Deposit Competition and Financial Fragility: Evidence from the US Banking Sector

Mark Egan, Ali Hortaçsu, and Gregor Matvos

June 1, 2014

Abstract

PRELIMINARY AND INCOMPLETE, PLEASE DO NOT CITE WITHOUT PERMISSION. We develop and estimate an empirical model of the U.S. banking sector using a new data set covering the largest U.S. banks over the period 2002-2013. Our model incorporates rich consumer preferences on the deposit demand-side and endogenous bank bankruptcy decisions on the supply-side as well as competition between banks in the spirit of Matutes and Vives (1996). Our demand estimation results suggest that a bank's ability to attract uninsured rather than insured deposits depends critically on its financial solvency. We use estimated demand elasticities for interest rates, CDS spreads and bank balance sheet information to calibrate the model. At the estimated parameter values, our model suggests that banks were financially fragile at the height of the crisis in 2009. In addition to the realized equilibrium outcome, the same fundamentals supported additional equilibria, in which bankruptcy probabilities and interest rates in the banking sector were significantly higher. We use our model to assess recent and proposed bank regulatory changes. In particular, we find that increasing FDIC insurance could improve the equilibrium survival probabilities across the banking system, and could actually lower the cost of providing FDIC insurance. Conversely, we find that certain interventions to bank risk limits may actually lower banks' equilibrium survival probabilities.

1 Introduction

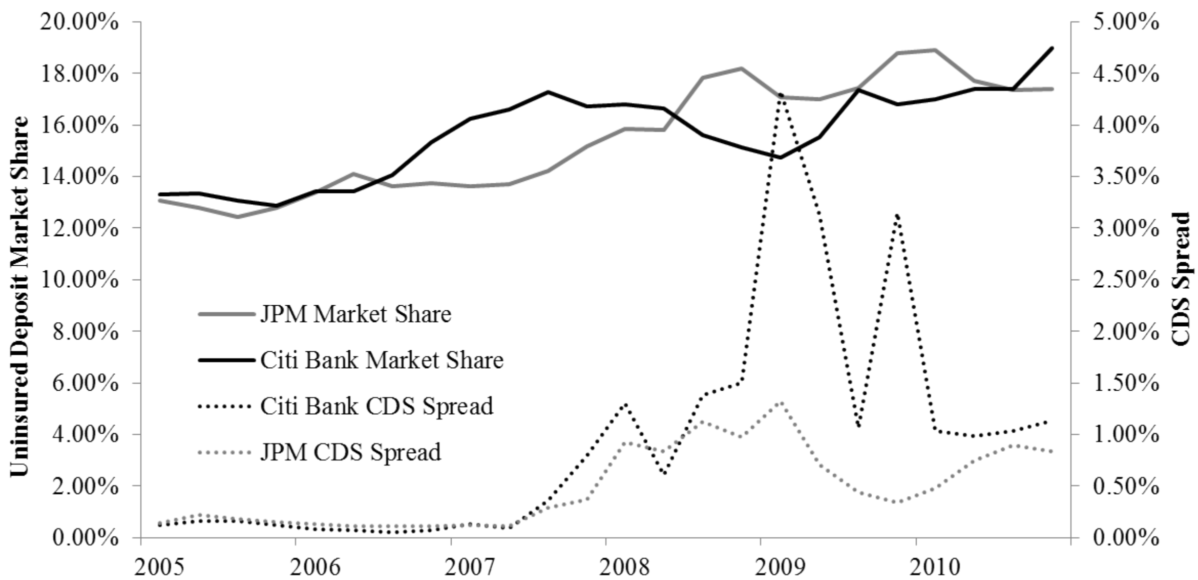
The recent financial crisis has brought renewed attention to the stability of the banking sector and optimal bank regulation. Although an extensive theoretical literature has studied banking stability (Diamond Dybvig 1983, Goldstein and Pauzner 2005) these models do not lend themselves to quantitative assessment. We develop and calibrate a quantitative model of the U.S. banking sector, which features run-prone depositors and endogenous bank default. We confront the model using a new data set covering the largest U.S. banks over the period 2002-2013. We find that uninsured deposits are responsive to bank distress, and that the elasticity is large enough to have introduced the possibility of multiple equilibria at the peak of the crisis in 2009, suggesting that the banking sector was very fragile. We study how competition for deposits among banks affects the feedback between bank distress and deposits, and transmits shocks from one bank to the system. Last, we use our model to analyze the proposed bank regulatory changes and find that the regulations could produce substantial unintended consequences.

The central force in our model builds on standard bank run models: demand from uninsured depositors depends on the financial health of the bank. We depart from current bank fragility models by adding realistic consumer preferences over different types of deposits and banks, but also feature depositors' concerns about financial distress of banks, since they may loose their uninsured deposits. Second, we take the demand model that results from such preferences to the data on deposit rates and bank market shares using a standard industrial organization model of demand (Berry Levinsohn Pakes, 1995). The estimates of the elasticity of deposit demand with respect to financial distress provide substantial discipline on the magnitude of self fulfilling runs that the model can generate. We can therefore study how realistic features of consumer demand interact with financial distress and give rise to feedback effects that drive bank fragility.

A simple cut of the data in Figure 1 suggests that financial distress of banks affects their ability to attract uninsured deposits. We plot the relationship between the uninsured deposit market shares and financial distress for Citi Bank and JPMorgan Chase over the period 2005 through 2010.[1] As distress of Citi Bank increases relative to JPMorgan, the market share of uninsured deposits of Citi decreases and the market share of JPMorgan increases. Using variation in the level of financial distress, we estimate depositors' preferences to financial distress. Our estimates suggest that uninsured depositors are relatively sensitive to bank financial distress, tending to withdraw deposits when their bank experiences financial distress: a 100bps increase in the risk neutral probability of bankruptcy results in a market share decline of 7%. On the other hand, we find little evidence suggesting that insured depositors respond to financial distress which suggests consumers treat FDIC insurance as credible and relatively frictionless.

[1] We measure distress using Credit Default Swap Spreads (CDS)

Figure 1: Deposit Rates vs Financial Distress - Citi Bank and JPMorgan Chase



Because consumers are sensitive to financial distress, a bank in financial distress has to offer higher interest rates on its deposits, which decreases its profitability. Because uninsured deposits represent half of the deposits held by the banks in our sample, this decline in profits can be substantial, driving the bank further in distress. To better understand and quantify this feedback effect, we formally model how a bank responds to demand for deposits through simultaneous financing and pricing decision. A bank earns profits by taking deposits, on which it pays an interest rate, and invests these in profitable projects. The bank has to choose what interest rate to set on its deposits, and its equity holders have to decide whether to continue to service the debt in spirit of Leland (1994) and Hortaçsu er al. (2011). We show that this model can feature multiple equilibria: good equilibria in which the bank is safe and consumers are willing to deposit savings at a low interest rate making the bank profitable, and bad equilibria, in which consumers do not trust the bank to survive, lowering its profitability and increasing its chances of default.

The last significant ingredient in our model is the competition between banks. Differentiated banks compete amongst each other by setting deposit rates to attract both insured and uninsured depositors. Bank competition affects the propagation of adverse shocks to banks in two dimensions. Fist, competition from other banks allows consumers to more easily switch to a non-distressed bank. Second, competition in the product market can transmit financial distress from one bank to others.

One of the primary advantages of our banking model is that it lends itself to empirical estimation/calibration. We observe banks' choices of interest rates on insured and uninsured deposits as well as the resulting market shares, its debt burden, and risk neutral probability of bankruptcy. With the addition of demand estimates, these allow us to calibrate the quantities we do not observe, the mean and variance of returns on deposits for each bank, that reconcile the behavior of banks with observed quantities.

At the estimated parameter values, our model has multiple equilibria across which equilibrium survival probabilities and interest rates differ significantly. Banks are at the "better equilibrium" in terms of a higher chance of survival. For example, Wells Fargo's market implied risk neutral probability of default as of March 2009 was 2.73%. Our model indicates an additional equilibrium exists in which Wells Fargo defaults with probability 52.20%. The multiple equilibria results can be interpreted as follows. Consumers rationally believed that there was a 2.73% chance that Wells Fargo would default in March 2009. However, the same fundamentals support an equilibrium in which Wells Fargo would default with a risk neutral probability of 52.20% in March 2009. In this equilibrium consumers would correctly believe that Wells Fargo was more likely default and would withdraw their deposits which would in turn lower the profitability of Wells Fargo and increase its probability of default.

We also use our calibrated model to assess the recent and proposed bank regulatory changes. In particular we find that increasing FDIC insurance could improve banking stability and could actually lower the cost of providing FDIC insurance. Conversely, we find evidence suggesting that imposing bank risk limits may be counterproductive and could actually destabilize the banking sector.

Bank regulation has quickly evolved in the aftermath of the recent financial crisis. The Federal Deposit Insurance Corporation (FDIC) substantially increased deposit insurance coverage in an effort to increase stability and confidence in the banking sector. Starting in October 2008, the FDIC raised the threshold on deposit insurance from $100k to $250k. Then as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act, the FDIC offered unlimited insurance coverage on all non interest-bearing transaction accounts starting on December 31, 2010 through December 31, 2012 (FDIC 2014). The Dodd-Frank provision increased FDIC insurance coverage by an additional 13%.[2] More recently, federal regulators approved a new rule imposing more stringent risk limits on the largest US banks that are set to be enforced starting in 2018 (Eavis 2014).

Our empirical and theoretical analysis relates to several strands in the banking and industrial organization literature. Our banking model builds on the automaker model from Hortaçsu et al. (2011). Our model is also in the spirit of the existing literature on bank runs and financial stability including the seminal work of Diamond Dybvig (1983) and more recently Kashyap et al. (2014) analysis of the banking sector and financial regulations. Our model also ties into the existing global games literature (Goldstein and Pauzner

[2] We approximate the shift in uninsured deposits to insured deposits using the change in total uninsured deposit levels as of December 31, 2010 relative to September 30, 2010.

2005, Angeletos and Werning 2006). The role of consumer expectations and the public market CDS signal determine the market equilibrium. Similar to Matutes and Vives (1996), our model emphasizes the strategic interaction among banks.

The empirical results of our paper correspond to the existing literature on empirical bank runs and deposit insurance. Iyer and Puri (2012) use an unique event study data, to examine how depositors responded to financial distress and a subsequent bank run for a large Indian bank. Our paper also relates to Calomiris and Mason (2003) which examines the role bank fundamentals played in bank runs occurring during the Great Depression. The empirical findings from our demand estimates closely relate to the findings from Soledad et al. (2001). Soledad et al. examines how depositors respond to bank financial distress during the banking crises that occurred in Argentina, Chile and Mexico during the 1980s and 1990s. Lastly, our empirical results relate to Hortaçsu et. al (2013) which measures the cost of financial distress in the automaker industry.

The remainder of the paper is laid out as follows. Section 2 describes the data used to estimate the deposit demand system and calibrate our theoretical model. In Section 3, we develop and estimate demand system for both insured and uninsured deposits. Section 4 develops our theoretical and empirical model of the banking sector. In Section 5 use our calibrated banking model to assess the stability of the banking sector and evaluate several proposed bank regulations. Lastly, Section 6 concludes the paper.

2 Data

Our data set covers sixteen of the largest US retail banks over the period 2002-2013. A primary objective of our study is to empirically measure how both uninsured and insured depositors respond to financial distress in the retail banking sector. We measure a bank's level of financial distress using its credit default swap (CDS) spread and measure the response of depositors using insured and uninsured deposit levels while conditioning on deposit rates and other bank characteristics. Table 1 summarizes our deposit and CDS data.

Table 1: Deposit Level, Interest rate and CDS Summary Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Ins. Deposits ($bn)	566	141.0	162.0	11.27	845.6
Unins. Deposits ($bn)	566	160.8	205.2	4.083	939.0
CDS Spread	566	0.829%	0.878%	0.0471%	5.47%
CD Spread (Min. Dep. = $10k, Mat= 1yr)	566	-0.313%	0.705%	-2.66%	2.03%
CD Spread (Min. Dep. = $100k, Mat= 1yr)	564	-0.217%	0.695%	-3.67%	2.03%

CDS gives us a direct and daily market measure of the financial solvency of each banking institution. CDS is a highly liquid financial derivatives contract in which the seller of the CDS contract agrees to compensate the buyer of the contract in the event a third party defaults. For example, the five year CDS spread for Bank of America in March 2009 was 3.19%. The CDS buyer agrees to pay 3.19% to the contract seller over a five year period or until Bank of America defaults. If Bank of America defaults, the CDS seller compensates the buyer of the CDS contract. Our CDS data comes from the Markit Database. We measure financial distress at the monthly level using the average daily CDS spread for the five year CDS contract. The average CDS spread in our data set is 0.87% which corresponds to a modest 1.43% annual probability of default.[3] The advantage measuring default risk using the CDS spread over other ad hoc balance sheet measures is that it is a public, tradeable, market rate that directly measures the default risk of a bank.

We examine the relationship between deposit levels and CDS to determine how depositors respond to financial distress. Our deposit level data comes from the FDIC's Statistics on Depository Institutions. The FDIC provides quarterly estimates of uninsured and insured deposit levels for all FDIC insured banks. The level of uninsured deposits ranges from $4.10 billion to $939.0 billion in our sample. On average, uninsured deposits account for just over half (53.36%) of total deposits for the banks in our sample.

We also examine how depositors respond to financial distress by looking at the relationship between deposit rates and financial distress. Theory suggests that uninsured depositors and potentially insured depositors will demand compensation, in the form of higher deposit rates, for taking additional default risk. In other words, banks under financial distress will offer higher deposit rates for uninsured and potentially insured deposits. Previous banking literature has been hampered by the lack of access to accurate and large scale deposit rate data. We use a new and novel deposit rate data set from RateWatch which includes daily branch level deposit rate data for several different types of accounts. Specifically, we measure deposit rates using certificate of deposit (CD) rates with maturities ranging from one month to five years. We do not separately observe deposit rates for insured and uninsured deposits. However, certificates of deposits have different minimum deposit requirements. We use heterogeneity in the minimum deposit levels to help pinpoint the effect of deposit insurance on deposit rates. Since deposits in excess of $100k ($250k after October 2008) are not covered by FDIC insurance, we interpret CDs with minimum deposits of $10k to be more likely to be fully insured than CDs with minimum deposits of $100k. We calculate deposit rates for each bank and account type (minimum deposit and maturity) using the median deposit rate offered at the monthly level.

To assess the effect of default risk on deposit rates we decompose deposit rates into two components, the

[3]We calculate the probability of default under a risk neutral model with a constant hazard rate under the assumption that LIBOR is 3% and the recovery rate is 40%. See Hull (2012) for further details.

prevailing risk free rate and the corresponding spread/premium. We define the $Deposit\_Rate\_Spread_{j,i,m,t}$ as the difference between the certificate of deposit rate offered by bank j with maturity m at time t minus the constant maturity treasury rate (CMT) with maturity m at time t. Here $i \in \{0, 1\}$ indicates the minimum deposit level with $i = 1$ if the certificate of deposit requires a minimum deposit level of \$100k and $i = 0$ if the minimum deposit level is \$10k.

$$Deposit\_Rate\_Spread_{j,i,m,t} = CD\_Rate_{j,i,m,t} - CMT\_Rate_{m,t}$$

Table 1 summarizes the deposit rate spread for one year CDs with minimum deposit levels of \$10k and \$100k. As expected, the average deposit rate is higher for the CDs with the \$100k minimum deposit threshold than for CDs with a \$10k minimum deposit threshold.

3 Demand for Bank Deposits

We develop and estimate a demand system for uninsured and insured bank deposits. The two parameters of interest are how deposit demand responds to changes in the deposit rate and changes in a bank's level of financial distress. Furthermore, we examine how the demand response of uninsured depositors to changes in deposit rates and financial distress differs from the demand response of insured depositors.

3.1 Demand Specification

We model demand for deposits in a discrete choice framework. Demand for insured deposits is a function of fixed bank characteristics δ_k and the offered deposit rate i^I_k. Consumer j derives indirect utility $u^I_{j,k}$ from holding insured deposits at bank k where

$$u^I_{j,k} = \delta_k + \alpha i_k + \xi^I_j + \varepsilon^I_{j,k} \tag{1}$$

The parameter $\alpha > 0$ measures the consumer's interest rate sensitivity while ξ_j and $\varepsilon_{j,k}$ are unobserved (by the econometrician) utility shocks.

Demand for uninsured deposits closely mirrors that of insured deposits except that it incorporates the expected cost of bankruptcy. In the event of a bankruptcy, uninsured depositors lose utility flow $\gamma > 0$. Letting ρ_k denote the probability a bank defaults in a given period, the indirect utility derived by consumer j at bank k is given by

$$u^N_{j,k} = \delta_k - \rho_k\gamma + \alpha i^N_k + \xi^N_J + \varepsilon^N_{j,k} \tag{2}$$

Although not explicit in the indirect utility formulations, we allow the bank fixed effects and interest rate sensitivity parameters to vary across insured/uninsured deposits as denoted by the superscripts I and N. We assume that the consumer specific utility shocks $\varepsilon^I_{j,k}$ and $\varepsilon^N_{j,k}$ are distributed iid Type 1 Extreme Value. Consequently the deposit demand system follows the conventional logit form.

3.2 Demand Estimation

Using bank characteristics and market share data described in Section 2, we estimate the utility parameters from equations (2) and (1). The logit demand system lends itself to the following linear regression specification. We regress the logged market share on the risk neutral probability of default and deposit rate spread (as measured using the one year CD rate) relative to the outside option.

$$\begin{aligned} \ln s_{k,t} - \ln s_{0,t} &= \delta_k - \gamma(\rho_{k,t} - \rho_{0,t}) + \alpha(CD\_Spread_{k,t} - CD\_Spread_{0,t}) + \epsilon_{k,t} \\ \widetilde{\ln s_{k,t}} &= \delta_k - \gamma\widetilde{\rho}_k + \alpha \widetilde{CD\_Spread}_{k,t} + \epsilon_{k,t} \end{aligned} \tag{3}$$

For each bank k, we normalize the bank market share and characteristic variables relative to the outside option (i.e. $\widetilde{\ln s_{k,t}} = \ln s_{k,t} - \ln s_{0,t}$). We define the outside option for both uninsured and insured deposits as all other banks outside of the sixteen in our data set and normalize$\delta_0 = 0$. We include quarter fixed effects when estimating specification (3) to capture the unobserved characteristics of the outside good, $\rho_{0,t}$ and $CD\_Spread_{0,t}$. To allow for parameter heterogeneity across deposit types, we estimate the demand system separately for insured and uninsured deposits.

Two empirical issues arise when estimating specification (3): the simultaneity/endogeneity of deposit rates and the probability of default. Just as the CDS spread impacts the level of deposits, the level of deposits may impact the CDS spread. To circumvent the simultaneity problem we use an instrumental variables strategy. We instrument for CDS using net loan charge-offs relative to assets. Loan charge-offs represents the net value of loans and leases that were removed from the bank's balance sheet because of uncollectability.

The validity of our instrumental variables strategy requires that our instruments satisfy the instrument relevancy and exogeneity conditions. The instrument relevancy condition requires that net loan charge-offs is correlated with the CDS spread conditional on the other covariates. We argue and find empirically that loan charge-offs impact the profitability of a bank which in turn impacts its probability of default. The instrument exogeneity condition requires that conditional on the CDS level, bank deposits are uncorrelated with net loan charge-offs. Bank depositors are analogous to bank debt holders in that they are not residual claimants. Depositors and bank debt holders only care about the profitability of a bank in that it impacts the probability that the bank defaults. For these reasons our instrument should only impact depositor behavior through their effect on the CDS rate rather than through other channels.

In the spirit of Hausman (1996), we instrument for uninsured (insured) deposit rates for each bank using the corresponding insured (uninsured) deposit rate lagged by one quarter. Conceptually, the relevancy condition of the instrument requires that a bank's cost of servicing/accepting deposits is similar for both types of deposits and correlated over time. The instrument exogeneity condition requires that unobserved component of demand for uninsured (insured) deposits is uncorrelated with the unobserved component for insured (uninsured) deposits from the previous quarter. As a robustness check, we also instrument for deposit rates using merger exposure and a set of Berry Levinsohn Pakes (BLP) (1995) type instruments. The merger exposure instrument measures the percentage of each bank's deposits that were exposed to a merger in the previous period. The BLP instruments are the average deposit characteristics of competing banks lagged by one period, including the CDS spread, deposit rate and non-interest expenditures (excluding salary and property/equipment expenditures). As shown in the appendix Table A-1 we find quantitatively similar results when estimating the demand system using the Hausman and alternative set of instruments.

Table 2: First Stage IV Results

Variables	CD Spread	Prob. of Def	CD Spread	Prob. of Def
CD Spread (Ins/Unins)	0.35***	0.16	0.25***	-0.11
	(0.05)	(0.11)	(0.04)	(0.10)
Loan Charge-Offs	-0.11	1.63***	-0.19**	1.49***
	(0.09)	(0.21)	(0.08)	(0.21)
Uninsured Deposits	X	X		
Insured Deposits			X	X
Observations	530	531	531	531
R-squared	0.804	0.861	0.846	0.868

*** p<0.01, ** p<0.05, * p<0.10

We estimate each specification using weighted least squares. Each observation is weighted by the square root of the market size.

All specifications include bank and quarter fixed effects and control for the number of bank branches.

Table 2 displays the first stage IV results. Columns (1) and (2) denote the results for uninsured deposits while columns (3) and (4) indicate the results for insured deposits. The Hausman instrument for the CD spread is positive and significant when we regress CD spread on our instruments and the the full set of regressors. Similarly, loan charge-offs is positive and significantly correlated with the risk neutral probability of default. Although these first stage results do not guarantee instrument relevancy, the set of instruments are individually significant and carry the expected signs. For both uninsured and insured deposits, the set of instruments yield Cragg-Donaldson Wald F statistics of over 20. In all IV specifications we reject (at the

5% level) the null hypothesis that relative asymptotic bias is greater than 5%. (Stock and Yogo 2005).

3.3 Estimation Results

We separately estimate the demand specification for insured and uninsured deposits using market share data from our unbalanced panel of sixteen banks over the period 2002-2013. Observations for each specification are at the quarterly level.

Tables 3 displays the demand estimates for uninsured deposits. Columns (1)-(3) are estimated using weighted least squares and differ in terms of the controls used. Column (4) displays the instrumental variables results. As expected, we estimate a positive and statistically significant relationship between the demand for deposits and the offered interest rate (CD spread) in each specification. The potential negative correlation between price and unobserved demand shocks would bias our simple OLS estimated interest rate sensitivity parameters downwards which indeed appears to be the case when comparing column (3) to column (4). We estimate $-\gamma$ to be negative in all four specifications and statistically significant in three out of the four specifications. The results from column (4) can be interpreted as a 100bps in the risk neutral probability of default is associated with a 7% percentage[4] decrease in market share.

TABLE 3: DEMAND FOR UNINSURED DEPOSITS

Variables	(1)	(2)	(3)	(4)
CD Spread (α)	27.53***	38.28***	7.21**	30.57***
	(6.87)	(11.20)	(2.85)	(9.15)
Default Prob. ($-\gamma$)	-7.30**	-7.73*	-1.26	-7.55*
	(3.37)	(4.59)	(1.25)	(3.90)
Quarter Fixed Effects		X	X	X
Bank Fixed Effects			X	X
IV				X
Observations	564	564	565	530
R-squared	0.390	0.398	0.970	0.965

*** p<0.01, ** p<0.05, * p<0.10

We estimate each specification using weighted least squares. Each observation is weighted by the square root of the market size.

All specifications control for the number of bank branches.

Tables 3 displays the results of our baseline demand specification for insured deposits. The specifications in columns (1)-(3) are estimated using weighted least squares while the specification displayed in column (4) is estimated using instrumental variables. Similar to our demand specification for uninsured deposits, we estimate a positive and significant relationship between CD spread and demand in all four specifications.

[4] We calculate the semi-elasticity under the assumption that the initial market share was 7% and $\gamma = 7.55$

The estimated interest rate sensitivity in the IV specification is larger than the corresponding estimate in column (3) which suggests that our least squares estimates of interest rate sensitivity are indeed biased downwards due to the aforementioned endogeneity concerns. The estimates from column (4) imply that the demand for deposits is price (deposit rate) inelastic with an elasticity of 0.17.[5].

Table 4: Demand for Insured Deposits

Variables	(1)	(2)	(3)	(4)
CD Spread (α)	15.80***	32.48***	7.15**	17.89*
	(2.63)	(5.17)	(2.97)	(9.76)
Quarter Fixed Effects		X	X	X
Bank Fixed Effects			X	X
IV				X
Observations	566	566	566	531
R-squared	0.787	0.804	0.949	0.946

*** p<0.01, ** p<0.05, * p<0.10

We estimate each specification using weighted least squares. Each observation is weighted by the square root of the market size.

All specifications control for the number of bank branches.

As a test of the potential effectiveness of deposit insurance, we include the risk neutral probability of default as an additional regressor when estimating demand for insured deposits. Table 4 displays the insured deposit specification results when we include risk neutral probability of default as an additional regressor. There are two main takeaways from Table 4. First, with the slight exception of the IV estimates, the estimated deposit rate sensitivities in Table 4 are nearly indistinguishable from the corresponding estimates in Table 3. Secondly, the estimated insured deposit demand sensitivity with respect to default risk, $-\gamma$, is negative in three out of the four specifications but not statistically significant from zero in any of the specifications. Contrasting these insured demand estimates with the uninsured demand estimates displayed in Table 3 suggests that uninsured depositors are more sensitive to the financial distress of a banking institution. Although we cannot definitively conclude that insured depositors do not respond to changes in bank financial distress, these results are consistent with the view that FDIC deposit insurance is credible and relatively frictionless. The results from the IV robustness check displayed in the appendix table A-1 are also consistent with the view that uninsured depositors respond to bank financial distress while insured depositors do not respond to bank financial distress.

[5] We calculate the demand elasticity using an initial share of 7.00% and $\alpha = 17.89$

Table 5: Demand for Insured Deposits

Variables	(1)	(2)	(3)	(4)
CD Spread (α)	15.91***	32.42***	7.15**	7.81
	(2.96)	(5.17)	(2.97)	(11.86)
Default Prob. ($-\gamma$)	-0.11	-0.83	0.08	-6.87
	(1.41)	(1.83)	(1.17)	(4.38)
Quarter Fixed Effects		X	X	X
Bank Fixed Effects			X	X
IV				X
Observations	566	566	566	531
R-squared	0.787	0.804	0.949	0.944

*** p<0.01, ** p<0.05, * p<0.10

We estimate each specification using weighted least squares. Each observation is weighted by the square root of the market size.

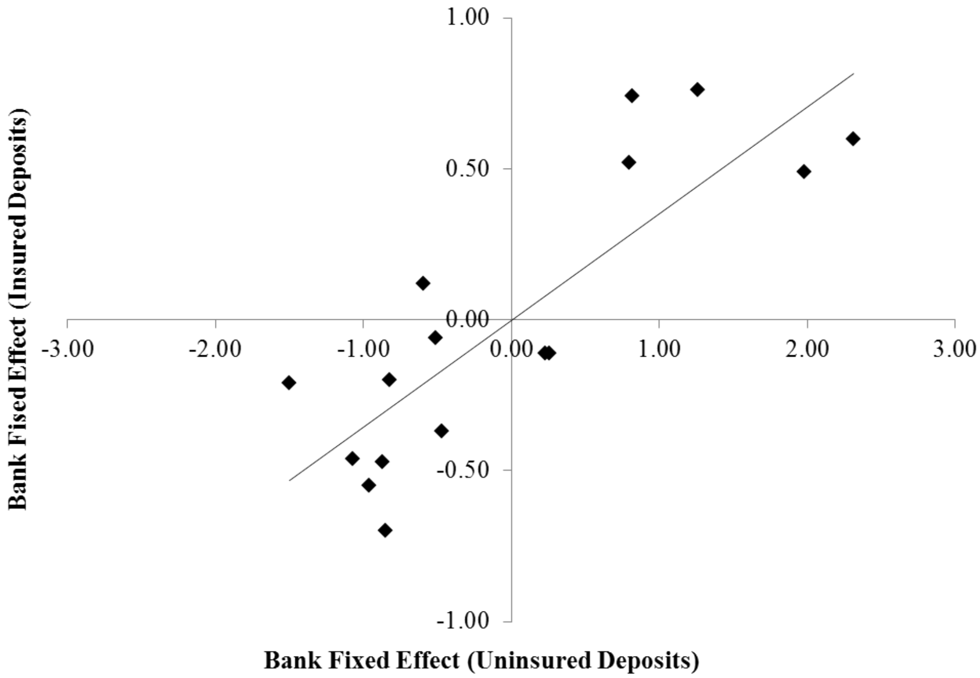
All specifications control for the number of bank branches.

We report the estimated bank brand fixed effects for the preferred specifications (Column 4 in Tables 3 and 4) for both uninsured and insured deposits in Table 6 and Figure 2. Figure 2 illustrates that bank brand effects are positively correlated across uninsured and insured deposit markets. The largest five banks by deposit size (Bank of America, Citi Bank, JPMorgan Chase, Wachovia and Wells Fargo) have largest insured and uninsured brand effects. Our demand specifications control for the number of branches, so it is not necessarily the case that largest banks would have the strongest brand effects. One important thing to note is that although deposit bank brand effects are correlated across deposit types, they are not perfectly correlated. For example, Santander has the lowest (16th) ranked brand effect for uninsured deposits while it has the 10th highest brand effect for insured deposits. The heterogeneity across banks and more specifically across deposit types has important implications for the effect of FDIC insurance coverage policy changes. These results suggest that the changes in FDIC insurance coverage affected the profitability and stability of banks asymmetrically.

Table 6: Bank Fixed Effects (Normalized)

Bank	Uninsured Dep.	Insured Dep.
Bank of America	1.26***	0.76***
Branch Banking and Trust	-0.47***	-0.37***
Citi Bank	2.31***	0.60***
Fifth Third Bank	-0.85***	-0.70***
HSBC	0.26***	-0.11***
JPMorgan Chase	1.98***	0.49***
KeyBank	-0.87***	-0.47***
PNC Bank	-0.51***	-0.06***
RBS	-0.96***	-0.55***
Regions Bank	-0.82***	-0.2***
Santander	-1.50***	-0.21***
SunTrust Bank	-0.59***	0.12***
TD Bank	-1.07***	-0.46***
US Bank	0.23***	-0.11***
Wachovia	0.82***	0.74***
Wells Fargo	0.8***	0.52***

Figure 2: Bank Fixed Effects (Normalized)



Overall, our demand deposit specifications yield three critical results for bank policy. First, demand for both insured and uninsured deposits appears to be relatively sensitive to the offered interest rate. A 100bps increase in deposit rate is associated with a 16.54-28.43% increase in market share.[6] Secondly, we estimate a negative and significant relationship between the probability a bank defaults and demand for its uninsured deposits. Conversely, we do not find a negative and statistically significant relationship between a bank's probability of default and demand for its insured deposits. Although these results do not confirm the credibility of FDIC insurance, they are consistent with the view that FDIC insurance is credible and relatively frictionless. Lastly, we find that five major US banks have the strongest brand effects and there exists a fair amount of heterogeneity in the strength of brand effects across banks and deposit markets. These three empirical findings have important implications for bank stability and optimal bank policy.

4 Model

We develop a dynamic discrete time model of retail banking that incorporates financial distress and partial deposit insurance. The model emphasizes a bank's strategic interactions between depositors and its competitors. One of the key features of the model is that consumer demand for uninsured deposit accounts is a function of the financial solvency of the banking institution. And at the same time, the financial solvency

[6] We calculate the demand semi-elasticities using an initial share of 7.00%, $\alpha = 17.89$ and $\alpha = 30.57$.

of the bank is a function of the number of deposits that the banks is able to attract. The simultaneous relationship between demand and financial distress creates the potential for multiple equilibria in the banking sector. We then calibrate our model using the estimated utility parameters from Section 3 and additional bank balance sheet data. The calibrated model is then used to assess stability in the banking sector.

4.1 Model Framework

We extend the automaker model from Hortaçsu et al. (2011) to the retail banking sector. In the model banks compete amongst each other for both insured and uninsured deposits by setting deposit rates. Consumers select deposit accounts based on deposit rate, probability the bank defaults, and other bank characteristics. Each period banks set insured and uninsured deposit rates and then decide to continue operations or declare bankruptcy depending on the profitability of the bank. Bankruptcy penalizes uninsured depositors while leaving insured depositors unaffected. We assume that depositors are fully rational and anticipate the probability of default and incorporate this information into their bank selection process using publicly available information.

Consumers possess demand both insured and uninsured deposits. The indirect utility derived by uninsured and insured deposits follows the formulation laid out in Section 3.1 in equations (1) and (2)

$$\begin{aligned} u^I_{j,k,t} &= \delta_k + \alpha i_{k,t} + \xi^I_{j,t} + \varepsilon^I_{j,k,t} \\ u^N_{j,k,t} &= \delta_k - \rho_{k,t}\gamma + \alpha i^N_{k,t} + \xi^N_{J,t} + \varepsilon^N_{j,k,t} \end{aligned}$$

where δ are bank fixed effects, ρ is the probability of default and i is the offered deposit rate while ξ and ε are unobserved (by the econometrician) utility shocks. The parameter α measures depositors sensitivity to interest rates while γ measures the utility flow loss in the event of a bankruptcy. Although not explicit in the indirect utility formulations, we again allow the bank fixed effects and interest rate sensitivity parameters to vary across insured/uninsured deposits as denoted by the superscripts I and N. Under the maintained assumption that the utility shocks $\varepsilon^I_{j,k}$ and $\varepsilon^N_{j,k}$ are distributed iid Type 1 Extreme Value, bank k's market shares for insured and uninsured deposits are given by

$$s^I_k = \frac{exp(\delta_k + \alpha i^I_k + \xi^I_j)}{\sum_{l=1}^{L} exp(\delta_l + \alpha i^I_l + \xi^I_l)},\ s^N_k = \frac{exp(\delta_k - \rho_k\gamma + \alpha i^N_k + \xi^N_j)}{\sum_{l=1}^{L} exp(\delta_l - \rho_k\gamma + \alpha i^N_l + \xi^N_l)}$$

We denote the number of consumers searching for insured deposits and uninsured deposits M^I and M^N such that the level of deposits at bank k is given by $M^I_k s^I_k + M^N_k s^N_k$.

Banks compete against each other for depositors, each seeking to maximize firm value. A bank's profit maximization problem involves a three-part decision process: setting its insured deposit rate, setting its uninsured deposit rate, and then ultimately deciding to continue its operations or declare bankruptcy. Banks earn a period profit based on its return on deposits net of financing and other operational costs.

$$\pi_t = M^I s^I (R_t - c - i^I) + M^N s^N (R_t - i^N) - b$$

Each period, banks disburse profits to their equity holders. Banks earn the stochastic return R on the total level of deposits, regardless of deposit type, earning net returns $R - c - i$ on insured deposits and $R - i^N$ on uninsured deposits. The term c represents the non-interest costs of servicing insured depositors relative to uninsured depositors (i.e. deposit insurance premiums). We assume that bank returns are normally distributed with mean μ_R and variance σ_R and are i.i.d across banks and time. In addition to deposits, banks are financed with a consol bond which pays an infinite stream of coupons b. If a bank discontinues servicing its debt obligations, the bank declares bankruptcy and ceases all further operations and payments to equity holders. The corresponding value of the firm to equity holders just prior to period t is given by

$$V_t = \mathrm{E}\left[\max\left\{M^I s^I (R_t - c - i^I) + M^N s^N (R_t - i^N) - b + \frac{\mathrm{E}[\pi_{t+1}]}{1+r}, 0\right\}\right]$$

The value function illustrates the bank's continuation/ bankruptcy decision given the realized return on deposits and emphasizes the notion of limited liability. The ability to default provides equity holders with a payout function that resembles an option on the return on deposits. Equity holders participate in the upside of the stochastic return R with limited liability on the downside.

We now characterize the optimal rate setting and bankruptcy decision policies for retail banks. Note that because bank returns shocks are i.i.d. and market parameters are constant[7] the problem is stationary and hence, banks use the same interest rate setting and bankruptcy decision policies from period to period. For ease of exposition, we first solve for the optimal bankruptcy decision by taking the interest rate setting decisions as given. A bank's bankruptcy decision depends on the value of the bank to equity holders. As discussed in Hortaçsu et al. (2011), banks optimally declare bankruptcy if and only if the stochastic return on deposit falls below some cutoff level $\bar{R}$. Given that the value of the bank is zero in default (i.e. $M^I s_k^I(\bar{R} - i^I) + M^N s_k^N(\bar{R} - i^N) - b_k + \frac{E[\pi_t]}{1+r} = 0$), Hortaçsu et al (2011) show that the optimal cutoff rule is characterized by

$$\frac{(1+r)}{(M^i s^I + M^N s^N)}\left(b - M^I s^I(\bar{R} - c - i^I) + M^N s^N(\bar{R} - i^N)\right) = \int_{\bar{R}}^{\infty} (R' - \bar{R}) dF(R') \tag{4}$$

[7]We assume that the in the event of a bankruptcy a new identical bank replaces failed bank in the proceeding period.

The optimal cutoff rule $\bar{R}$ corresponds directly to the risk neutral probability of default $\rho_k = \Phi\left(\frac{\bar{R}-\mu_R}{\sigma_R}\right)$. A critical result arising from the bankruptcy cutoff condition (eq. 4), is that the cutoff rule and consequently the probability of default need not be unique. Since consumer utility for uninsured deposits depends on bank survival and bank survival depends on consumer demand, the model generates potential feedback loops. A key consequence of such feedback loops is that perceived default risk can be self-fulfilling: a decrease in demand for deposits raises the probability a bank defaults and vica versa.

Prior to the start of each period, banks set the deposit rate for insured and uninsured deposits to maximize the expected return to equity holders. Given the limited liability of equity holders and the assumed distribution of returns, the bank's rate decision for uninsured/insured deposits can be written as

$$\max_{i^I, i^N} M^I s_k^I \left[\mu_R + \sigma_R \lambda\left(\frac{\bar{R}-\mu_R}{\sigma_R}\right) - c - i^I\right] + M^N s_k^N \left[\mu_R + \sigma_R \lambda\left(\frac{\bar{R}-\mu_R}{\sigma_R}\right) - i^N\right]$$

where $\lambda(\cdot)$ is the inverse mills ratio. We assume that banks compete for deposits by playing a differentiated product Nash Bertrand deposit rate setting game for both types of deposits. The corresponding first order conditions for i^I and i^N are

$$\text{Insured Deposits:} \quad \alpha\left[\mu_R + \sigma_R \lambda\left(\tfrac{\bar{R}-\mu_R}{\sigma_R}\right) - c - i^I\right](1 - s^I) = 1 \tag{5}$$

$$\text{Uninsured Deposits} \quad \alpha\left[\mu_R + \sigma_R \lambda\left(\tfrac{\bar{R}-\mu_R}{\sigma_R}\right) - i^N)\right](a1 - s^N) = 1 \tag{6}$$

Note that from the envelope theorem we have that have that $\frac{d\bar{R}}{di^N} = \frac{d\bar{R}}{di^S} = 0$. A key result here is that the probability of default (which is a direct function of $\bar{R}$) influences the rate setting decision for insured deposits even though insured depositors are not subject to default risk. Furthermore, because of limited liability, firms that are more likely to default may also set higher deposit rates to attract more depositors.

4.2 Model Calibration

We calibrate the model using our retail banking data set to test for multiple equilibria in the banking sector and analyze the recent bank regulatory changes. We use the demand estimates from Section 3 to recover the utility parameters and then calibrate the remaining parameters using bank balance sheet data. The model calibration provides new insight on how susceptible banks were to runs during the financial crisis and the potential policy implications.

We use utility parameters corresponding to the IV demand estimates in Tables 3 and 4 in Section 3. Table 7 summarizes the utility parameters used in the calibration exercise. Given that we did not estimate a significant relationship between the probability a bank defaults and its demand for insured deposits, we let $\gamma = 0$ for insured depositors.

Table 7: Utility Parameters for Model Calibration

Parameter	Uninsured Dep.	Insured Dep.
α	30.57	17.89
$-\gamma$	-7.55	

The uninsured deposit utility parameters correspond to the IV estimates in Table 3.
The insured deposit utility parameters correspond to the IV estimates in Table 4.

In addition to the interest rate and default sensitivity parameters α^I, α^N, and γ, we are also able to recover the unobservable bank specific utility shocks $\xi^I_{j,t}$ and $\xi^N_{j,t}$ from our regression specification. We use the residuals from specification (3) to calculate the set of unobservable characteristics $\xi^I_{j,t}$ and $\xi^N_{j,t}$ at each time period for each bank such that estimated market shares are equal to the true observed market shares.

Given the utility parameters, the remaining parameters solve for in the model are the mean and standard deviation of the stochastic returns (μ_R, σ_R) and the non-interest cost of insured deposits (c). We allow these cost and return on deposit variables to vary across banks. We calibrate the remaining parameters using bank balance sheet data from the peak of the financial crisis in March 2009. Using the bankruptcy condition (eq. 4) and first order conditions for insured (eq. 5) and uninsured deposits (eq. 6) we are able to solve for c, σ_R, and μ_R for each bank in our data set. The key variables needed to calibrate the model are the interest rate, debt and return on deposits for each bank. We assume a discount rate of 10% for each bank. We compute the debt service rate for each bank as the sum of the five year CDS spread and the five year CMT rate in March 2009. The CDS spread measures the bank's credit spread while the CMT rate measures the risk free market interest rate. We calculate debt service b_k as the product of the bank debt service rate and non-deposit liabilities.

Figure 3: Calibrated Mean Returns

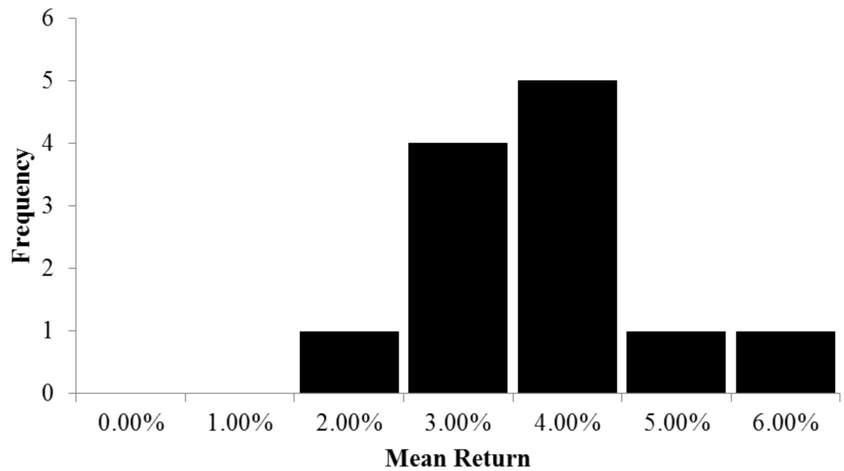
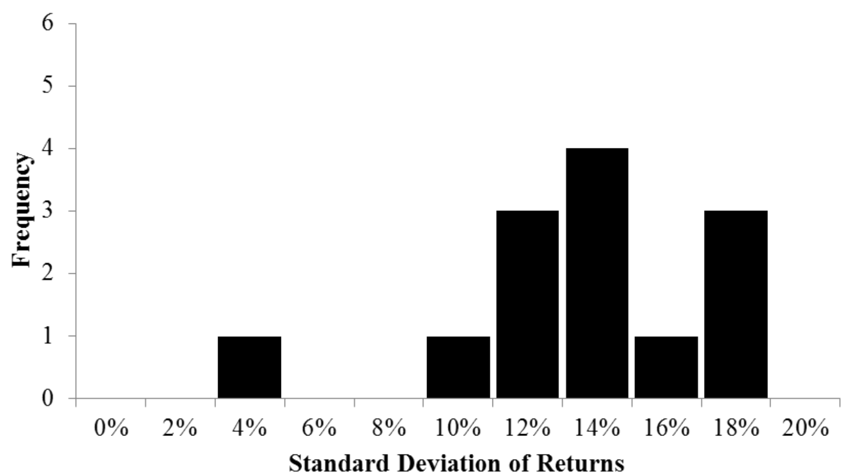


Figure 4: Calibrated Standard Deviation of Returns



The calibrated values of μ_R and σ_R are displayed in Figures 3 and 4. The calibration results imply that the cost of servicing uninsured depositors is 2.10% percentage points more expensive than servicing uninsured depositors (i.e. $\bar{c} = -2.10\%$ and c ranges from -1.00% to -2.83%). The estimated and calibrated parameters are inline with the theoretical expectations and the historical returns/costs of banks.

5 Counterfactual Analysis

We use our calibrated model to assess the stability of the retail banking sector and examine the implemented and proposed banking regulations. We first check the model for multiple equilibria with respect to the probability of default. If there exists multiple equilibrium default probabilities, a shift in consumer expectations over the financial solvency of a bank could produce a self-fulfilling change in a bank's probability of default. Furthermore, a shift in one bank's level of financial distress can spread to other banks through equilibrium deposit competition effects. We then examine the effect of the 2010 FDIC insurance limit change on financial stability in the banking sector and the cost of providing deposit insurance. Lastly, we examine the effect of imposing risk limits on the financial stability in the retail banking sector.

5.1 Multiple Equilibria

We use the calibrated model to check for multiple equilibria with respect to each bank's probability of default. We find that multiple equilibria exist for each bank in our data set and that, in general, each bank is at the "better equilibrium" in terms of a higher chance of survival. For example, Wells Fargo's market implied risk neutral probability of default as of March 2009 was 2.73%. Our model indicates an additional equilibrium exists in which Wells Fargo defaults with probability 52.20%. The multiple equilibria results can be interpreted as follows. Consumers rationally believed that there was a 2.73% chance that Wells Fargo would default in March 2009. However, if consumers all of the sudden believed that there was a 52.20% chance that Wells Fargo would default in March 2009, those beliefs would also be rational even though the underlying fundamentals of Wells Fargo remained the same. If consumers believed that Wells Fargo was more likely default they would start to withdraw their deposits which would in turn lower the profitability of Wells Fargo and increase its probability of default.

We check for multiple solutions to equation (4) using the estimated/calibrated parameters. Specifically, we check for whether multiple cut-off values, $\bar{R}$, or equivalently default probabilities, satisfy the bankruptcy condition. A change in the probability of default (ρ_k) shifts both the left hand side (LHS) and right hand side (RHS) of the bankruptcy condition through its impact on $\bar{R}_k$ but also through its impact on deposit market shares and the equilibrium deposit rate and probability of default vectors. For each value of ρ_k, we calculate the new equilibrium uninsured and insured deposit rate vector and equilibrium probability of default vector as per first order conditions (eq. 5, 6, and 4) for each bank and then calculate the implied market shares from the multinomial logit formula.[8] Figure 5 displays the LHS and RHS of equation (4) as a function of the probability of default for JPMorgan Chase. The intersection of the two equations represent equilibrium outcomes. Given the fundamentals for JPMorgan Chase, the model implies that both a 2.14% and 61.80% probability of default are equilibrium outcomes.

[8]Empirically search for new equilibria using the Broyden Secant Method as part of the 'nleqslv' package in R.

Figure 5: Model Calibration - JPMorgan Chase

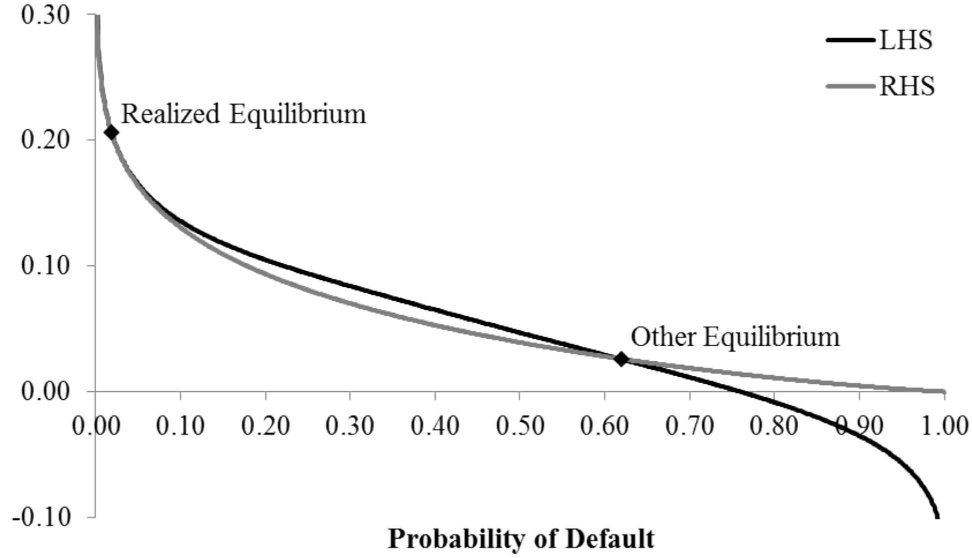


Table 8: Multiple Equilibrium Default Probabilities

Bank	Realized Default Prob.	Other Eq. Default Prob.
Bank of America	5.11%	36.80%
Citi Bank	6.87%	99.40%
Fifth Third Bank	0.96%	73.30%
HSBC	2.78%	67.00%
JPMorgan Chase	2.14%	61.80%
KeyBank	7.37%	70.50%
PNC Bank	4.54%	43.90%
Regions Bank	0.38%	75.70%
SunTrust Bank	4.40%	74.00%
TD Bank	2.30%	84.60%
US Bank	2.67%	64.90%
Wachovia	3.80%	59.50%
Wells Fargo	2.73%	52.20%

Column (1) displays the realized equilibrium risk neutral probability of default as of March 31, 2009.
Column (2) displays a non-exhaustive list of other equilibrium default probabilities.

We use the calibration results to check for multiple solutions to equation (4) as described above for each of the thirteen banks in our calibration sample.[9] Table 8 summarizes the multiple equilibria results for all thirteen banks. The first column displays realized equilibrium default probabilities as implied by the market CDS spread in March 2009. The second column displays other potential equilibrium default probabilities. Multiple equilibria exist for each bank in our data set. These results suggests that the vast majority of major U.S. retail banks were potentially susceptible to bank runs during the peak of the financial crisis.

5.2 Deposit Competition and Contagion of Financial Distress

The strategic interaction of banks through deposit competition allows for financial contagion in the banking sector. The optimal pricing and bankruptcy decisions of a bank depend critically on the characteristics of competing products. One such key characteristic is each bank's probability of default.

Consider how bank k responds when one of its competing banks j experiences an exogenous increase in its probability of default. All else equal, bank $k's$ uninsured deposit market share, s_k^N, increases. Bank $k's$ bankruptcy condition (4) can be rewritten as follows

$$\underbrace{b_k - M^I s_k^I(\bar{R}_k - c_k - i_k^I) - M^N s_k^N(\bar{R}_k - i_k^N)}_{\text{Cost of Staying in Business}} = \underbrace{\frac{\left(M^i s_k^I + M^N s_k^N\right)}{(1+r)} \int_{\bar{R}_k}^{\infty} (R' - \bar{R}_k) dF_k(R')}_{\text{Future Profits}}$$

An increase in s_k^N increases bank $k's$ future expected profits but it also increases its cost of staying in business when it receives an adverse income shock. In general, the equilibrium effect on bank $k's$ probability of default is ambiguous.

We use our calibrated model to examine the transmission of an exogenous increase in one bank's probability of default to the financial sector. We consider the hypothetical scenario where the probability Citi Bank defaults increases by 5.00% points from 6.87% to 11.87%. Table 9 illustrates an equilibrium outcome of the exogenous increase in financial distress for each bank in our sample.[10] Our model estimates suggest that the risk neutral probability of default for other banks in the sample would increase by 0.01% on average, but as much as 1.80% for certain banks.

[9] The calibration sample includes all of the banks in panel data set that we have data for from March 2009.

[10] As discussed in the previous section, the model allows for multiple equilibria. We search for new equilibria using the Broyden Secant Method and initiating the algorithm at the observed equilibrium. We report the first equilibrium found by the algorithm.

Table 9: Contagion of Financial Distress

Bank	Realized Default Prob.	Counterfactual Default Prob.
Bank of America	5.11%	6.87%
Citi Bank	6.87%	11.87%
Fifth Third Bank	0.96%	0.96%
HSBC	2.78%	2.48%
JPMorgan Chase	2.14%	1.25%
KeyBank	7.37%	7.13%
PNC Bank	4.54%	4.23%
Regions Bank	0.38%	0.39%
SunTrust Bank	4.40%	3.72%
TD Bank	2.30%	2.76%
US Bank	2.67%	2.56%
Wachovia	3.80%	4.19%
Wells Fargo	2.73%	2.74%

Column (1) displays the realized equilibrium risk neutral probability of default as of March 31, 2009.
Column (2) displays an equilibrium outcome from the calibrated model if Citi Bank's probability of default were to exogenously increase by 5.00%.
Multiple counterfactual equilibria potentially exist. We report the first equilibrium found using the Broyden Secant Method initiated at the initial observed/realized equilibrium.

5.3 FDIC Insurance Limit Change

During the financial crisis the FDIC raised the limit on deposit insurance multiple times. First, in October 2008 and then as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010. We use our calibrated model to estimate the effect such a policy would have had during the peak of the financial crisis in March 2009.

We simulate the FDIC policy change under the assumption that the total number of insured deposits available, M^I, increases by 5.00% while the total number of uninsured deposits available, M^N, decreases by 5.00% as a result of the policy change. To put these numbers in perspective, each of the two FDIC policy changes increased the number of insured deposits by roughly 5.00-15.00%. Using the calibrated parameters, we calculate the new equilibrium according to the bankruptcy condition (eq. 4) and the interest rate first order conditions (eq. 5 and eq. 6).[11]

Table 10: FDIC Insurance Limit Change

Bank	Prob. of Default.	Counter-factual	Δ Ins. Cost
Bank of America	5.11%	9.54%	$13,465m
Citi Bank	6.87%	6.42%	-$107m
Fifth Third Bank	0.96%	0.86%	-$9m
HSBC	2.78%	2.24%	-$124m
JPMorgan Chase	2.14%	2.61%	$933m
KeyBank	7.37%	9.54%	$636m
PNC Bank	4.54%	2.83%	-$507m
Regions Bank	0.38%	0.34%	-$9m
SunTrust Bank	4.40%	2.61%	-$864m
TD Bank	2.30%	1.70%	-$122m
US Bank	2.67%	2.16%	-$200m
Wachovia	3.80%	2.54%	-$1,874m
Wells Fargo	2.73%	2.18%	-$542m

Column (1) displays the realized equilibrium risk neutral probability of default as of March 31, 2009.
Column (2) displays the computed conterfactual equilibrium risk neutral probability of default if the FDIC were to offer deposit insurance to an additional 5.00% of uninsured deposits.
Column (3) displays the change in the hypothetical equilibrium cost of the FDIC policy change relative to the old policy. We calculate the cost change as the difference in expected insurance payout. Negative values represent a surplus to the FDIC.
Multiple counterfactual equilibria potentially exist. We report the first equilibrium found using the Broyden Secant Method initiated at the initial observed/realized equilibrium.

Table 10 displays the counterfactual results for each bank in our data set. Column (1) displays the realized equilibrium while column (2) displays the computed equilibrium in the counterfactual scenario. Our results suggest that the FDIC limit increase would have lowered the probability of default for ten of the thirteen banks in our data set. The heterogeneity in bank brand effects across banks and products described

[11] As discussed in the previous section, the model allows for multiple equilibria. We search for new equilibria using the Broyden Secant Method and initiating the algorithm at the observed equilibrium. We report the first equilibrium found by the algorithm.

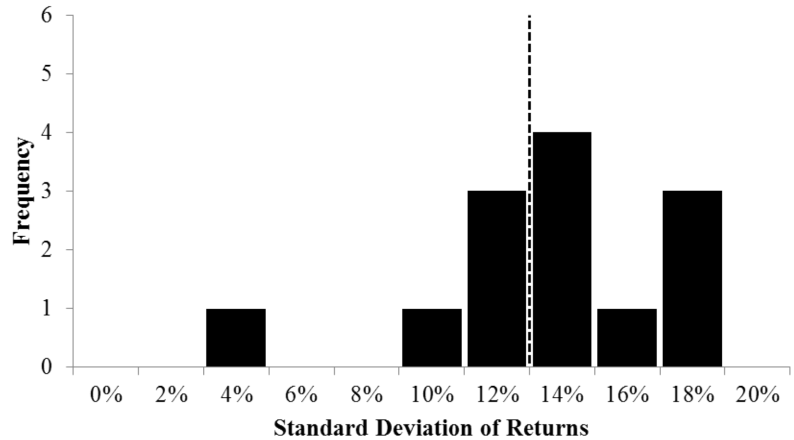
in Section 3.3 and heterogeneity in the cost of servicing insured depositors (c_k) help explain part of the asymmetric effect of increased FDIC insurance. Overall, the calibration results suggest that increased FDIC would have improved financial stability on average.

Given the hypothetical probability of default, we calculate the expected FDIC insurance payout under the two policy regimes. We calculate the hypothetical payout under the assumption that deposit shares remain the same and that the recovery rate in the event of a default is 40%. Column (3) displays the difference in expected payouts under the counterfactual scenario relative to the realized outcome. Increasing the deposit insurance limit impacts the FDIC's cost of providing insurance in two ways. The FDIC limit change increases the FDIC's insurance payout in the event of default but it also potentially lowers the probability that each bank defaults. Our simulation results indicate that increasing FDIC insurance limit would have actually lowered the expected insurance cost for ten of the thirteen banks in our data set. Overall, our empirical results suggest that increasing the deposit insurance limit in 2009 would have likely improved the stability of the banking sector and would have actually lowered the cost of providing deposit insurance for the majority of the banks in our sample.

5.4 Risk Limits

The recent financial crises prompted regulators to examine putting risk limits on financial institutions. We use our model to consider the effect of restricting the risk banks are eligible to undertake. Specifically, we impose a counterfactual policy in which banks are forced to hold securities/investments that cap the standard deviation of income/returns σ_R at 12.00%. Figure 6 illustrates the calibrated standard deviation of returns relative to the imposed cap. For simplicity we assume that all banks in excess of the risk limit reduce σ_R to 12.00% exactly. The majority of banks in the sample (eight of the thirteen) would be forced to reduce the volatility of their returns.

Figure 6: Model Calibration - Standard Deviation of Returns



Placing risk limits on banks produces two offsetting effects on the financial stability of banks. On one hand, risk limits lower the probability that a bank experiences an adverse income shock; negative income shocks are less common. On the other hand, risk limits lower the future value of the firm which makes default less costly. All else equal

$$\frac{d\bar{R}}{d\sigma} \leq 0$$

In other words, a given adverse income shock is more likely to drive a bank into bankruptcy.

Table 11: Bank Risk Limits

Bank	Prob. of Default.	Prob. of Default (12% Cap)
Bank of America	5.11%	8.81%
Citi Bank	6.87%	7.19%
Fifth Third Bank	0.96%	0.86%
HSBC	2.78%	2.18%
JPMorgan Chase	2.14%	1.28%
KeyBank	7.37%	9.53%
PNC Bank	4.54%	3.05%
Regions Bank	0.38%	0.01%
SunTrust Bank	4.40%	0.18%
TD Bank	2.30%	0.02%
US Bank	2.67%	1.40%
Wachovia	3.80%	0.08%
Wells Fargo	2.73%	0.68%

Column (1) displays the realized equilibrium risk neutral probability of default as of March 31, 2009.
Column (2) displays the computed counterfactual risk neutral probability of default if the regulators were to impose a risk limit of $\sigma_R \leq 12.00\%$. Multiple counterfactual equilibria potentially exist. We report the first equilibrium found using the Broyden Secant Method initiated at the initial observed/realized equilibrium.

Table 11 illustrates the equilibrium effect of the hypothetical risk limit policy. As the theory predicted above, the risk limit produces an ambiguous effect on the probability that each bank defaults. Overall, the calibration results suggest that imposing risk limits of this form could be counterproductive. On average, the risk limit increases the probability each bank defaults by 0.83% points. Although risk limits lower the volatility of bank returns they also lower the profitability of banks which could potentially destabilize the banking sector.

6 Conclusion

Our paper develops a new empirical model of the banking sector which emphasizes bank competition and the strategic relationship between depositors and banks. Using a new deposit interest rate data set, we estimate a demand system for insured and uninsured deposits and calibrate our new empirical model of banking. Empirically, we find new evidence suggesting that the demand for holding uninsured deposits at a bank depends critically on its financial solvency. Conversely, we find little evidence indicating that insured depositors respond to changes in financial distress. On the theory side, our model illustrates the potential for multiple equilibria in the banking sector and the transmission of financial shocks through deposit competition. One primary advantage of the model is that we are able to calibrate it using our demand estimates and bank balance sheet data.

We use our calibrated model to assess the newly proposed bank regulations arising after the recent financial crisis. Recently, bank regulators have used both risk limits and deposit insurance in an attempt to increase stability in the banking sector. Our model suggests that both policies produce asymmetric effects across banks (both positive and negative) which could be undesirable from a policy standpoint. In general, our estimates suggest that expanding deposit insurance could improve financial stability and could even lower the cost of providing deposit insurance. On the contrary, imposing risk limits could increase instability in the banking sector as the future profitability of bank declines as a result of the risk limits. As US and international banking regulations continue to evolve in the aftermath of the financial crisis, our empirical model of banking provides a useful framework for analyzing the stability of the banking sector.

7 References

Angeletos, George- Marios and Ivan Werning. 2006. “Crises and Prices: Information Aggregation, Multiplicity and Volatility.” *American Economic Review* 96(5): 1720-1739.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. “Automobile prices in market equilibrium.” *Econometrica.* 63(4): 841-890.

Calomiris, Charles and Joseph Mason. 2003. “Fundamentals, Panics, and Bank Distress During the Depression.” *American Economic Review.*

Diamond, Douglas and Phillip Dybvig. 1983. “Bank Runs, Liquidity, and Deposit Insurance.” *Journal of Political Economy.* 91: 401-419.

Eavis, Peter. 2014. “Banks Ordered to Add Capital to Limit Risks.” *The New York Times.* April 9, 2014: A1. Print

Federal Deposit Insurance Corporation. 2014. . *Changes in FDIC Deposit Insurance Coverage.* Available at: http://www.fdic.gov/deposit/deposits/changes.html. Accessed: 05/04/2014.

Goldstein, Itay and Ady Pauzner. 2004. “Demand-Deposit Contracts and the Probability of Bank Runs.” *The Journal of Finance.* LX(3): 1293-1328

Hausman, Jerry. 1996. “Valuation of New Goods Under Perfect and Imperfect Competition,” in T. Bresnahan and R. Gordon, eds., *The Economics of New Goods*, Studies in Income and Wealth Vol. 58, Chicago: National Bureau of Economic Research

Hortaçsu, Ali, Gregor Matvos, Chaehee Shin, Chad Syverson, and Sriram Venkataraman. 2011. ”Is An Automaker’s Road to Bankruptcy Paved with Customers’ Beliefs?” *The American Economic Review.* 101(3): 93-97.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman. 2013. “Indirect Costs of Financial Distress in Durable Goods Industries: The Case of Auto Manufacturers.” *Review of Financial Studies.* 26(5):: 1248-1290.

Iyer, Rajkamal and Manju Puri. 2012. “Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks.” *American Economic Review.* 102(4):1414-1445

Kashyap, Anil K, Dimitrios P. Tsomocos and Alexandros P. Vardoulakis. 2014. “Does Macroproduential Regulation Change Bank Credit Supply?” Working Paper.

Leland, Hayne E. 1994. “Corporate Debt Value, Bond Covenants and Optimal Capital Structure.” *Journal of Finance*, 49(4): 1213-1252

Matutes, Carmen and Xavier Vives. 1996. "Competition for Deposits, Fragility and Insurance." *Journal of Financial Intermediation*, 5: 184-216.

Soledad, Maria, Martinez Peria, and Sergio L. Schmukler. 2011. "Do Depositors Punish Banks for Bad Behavior? Market discipline, deposit insurance, and banking crises." *Journal of Finance*. 56(3): 1029-1051.

Stock, James H. and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." in James H. Stock and Donald W.K. Andrews, eds, *Identification and Inference for Econometric Models: Essays in Honor of Thomas J. Rothenberg*. Cambridge University Press

8 Appendix

Table A-1: Demand Estimation - IV Robustness Check

Variables	Uninsured	Insured	Insured
CD Spread (α)	14.18**	20.04***	20.36***
	(5.58)	(7.26)	(7.24)
Default Prob. ($-\gamma$)	-3.38**	-0.96	
	(1.72)	(1.60)	
Quarter Fixed Effects	X	X	X
Bank Fixed Effects	X	X	X
IV	X	X	X
Observations	530	531	531
R-squared	0.971	0.946	0.946

*** p<0.01, ** p<0.05, * p<0.10

Each observation is weighted by the square root of the market size.

All specifications control for the number of bank branches.

The set of instruments include loan charge-offs, lagged merger exposure and the lagged average characteristics of competing products (CDS spread, CD Rate, additional non-interest expenditures)