slower for a bank with higher belief in the possibility of a bailout. In particular, the different speed of adjustment is clearly shown in loan investment (Panel A of Figure 4). For banks in the fifth quintile, even after re-scaling the variables by the average for all surviving banks, the relative amounts invested in risky loans under the two different beliefs are very similar (approximately 120% of the average bank's loan investments). When the bailout belief is $\hat{\eta}$, the level of loan investment by a bank very close to bankruptcy (first quintile) is only 59% of that of a bank very far away from bankruptcy (fifth quintile). On the other hand, when the bailout belief is 1% higher, the level of loan investment by a bank in the first quintile is about 71% of that of a bank in the fifth quintile. Hence, a bank with stronger belief is less sensitive to distance from bankruptcy, and while a bank with strong belief does decrease its risky investments as it approaches bankruptcy, it does not decrease its risky investments as much as a bank with a weak belief.

Panel B reveals a similar pattern on the borrowing side. When the bailout belief is $\hat{\eta}$, the amount of risky debt issued by a bank in the first quintile is 77% of that of a bank in the fifth quintile. When the bailout belief is 1% higher than $\hat{\eta}$, the amount of risky debt issued by a bank in the first quintile is 86% of that of a bank in the fifth quintile. In other words, a bank with the original belief reduces both its risky loan investment and risky debt much more than a bank with 1% higher belief when they approach bankruptcy.

Panel C shows that such changes in behavior are also reflected in the interest rates on risky debt. A bank with higher belief is willing or required to pay an interest rate more than 6 basis points higher, on average, than that of a bank with the original belief, when very close to bankruptcy (first quintile). The first quintile may include two groups of banks. One group behaves very carefully so as to remain in business, while the other group takes many risks, hoping to escape the bad situation or be rescued after filing for bankruptcy. Due to the behavior of the latter group, the interest rate increases to almost four times (3.89% per annum) the risk-free rate of return on deposits (1%).

5.2 Reserve Requirements

Comparative statics using the reserve requirement ratio are useful to study effects of monetary policy. A small change in the reserve requirement ratio can have a huge impact on an economy. For instance, the higher the reserve requirement, the less money banks will have to lend.

Recall that, in the model, the reserve requirements are determined by insured deposits held at a bank and is set to 10%. I vary the reserve requirement rate from 0% to 20% and plot the reactions in Figure 5. The plots are smoothed by the spline method proposed by Cleveland and Devlin (1988). As the theory states, Panel A shows that the higher the reserve requirement, the less a bank lends, simply because it has less money available to lend out. Panel B shows that a bank issues the least amount of debt at a point slightly below the current reserve requirement ratio of 10%. While the reserve requirement is increasing up to the point of 8–9%, a bank decreases its risky borrowing. This risk-reducing behavior is because the cash reserves earn nothing in the model. If the bank has more money in cash reserves, it should borrow less in order to meet its debt obligations. However, as the reserve requirement rate increases beyond that 8–9%, the bank borrows more, since it does not have enough money to invest.

[Insert Figure 5]

In Panels C and E of Figure 5, the interest rate and bankruptcy frequency are minimized when the reserve requirement rate is around 8–9%. If the goal of regulators is to minimize bank risk-taking – measured by the number of banks that go bankrupt (as in Dam and Koetter (2012)) or by the interest rate on risky debt – they may want to maintain the current reserve requirement ratio of 10%, which is near the optimal level of 8–9%. However, if the goal is to maximize shareholder value, the regulators should not enforce any reserve requirement. Panel D shows that as the reserve requirement increases, shareholder value decreases monotonically. The higher the reserve requirement, the smaller margin the bank has for dividends to shareholders. Moreover, the bank has less income from investments but has to pay back more to its debt holders.

6 Out-of-Sample Test

This section tests whether the model can predict the amount of rescue funding provided by the U.S. government during the recent financial crisis. After the subprime mortgage crisis, the U.S. government announced its bailout plan of $700 billion, known as the Troubled Asset Relief Program (TARP). Under TARP, the Treasury provided capital to 736 financial institutions of all sizes throughout the nation, with a total outlay of about $200 billion.

I attempt to identify all banks, thrifts, or bank holding companies that received government assistance from TARP. I also identify their total assets in the quarter when they received the assistance, where the total assets are from the Bank Regulatory Database. If the institution is a bank holding company, the total assets of all related banks are summed. The final sample contains 585 financial institutions. Their average size is $10.9 billion, but the median is $309 million, suggesting a right-skewed distribution. In 2009, the average size and median size of U.S. commercial banks were about $2 billion and $146 million, respectively.

Figure 6 shows the ratio of the TARP capital injection to the total assets for each of the 585 financial institutions considered. The rescue funds amounted to, on average, 4.39% of the institution's total assets. Using the same criterion for size as in the model estimation, the amount of the capital injection is, on average, 6.75% of total assets for small institutions and 3.92% of total assets for large institutions. Although small institutions received a larger percentage of total assets, large institutions received much higher dollar amounts. On average, small institutions received $3.1 million and large institutions received $533.9 million.

[Insert Figure 6]

These actual numbers are comparable to the predictions made by the model. In the model, the amount of rescue funds, τ, is assumed to be equal to $|c|$ (see Section 2.5); the government provides funds sufficient for the distressed bank to meet its debt obligations. In the model estimation, the sample includes U.S. commercial banks *before* the recent crisis (the sample period is 1994–2007). The model simulation generates a hypothetical set of banks that represents the pre-crisis bank data. By simulating the model using the parameter estimates for the full sample (in Table III), the expected level of rescue funds is 4.21% of the bank's total assets. This percentage is surprisingly close to the actual average of 4.39% under TARP. This number is particularly notable because the amount of rescue funding is not included in the set of moments I try to match in the SMM procedure. For the subsamples of small and large banks using the parameter estimates in Tables IV and V, the percentages of rescue funds are 5.66% and 3.30%, respectively. These percentages are somewhat smaller than the actual rescue amounts under TARP (6.75% and 3.92%). Yet, in both the model predictions and actual data, the percentage is bigger for small banks than large banks.

The exercise in this section provides the model greater credibility. Given that the model assumes the government bailout in a very simple way and that the amount of actual rescue funding provided by TARP is not used in the estimation, the bailout prediction by the model is surprisingly close to the actual rescue funding provided in 2008–2009.

7 Ex Ante Bailout Beliefs

In the model, a bank believes that the government may intervene and rescue the bank with probability η in the event of bankruptcy. Here, I demonstrate the role of beliefs about bailout probabilities by blocking government intervention. This exercise helps us understand how the model fails to explain the real data if we incorrectly assume that banks do not believe in the government intervention.

First, I set η equal to 0 and simulate the model while keeping other five parameters fixed as in Table III. The moments of the simulated data are reported in Panel A of Table VI. Overall, the moments when $\eta = 0$ are different than the actual moments, as well as the simulated moments when $\eta = \hat{\eta}$. In particular, the most informative moments about this bailout belief parameter η – the ratio of deposits to total liabilities and the bankruptcy frequency – are very different from the actual moments. If a bank believes that the government would never intervene, the bank behaves more carefully. The bank in the model issues less risky debt, leading to a higher ratio of deposits to total liabilities than the actual ratio. In addition, the frequency of bankruptcy also decreases in light of this more conservative behavior. The autocorrelations of leverage and operating income are markedly low. Since a bank does not have any government backstop, bank behavior is more sensitive to shocks in each period.

[Insert Table VI]

Second, I constrain the expected bailout probability to be zero, and re-estimate the remaining five parameters of the model to match the nine moments, as in Section 3.2. Panel B of Table VI reports the parameter estimates. In order to match the data moments, the fire-sale price should be extremely high: 96%; that is, the model that does not include a government bailout can explain the bank data only if the banks can sell their existing loans almost at minimal discount. Since a bank's assets are illiquid and commonly sold at a substantial discount when the bank is in distress or when there are a limited number of buyers for the failed bank's assets (Shleifer and Vishny (1992) and Allen and Gale (1994)), the estimate of the fire-sale price is unrealistic.

The following excerpt, from the Merrill Lynch 10-Q filed on November 5, 2008, describes the sale price for assets of a failing financial institution.

> *On July 28, 2008, we (Merrill Lynch) agreed to sell $30.6 billion gross notional amount of U.S. super senior ABS CDOs to an affiliate of Lone Star Funds ("Lone Star") for a purchase price of $6.7 billion.*

The original value of the ABS CDOs was $30.6 billion, and was written down to $11.1 billion in the June 30, 2008 earnings report. The ABS CDOs were then sold for $6.7 billion, well below the listed book value. Hence, fire-sale prices are generally much lower than book value prices. Therefore, the government bailout plays a key role in the model. Without the possibility of government bailout, the model fails to match the data moments or requires unrealistic parameter values.

8 Conclusion

The government's bank rescue plans have been criticized for unintentionally creating incentives for banks to further engage in risk-taking behavior. This paper uses estimation of a dynamic model of a bank to investigate this possibility.

The estimation results show that banks anticipate a government bailout with a probability of 52.44%, conditional on bankruptcy. The findings also reveal that large banks believe more strongly that the government will intervene compared to small banks. When the model fails to account for bank faith in government assistance, the simulated results come far from matching data moments. Moreover, the model estimation results unrealistically propose that a distressed bank could sell assets in a fire sale at minimal discounts.

One of the counterfactual exercises shows that banks that anticipate government bailouts rely on risky debt and higher-risk investments more heavily, especially when closer to bankruptcy. In addition, banks with a higher bailout belief are willing to borrow at higher interest rates.

Further, comparative statics using reserve requirements find that the optimal reserve requirement ratio is near the current reserve requirement rate, which is useful if the goal of regulators is to minimize bank risk-taking. However, if regulators are more concerned about shareholder value in the banking sector, then they should not enforce any reserve requirements. The current model examines the case of bailouts of equity holders.

Appendix

A. Model Solution

The Appendix describes how to solve the model and the simulation procedure. First, to find a numerical solution, I discretize a finite state space for the four state variables, $\{q, l, d, z\}$. The loan amount l and the risky debt q lie between 0 and $A(\equiv 1)$. Both spaces are equally discretized. As for the deposit process, the AR(1) process is transformed into discrete state spaces using the quadrature method following Tauchen and Hussey (1991). The survival rate of the loan is truncated-normally distributed between 0 and 1, with mean μ_z and standard deviation σ_z.

The model is then solved via iterations of the Bellman equation. This yields the policy functions, $\{q', l'\} = h(q, l, d, z)$. To generate an artificial data set, I first take random draws of the survival rates of loans z and deposits d. Then, I simulate each bank to generate q and l using the policy functions while updating the shocks. I simulate each bank for 200 time periods and keep the last 100 time periods, corresponding to the sample period of the data, 1994–2007. The first 100 simulations are dropped in order to reach an optimal point.

B. Truncated-Normal Distribution

I adopt and modify the method proposed by Ada and Cooper (2003). Let n_z be the number of grids on z. First, $\{m_i\}_{i=1}^{n_z-1}$ is constructed such that:

$$\frac{\Phi\left(\frac{m_i-\mu_z}{\sigma_z}\right) - \Phi(\alpha)}{\Phi(\beta) - \Phi(\alpha)} = \frac{i}{n_z},$$

where $\Phi(\cdot)$ is the cumulative density function (CDF) of $N(0,1)$, $\alpha = \frac{0-\mu_z}{\sigma_z}$ and $\beta = \frac{1-\mu_z}{\sigma_z}$. Then, taking the inverse function of $\Phi(\cdot)$ yields:

$$m_i = \Phi^{-1}\left(\frac{i}{n_z}\big(\Phi(\beta) - \Phi(\alpha)\big) + \Phi(\alpha)\right)\sigma_z + \mu_z,$$

which are the points to discretize the space $[0,1]$. Next, define the abscissas $\{z_i\}_{i=1}^n$ such that z_i is the expected value of each interval between the m_is. That is,

$$\begin{aligned} z_i &= \mathbb{E}\big[z|z \in [m_{i-1}, m_i]\big] \\ &= \mu_z - \sigma_z \frac{\phi(\frac{m_i-\mu_z}{\sigma_z}) - \phi(\frac{m_{i-1}-\mu_z}{\sigma_z})}{\Phi(\frac{m_i-\mu_z}{\sigma_z}) - \Phi(\frac{m_{i-1}-\mu_z}{\sigma_z})} \quad i = 2, 3, \cdots, n-1, \end{aligned}$$

where $\phi(\cdot)$ is the probability density function (PDF) of $N(0,1)$. At the endpoints, $m_0 = 0$ and $m_n = 1$. By construction, the probability of each abscissa is $p_i = \frac{1}{n} \quad \forall i$.

C. SMM Estimation

Let x_{it} and $y_{its}(\beta)$ denote the data and the simulated data, respectively, $i = (1, \cdots, n)$, $t = (1, \cdots, T)$, and $s = (1, \cdots, S)$: T is the sample period and S is the number of simulated data sets. The artificial data sets are dependent on a set of parameters, β. The SMM is designed to find the optimal β to minimize the distance between a set of simulated moments, $m(y_{its}(\beta))$, and a set of actual moments from the data $m(x_{it})$. The moment vector can be written as:

$$g(x_{it}, \beta) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \Big[m(x_{it}) - \frac{1}{S} \sum_{s=1}^{S} m(y_{its}(\beta)) \Big].$$

The simulated moments estimator of β is the solution to:

$$\hat{\beta} = arg \min_{\beta} \; g(x_{it}, \beta)' \; \hat{W} \; g(x_{it}, \beta),$$

where $\hat{W}$ is a positive definite matrix that converges in probability to a deterministic positive definite matrix W.

Construction of the weight matrix, $\hat{W}$, uses the influence function method from Erickson and Whited (2002). When the influence functions are calculated, each of the variables is demeaned at the bank level to remove the heterogeneity in the data. The data are very heterogeneous, whereas the simulated data are heterogeneous only in terms of the shocks, and I am estimating the parameters of an average bank. The inverse of the covariance matrix of the moments is $\hat{W}$.

For the standard errors, I use a clustered weight matrix within time and bank, denoted Ω. The asymptotic distribution of β is given by:

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{d} N\big(0, \text{avar}(\hat{\beta})\big),$$

in which:

$$\text{avar}(\hat{\beta}) \equiv \Big(1 + \frac{1}{S}\Big)\Big[\frac{\partial g_n(\beta)}{\partial \beta} W \frac{\partial g_n(\beta)}{\partial \beta'}\Big]^{-1}\Big[\frac{\partial g_n(\beta)}{\partial \beta} W \Omega W \frac{\partial g_n(\beta)}{\partial \beta'}\Big]\Big[\frac{\partial g_n(\beta)}{\partial \beta} W \frac{\partial g_n(\beta)}{\partial \beta'}\Big]^{-1}.$$

References

Ada, Jerome and Russell W. Cooper (2003), *Dynamic Economics*. Cambridge, MA: MIT Press.

Aharony, Joseph and Itzhak Swary (1983), "Contagion effects of bank failures: Evidence from capital markets." *Journal of Business*, 305–322.

Allen, Franklin and Douglas Gale (1994), "Limited market participation and volatility of asset prices." *American Economic Review*, 933–955.

Ayotte, Kenneth and David A. Skeel Jr. (2010), "Bankruptcy or bailouts?" *Iowa J. Corp. L.*, 35, 469–849.

Basu, Kaushik (2011), "A simple model of the financial crisis of 2007-2009, with implications for the design of a stimulus package." *Indian Growth and Development Review*, 4, 5–21.

Bernardo, Antonio, Eric Talley, and Ivo Welch (2011), "A model of optimal government bailouts." *Working Paper*.

Boyd, John H and Gianni De Nicolo (2005), "The theory of bank risk taking and competition revisited." *The Journal of finance*, 60, 1329–1343.

Caballero, Ricardo J and Alp Simsek (2009), "Complexity and financial panics." Technical report, National Bureau of Economic Research.

Calvo, Guillermo (2012), "Financial crises and liquidity shocks a bank-run perspective." *European Economic Review*, 56, 317–326.

Chan-Lau, Jorge A. and Zhaohui Chen (2002), "A theoretical model of financial crisis." *Review of International Economics*, 10, 53–63.

Cheng, Haw and Konstantin Milbradt (2012), "The hazards of debt: Rollover freezes, incentives, and bailouts." *Review of Financial Studies*, 25, 1070–1110.

Cleveland, William S. and Susan J. Devlin (1988), "Locally weighted regression: an approach to regression analysis by local fitting." *Journal of the American Statistical Association*, 83, 596–610.

Congleton, Roger D (2009), "On the political economy of the financial crisis and bailout of 2008–2009." *Public Choice*, 140, 287–317.

Cooper, Russell W. and John C. Haltiwanger (2006), "On the nature of capital adjustment costs." *Review of Economic Studies*, 73, 611–633.

Cordella, Tito and Eduardo Levy Yeyati (2003), "Bank bailouts: Moral hazard vs. value effect." *Journal of Financial Intermediation*, 12, 300–330.

Dam, Lammertjan and Michael Koetter (2012), "Bank bailouts and moral hazard: Evidence from Germany." *Review of Financial Studies*, 25, 2343–2380.

De Nicolò, Gianni, Andrea Gamba, and Marcella Lucchetta (2011), "Capital regulation, liquidity requirements and taxation in a dynamic model of banking." *Liquidity Requirements and Taxation in a Dynamic Model of Banking*.

Diamond, Douglas W and Philip H Dybvig (1983), "Bank runs, deposit insurance, and liquidity." *Journal of political economy*, 401–419.

Erickson, Timothy and Toni M. Whited (2000), "Measurement error and the relationship between investment and q." *Journal of Political Economy*, 108, 1027–1057.

Erickson, Timothy and Toni M. Whited (2002), "Two-step GMM estimation of the errors-in-variables model using high-order moments." *Econometric Theory*, 18, 776–799.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajsek (2010), "Uncertainty, financial frictions, and investment dynamics." In *2010 Meeting Papers*, volume 1285.

Han, Chirok and Peter CB Phillips (2010), "GMM estimation for dynamic panels with fixed effects and strong instruments at unity." *Econometric Theory*, 12, 119.

He, Zhiguo and Wei Xiong (2009), "Dynamic bank runs." *Work. Pap., Univ. Chicago.*

Hennessy, Christopher A. and Toni M. Whited (2005), "Debt dynamics." *Journal of Finance*, 60, 1129–1165.

Hennessy, Christopher A. and Toni M. Whited (2007), "How costly is external financing? Evidence from a structural estimation." *Journal of Finance*, 62, 1705–1745.

Laeven, Luc and Ross Levine (2009), "Bank governance, regulation and risk taking." *Journal of Financial Economics*, 93, 259–275.

Lepetit, Laetitia, Emmanuelle Nys, Philippe Rous, and Amine Tarazi (2008), "Bank income structure and risk: An empirical analysis of European banks." *Journal of Banking & Finance*, 32, 1452–1467.

Mailath, George J and Loretta J Mester (1994), "A positive analysis of bank closure." *Journal of Financial Intermediation*, 3, 272–299.

Saunders, Anthony, Elizabeth Strock, and Nickolaos G Travlos (1990), "Ownership structure, deregulation, and bank risk taking." *Journal of Finance*, 45, 643–654.

Schneider, Martin and Aaron Tornell (2004), "Balance sheet effects, bailout guarantees and financial crises." *The Review of Economic Studies*, 71, 883–913.

Shleifer, Andrei and Robert W Vishny (1992), "Liquidation values and debt capacity: A market equilibrium approach." *Journal of Finance*, 47, 1343–1366.

Shrieves, Ronald E. and Drew Dahl (1992), "The relationship between risk and capital in commercial banks." *Journal of Banking & Finance*, 16, 439–457.

Stern, Gary H. and Ron J Feldman (2004), *Too Big to Fail: The Hazards of Bank Bailouts.* Brookings Inst Press.

Strebulaev, Ilya and Toni M. Whited (2012), "Dynamic models and structural estimation in corporate finance." *Foundations and Trends in Finance*.

Tauchen, George and Robert Hussey (1991), "Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models." *Econometrica: Journal of the Econometric Society*, 371–396.

Wilson, Linus and Yan Wendy Wu (2010), "Common (stock) sense about risk-shifting and bank bailouts." *Financial Markets and Portfolio Management*, 24, 3–29.

Table I: Bank Mergers

The FDIC reports all mergers that have been approved by the FDIC in a calendar year (Bank Merger Act Reporting Requirements). There are four categories: regular merger, corporate reorganization merger, interim merger, and probable failure or emergency merger. The FDIC also provides information about failed banks. The total number of banks is the number of banks in the Bank Regulatory Database in a given year.

Year	Mergers					Failed	Total #
	Regular	Reorg.	Interim	Emergency	All	Banks	of Banks
2000	157	198	63	6	424	7	9,209
2001	204	160	45	1	410	4	8,872
2002	145	116	60	6	327	11	8,594
2003	153	107	54	3	317	3	8,451
2004	153	130	43	3	329	4	8,305
2005	115	156	42	0	313	0	8,198
2006	169	158	38	0	365	0	8,169
2007	147	132	42	3	324	3	8,031
2008	104	136	35	27	302	30	7,788
2009	69	129	13	71	282	148	7,528
2010	90	122	12	71	295	154	7,259

Table II: Model Parameters

Panel A: Estimated Outside of the Model		
Description	Notation	Value
Risk-Free Rate	r_f	3%
Deposit Interest Rate	r_d	1%
Mean of Survived Loans	μ_z	96%
Reserve Requirement	α	10%
Panel B: Automatically Determined		
Discount Rate	β	$1/(1+r_f)$
Panel C: Estimated by SMM		
Description	Notation	Most Informative Moment
Drift of Deposits	μ_d	Mean of Deposits
Serial Correlation of Deposits	ρ_d	Serial Correlation of Deposits
Residual Std. Dev. of Deposits	σ_d	Variance of Deposits
Std. Dev. of Surviving Loans	σ_z	Variance of Charge-off Rtae
Bailout Probability	η	Deposits/Total Liabilities
Fire-sale Price	ξ	Bankruptcy Frequency
Percentage of Maturing Loans	δ	Leverage Process
Loan Interest Rate	r_l	Mean Income & Dividends
Loan Adjustment Cost	λ	Mean Charge-off Rate

Table III: Simulated Moments Estimation for Full Sample

Actual moments are calculated using a sample of commercial banks from the Bank Regulatory Database. The sample period is 1994 to 2007. Estimation is by simulated method of moments (SMM), which is designed to minimize the distance between the actual moments from the data and the simulated moments from the model. The moments for the actual data and the simulated data are constructed identically. Panel A reports the actual moments, as well as the simulated moments with t-statistics. Panel B reports the estimated structural parameters and the clustered standard errors in parentheses. μ_d is the drift of deposits; ρ_d is the serial correlation of deposits; σ_d is the standard deviation of the shock to deposits; η is the expectation of conditional probability of government bailout; σ_z is the standard deviation of the loan survival rate; ξ is the fire-sale price of loans; δ is the average portion of loans that mature in each period; r_l is the rate of return of loans; and λ is the loan adjustment cost coefficient.

Panel A: Moments

Descriptions	Actual	Simulated	t-stat.
Mean Debt/Assets	0.8962	0.9020	-1.9382
Autocorrelation Debt/Assets	0.8565	0.5270	0.1439
Std. Dev. Shock to Debt/Assets	0.0056	0.0022	0.0611
Mean Operating Income/Assets	0.2015	0.1888	2.1501
Mean Dividends/Assets	0.0108	0.0287	-9.0441
Mean Charge-offs/Assets	0.0060	0.0100	-1.1640
Std. Dev. Charge-offs/Assets	0.0075	0.0056	21.0600
Deposits/Total Liabilities	0.6650	0.6586	0.1051
Bankruptcy Frequency	0.0487	0.0450	1.5235
Mean Deposits/Assets	0.5960	0.5959	<0.0001
Variance Deposits/Assets	0.0074	0.0074	<0.0001
Autocorrelation Deposits/Assets	0.8930	0.8869	<0.0001

Panel B: Parameter Estimates

μ_d	ρ_d	σ_d	η	σ_z	ξ	δ	r_l	λ
0.0669	0.8878	0.0399	0.5244	0.0278	0.4642	0.6942	0.1061	0.0616
(0.0042)	(0.0071)	(0.0014)	(0.1940)	(0.0021)	(0.2261)	(0.0765)	(0.0272)	(0.0440)

Table IV: Simulated Moments Estimation for Small Banks

Actual moments are calculated using a sample of commercial banks from the Bank Regulatory Database. The sample period is 1994 to 2007. The size is defined by total assets. Small (large) banks are defined as those that are in the lower (higher) third of the distribution of total assets for each year. Estimation is by simulated method of moments (SMM), which is designed to minimize the distance between the actual moments from the data and the simulated moments from the model. The moments for the actual data and the simulated data are constructed identically. Panel A reports the actual moments, as well as the simulated moments with t-statistics. Panel B reports the estimated structural parameters and the clustered standard errors in parentheses. μ_d is the drift of deposits; ρ_d is the serial correlation of deposits; σ_d is the standard deviation of the shock to deposits; η is the expectation of conditional probability of government bailout; σ_z is the standard deviation of the loan survival rate; ξ is the fire-sale price of loans; δ is the average portion of loans that mature in each period; r_l is the rate of return of loans; and λ is the loan adjustment cost coefficient.

Panel A: Moments

Descriptions	Actual	Simulated	t-stat.
Mean Debt/Assets	0.8870	0.9122	-9.1987
Autocorrelation Debt/Assets	0.9061	0.7270	0.2952
Std. Dev. Shock to Debt/Assets	0.0023	0.0017	0.0662
Mean Operating Income/Assets	0.1919	0.1860	0.8142
Mean Dividends/Assets	0.0098	0.0283	-15.3295
Mean Charge-offs/Assets	0.0053	0.0094	-3.1898
Std. Dev. Charge-offs/Assets	0.0069	0.0040	68.5929
Deposits/Total Liabilities	0.7319	0.7118	0.3453
Bankruptcy Frequency	0.0970	0.0934	18.2714
Mean Deposits/Assets	0.5310	0.5306	$<$0.0001
Variance Deposits/Assets	0.0070	0.0070	$<$0.0001
Autocorrelation Deposits/Assets	0.8847	0.8738	$<$0.0001

Panel B: Parameter Estimates

μ_d	ρ_d	σ_d	η	σ_z	ξ	δ	r_l	λ
0.0673	0.8964	0.0321	0.3569	0.0151	0.6946	0.6423	0.1290	0.1873
(0.0031)	(0.0047)	(0.0010)	(0.0721)	(0.0031)	(0.1341)	(0.2682)	(0.0116)	(0.0112)

Table V: Simulated Moments Estimation for Large Banks

Actual moments are calculated using a sample of commercial banks from the Bank Regulatory Database. The sample period is 1994 to 2007. The size is defined by total assets. Small (large) banks are defined as those that are in the lower (higher) third of the distribution of total assets for each year. Estimation is by simulated method of moments (SMM), which is designed to minimize the distance between the actual moments from the data and the simulated moments from the model. The moments for the actual data and the simulated data are constructed identically. Panel A reports the actual moments, as well as the simulated moments with t-statistics. Panel B reports the estimated structural parameters and the clustered standard errors in parentheses. μ_d is the drift of deposits; ρ_d is the serial correlation of deposits; σ_d is the standard deviation of the shock to deposits; η is the expectation of conditional probability of government bailout; σ_z is the standard deviation of the loan survival rate; ξ is the fire-sale price of loans; δ is the average portion of loans that mature in each period; r_l is the rate of return of loans; and λ is the loan adjustment cost coefficient.

Panel A: Moments

Descriptions	Actual	Simulated	t-stat.
Mean Debt/Assets	0.9035	0.9066	-1.1161
Autocorrelation Debt/Assets	0.8309	0.2928	0.4834
Std. Dev. Shock to Debt/Assets	0.0015	0.0023	-0.1758
Mean Operating Income/Assets	0.2097	0.2044	0.5513
Mean Dividends/Assets	0.0147	0.0301	-9.1061
Mean Charge-offs/Assets	0.0068	0.0106	-5.8384
Std. Dev. Charge-offs/Assets	0.0076	0.0054	25.0367
Deposits/Total Liabilities	0.5876	0.5856	0.0254
Bankruptcy Frequency	0.0868	0.0841	0.4515
Mean Deposits/Assets	0.6497	0.6499	<0.0001
Variance Deposits/Assets	0.0053	0.0052	<0.0001
Autocorrelation Deposits/Assets	0.8990	0.8956	<0.0001

Panel B: Parameter Estimates

μ_d	ρ_d	σ_d	η	σ_z	ξ	δ	r_l	λ
0.0665	0.8747	0.0406	0.7620	0.0253	0.2232	0.7078	0.0995	0.0393
(0.0031)	(0.0059)	(0.0013)	(0.1113)	(0.0504)	(0.0781)	(0.0356)	(0.0189)	(0.0933)

Table VI: Effects of Bailout Belief η

I simulate the model while fixing $\eta = 0$ and generate a hypothetical set of banks. Panel A reports the simulated moments of the banks, the actual moments, as well as the simulated moments when $\eta = \hat{\eta}$, where $\hat{\eta}$ is the estimated value in Table III. Panel B presents the parameter values from the SMM estimation constraining the bailout belief η to be 0. For comparison, I report the parameter estimates of the full sample as in Table III.

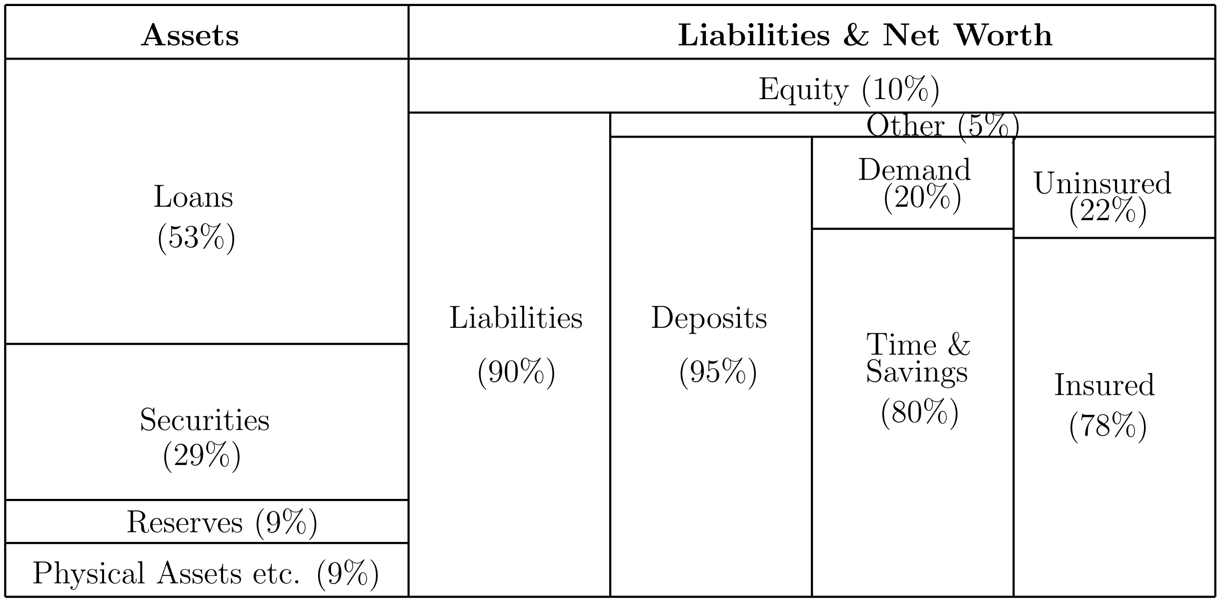
Panel A: Moments for Different η's

Description	Actual	$\eta = \hat{\eta}$	$\eta = 0$
Mean Debt/Assets	0.8962	0.9019	0.8452
Autocorrelation Debt/Assets	0.8565	0.5275	0.0803
Std. Dev. Shock to Debt/Assets	0.0056	0.0022	0.0017
Mean Operating Income/Assets	0.2015	0.1889	0.2596
Variance Operating Income/Assets	0.0018	0.0019	0.0003
Autocorrelation Operating Income/Assets	1.0006	0.8522	0.5818
Mean Dividends/Assets	0.0108	0.0287	0.0315
Mean Charge-offs/Assets	0.0060	0.0100	0.0144
Std. Dev. Charge-offs/Assets	0.0075	0.0056	0.0069
Deposits/Total Liabilities	0.6650	0.6584	0.7040
Bankruptcy Frequency	0.0487	0.0451	0.0009

Panel B: Parameter Estimates Constraining $\eta = 0$

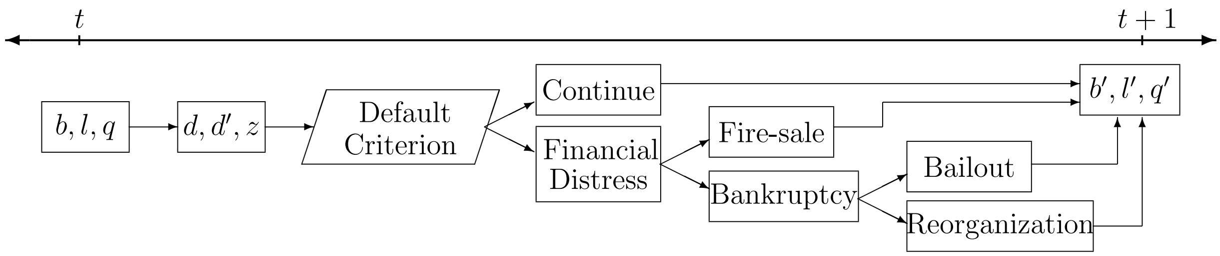
	η	σ_z	ξ	δ	r_l	λ
No restriction	0.5244	0.0278	0.4642	0.6942	0.1061	0.0616
$\eta = 0$	–	0.0174	0.9559	0.5415	0.0868	0.0223

Figure 1: Hypothetical Representative Balance Sheet



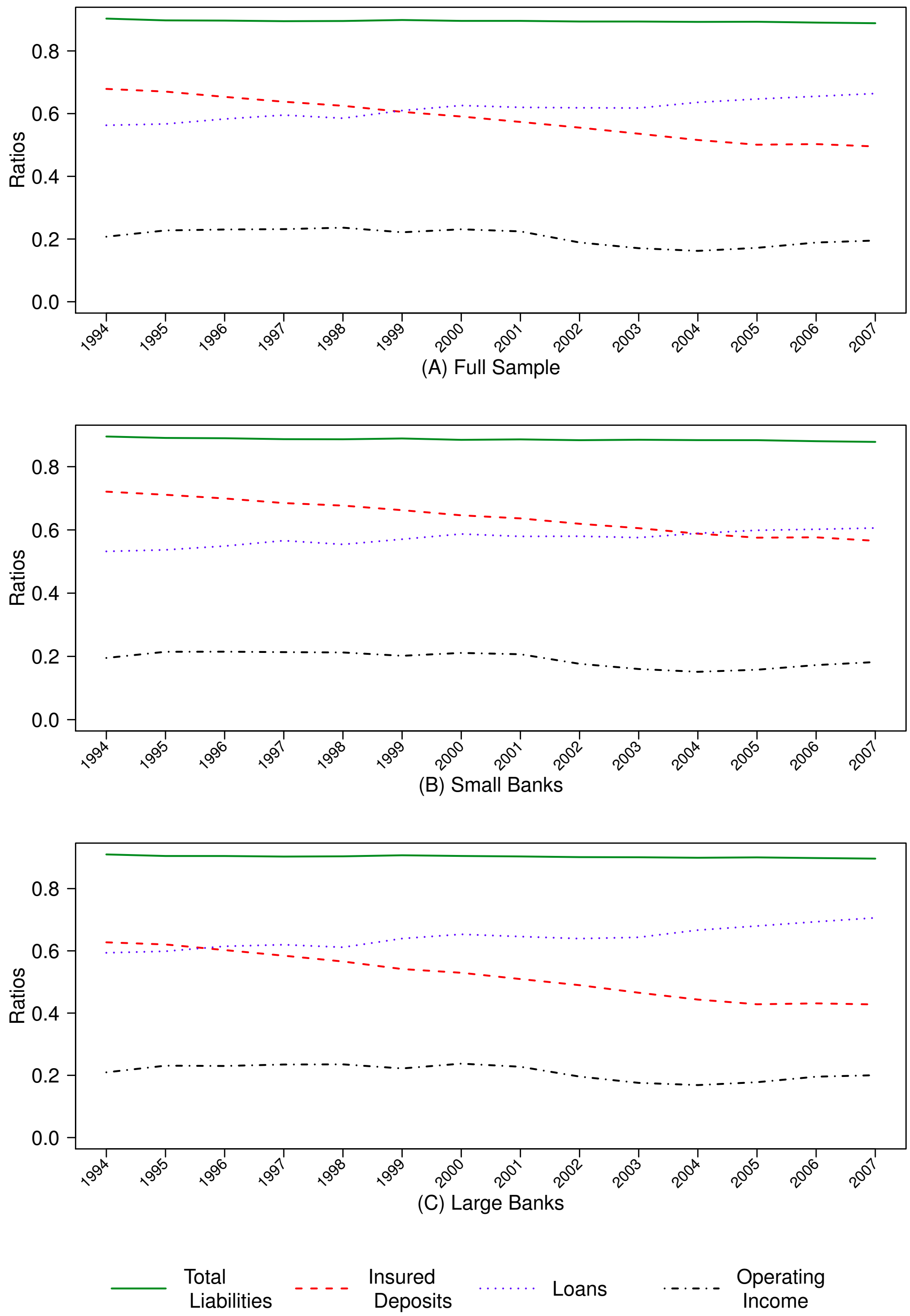
The percentages are category averages across U.S. commercial bank balance sheet. The data are from the Federal Reserve Bank of Chicago, the Bank Regulatory Database, which provides quarterly accounting data for commercial banks. The sample period is 1987 to 2008. The data variables are defined as follows: Total Assets (*RCFD2170*); Total Liabilities (*RCFD2950*); Total Deposits (*RCFD2200*); Demand Deposits (*RCON2210*); Time and Savings Deposits (*RCON2350*); Insured Deposits (*RCON2710* or *RCONF051*); Loans (*RCFD2170*); Securities (*RCFD0390*); Cash (*RCFD0010*); and Reserves (*RCFD3260*).

Figure 2: Timeline from Time t to $t + 1$



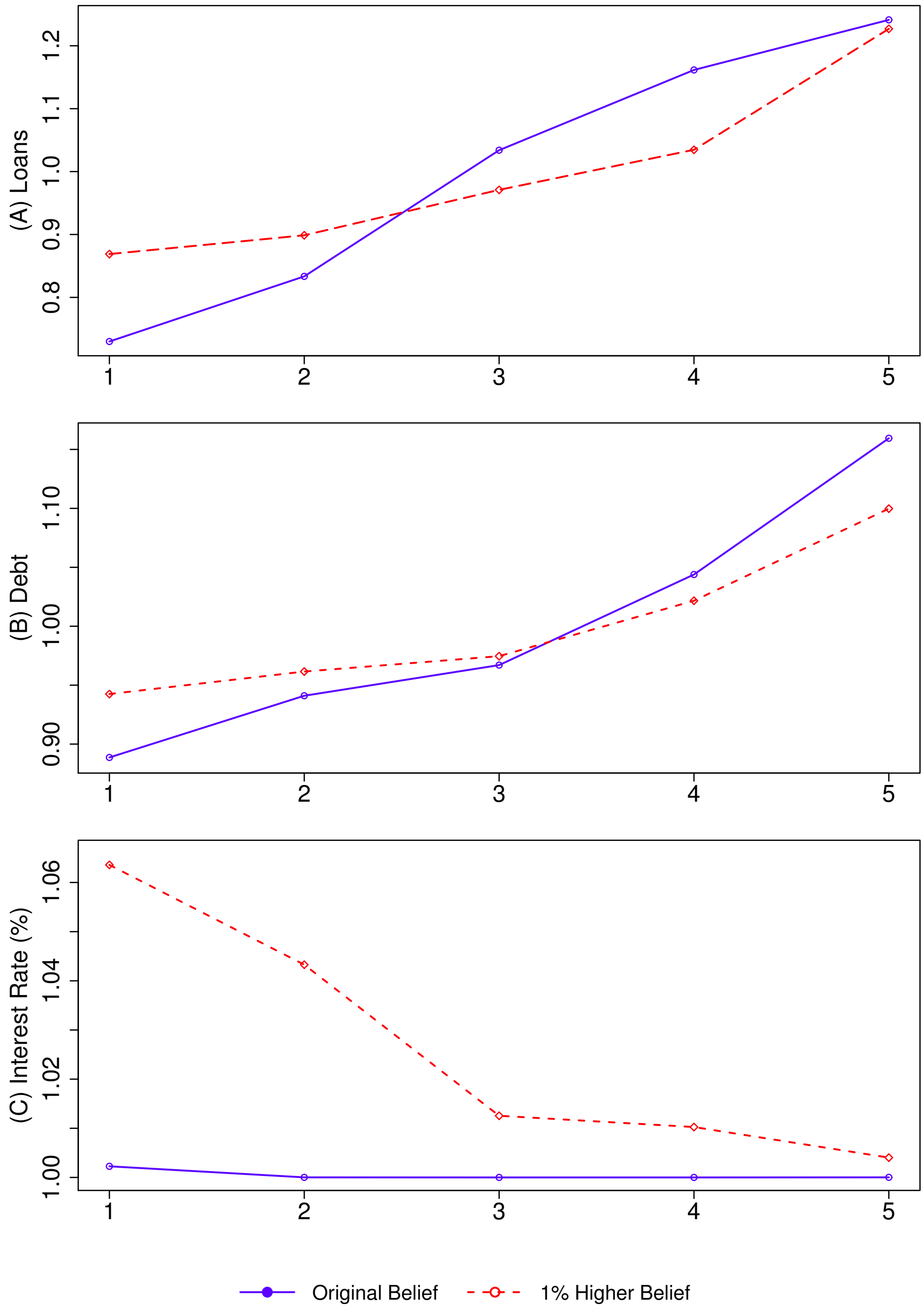
This figure summarizes a bank's problems between time t and time $t + 1$. Given the decision variables chosen in the previous period (b, l, q) as well as the observed shocks (d, d', z), a bank chooses its new investment and financing decisions (b', l', q') for the next period $t + 1$.

Figure 3: Time Series Patterns



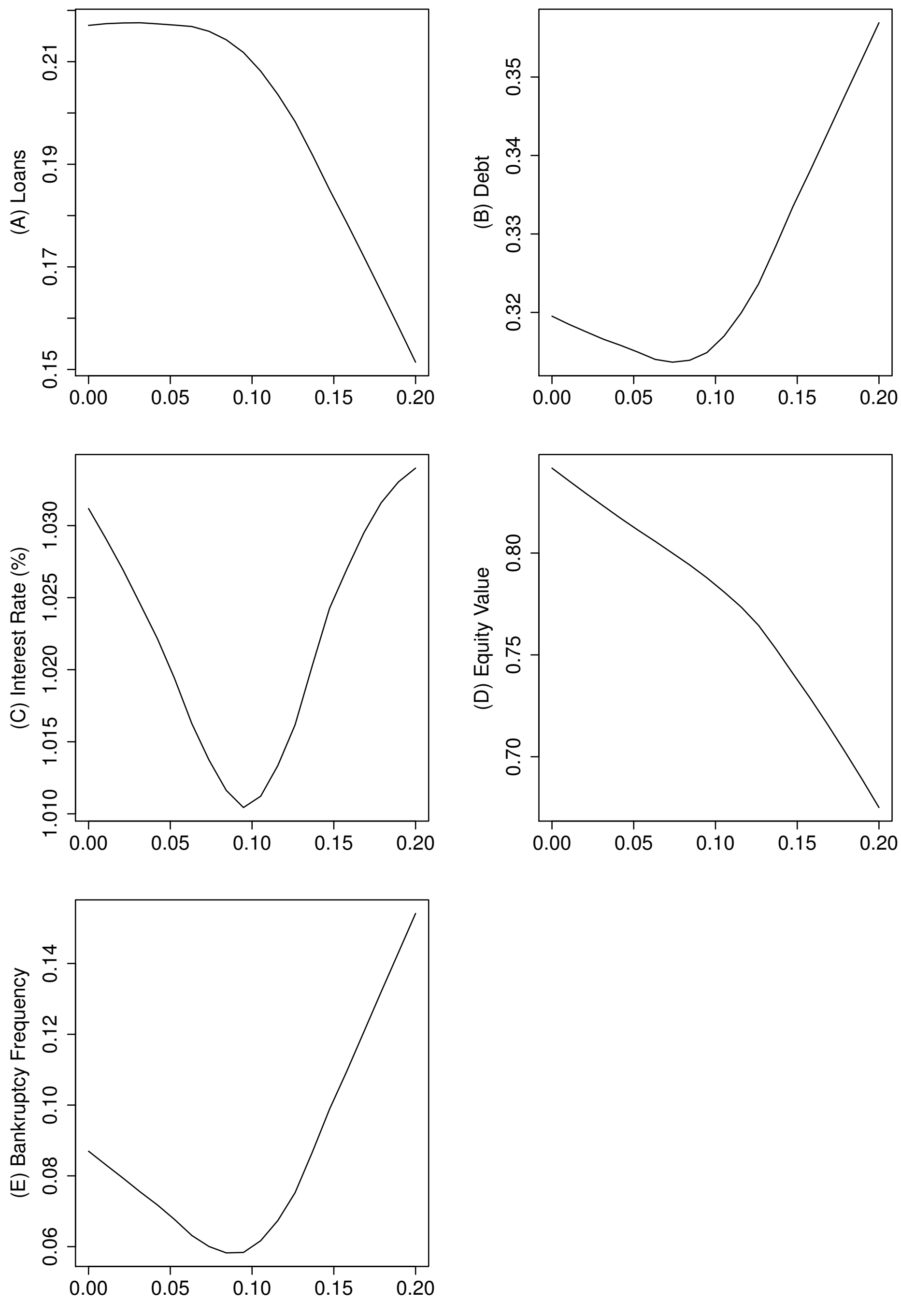
The sample includes U.S. commercial banks from the Bank Regulatory Database. The sample period is from 1994 to 2007. I report the yearly cross-sectional averages of some variables: total liabilities, insured deposits, loans, and operating income. Each variable is scaled by end-of-year total assets. The size is defined by total assets. Large (small) banks are defined as those whose total assets are in the lower (higher) third of the distribution of each year.

Figure 4: Dynamics of Banks nearing Bankruptcy



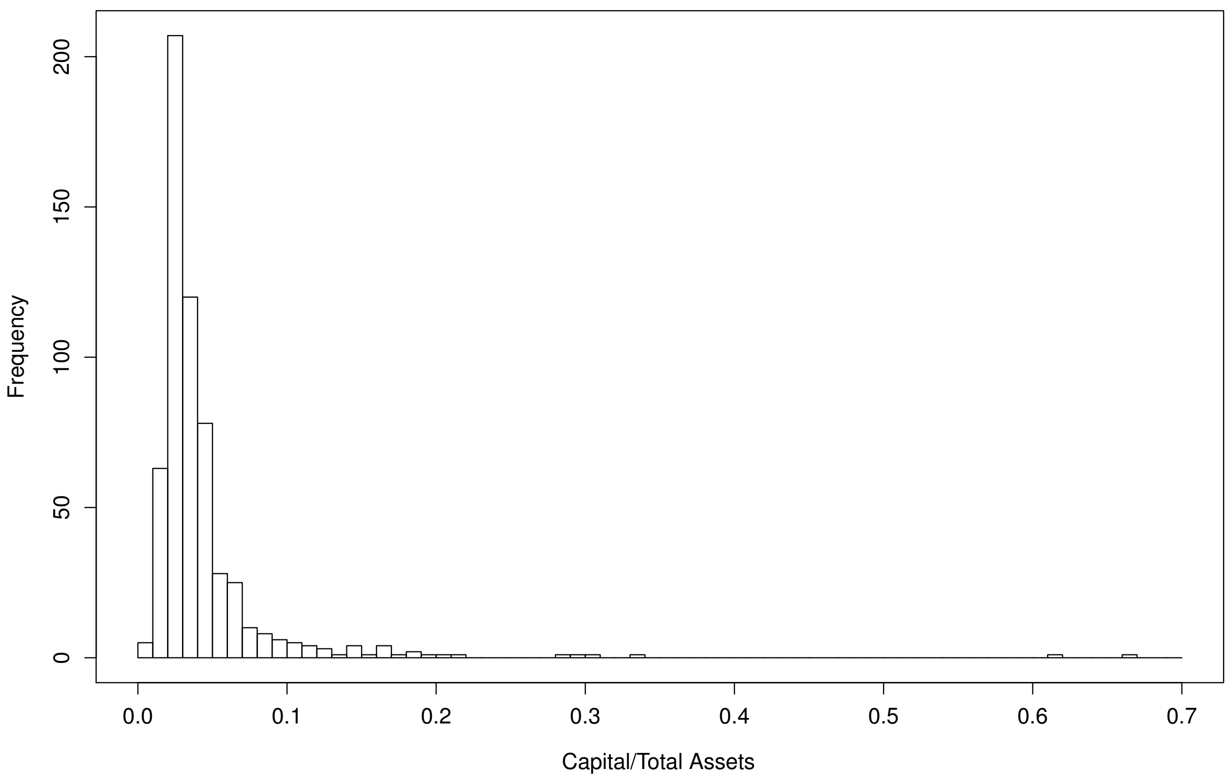
First, I simulate the model twice and generate 10,000 hypothetical banks in each iteration: one with the estimated value for the bailout belief $\hat{\eta}$ (blue solid line) as in Table III, and the other with 1% higher than $\hat{\eta}$ (red dotted line). Then, the simulated banks are ranked by their distance from bankruptcy, defined by cash balance plus remaining loans after fire-sales if necessary. Next, I split the simulated banks into five groups depending on distance from bankruptcy. Banks in the first (fifth) quintile are the closest to (farthest from) bankruptcy. Last, the averages of the variables are computed for each quintile.

Figure 5: Comparative Statics Using Reserve Requirements



I simulate the model 20 times while varying the reserve requirement ratio α from 0% to 20%, holding the rest of the parameters fixed at the levels in Table III. For each iteration, I generate 10,000 hypothetical banks and compute the averages of some variables. The plots are smoothed using the spline method.

Figure 6: Histogram of TARP



In 2008, the U.S government announced the Troubled Assets Relief Program (TARP) to purchase assets and equity from financial institutions to stabilize financial markets. Under TARP, 736 financial institutions received government assistance, although only 585 are identified for this analysis. The government rescue funds are scaled by the total assets of the financial institutions when they received assistance.