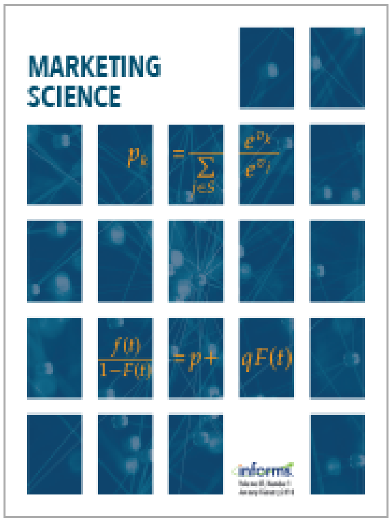

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Could Good Intentions Backfire? An Empirical Analysis of the Bank Deposit Insurance

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Abstract. The recent financial crisis led to the expansion of deposit-insurance coverage in many countries. We develop a structural model of the banking market in which banks act as financial intermediaries between consumers who have funds and businesses that seek loans, and explore the implications of such policies for banks and depositors. Our results indicate the policy could erode market discipline and increase banks' moral hazard. As a result, banks extend their lending to riskier loans than they would have in the absence of the policy. We find this policy may even harm consumers. Moreover, market competition magnifies the lack of market discipline and induces additional moral hazard for excessive risk taking. Counterfactuals indicate banks may reduce their deposit interest rates by 2.7% in a duopoly market and almost triple their risk caps under the new policy. The estimated losses of depositors' welfare are equivalent to at least a 3.27% drop in deposit interest rates.

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Keywords: deposit insurance • market discipline • moral hazard • consumer welfare • structural model • indirect inference

1. Introduction

Policy makers and/or firms often advocate the disclosure of certain information, subsidize certain groups of people, or enforce particular regulation in the hope of preventing market failure. For example, restaurants in some markets are required to display hygiene quality grade cards to consumers (Jin and Leslie 2003, 2009). Regulators in China, together with some big online platforms, recently contemplated a proposal to enforce certain quality-guarantee policies in online transactions. Another prominent example from these proactive policies is the recent global trend to expand the deposit-insurance schemes after the 2008 financial crisis, to strengthen depositors' confidence in the security of their money at the banks and reduce the chance of panic-based bank runs.[1] For instance, the United States increased the ceiling of insured deposits from \$100,000 to \$250,000 in 2008, and the European Union doubled its coverage limit by the end of 2009 to €100,000. Unlike policymakers, who reached a general consensus that policies such as deposit insurance are desirable, academics argue that the introduction of this safety net could weaken market discipline and might induce moral hazard for excessive risk taking. As a result, banks behave more opportunistically, which in turn could harm depositors (Demirgüç-Kunt and Kane 2002).

In this paper, we explore the market discipline before and after the deposit-insurance-coverage change and investigate its implications for banks' moral hazard and consumer welfare. We separately analyze the effects of banks' moral hazard on banks' risk-taking behaviors and deposit interest rates, and compare them across different market structures. We separate the gains and losses to consumer welfare from the new policy and perform similar comparisons across demographic groups and under different market structures.

We develop a structural model of the retail banking industry to study the interactions between depositors and banks. Our model of consumer demand for retail bank deposits extends the literature of banking choice by allowing endogenous saving. A depositor's saving at a bank depends on the bank's deposit interest rate, its default risk, and the depositor's outside (investment) options. We model a bank as a profit-maximizing financial intermediary that uses the deposit interest rate to compete for funds in deposit markets and sets a risk cap to shape its loan portfolio in credit markets. We characterize the default risk of a bank's loan portfolio by considering the fraction of a bank's loans that are impaired. Built on the distribution of such a fraction, we bridge the gap between the default risk of a bank's loan portfolio and its failure rate, so a bank's default risk is endogenously determined by its optimal instruments in both markets.

We utilize a two-year repeated cross-sectional data set that contains characteristics of banks in all metropolitan statistical areas (MSAs) in the United States before and after the recent financial crisis. The data set is compiled from Federal Reserve Board call reports and the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits surveys for 2007 and 2009. The Survey of Consumer Finances 2007/2009 two-year data set provides information on consumer savings. This data set oversamples rich people, so we use local income distributions generated from the 2006 and 2008 censuses to reweigh the corresponding distributions in the survey.

We estimate consumers' risk preferences, their preferences for bank deposit services, and the distribution of their outside options. We allow consumers' risk preferences and the distribution of their outside options to vary over time, because the 2008 financial crisis crippled financial markets, so investors might become more risk averse. Barberis et al. (2001) show investors may exhibit more risk aversion in financial decision making if the outcomes of their prior investments were disappointing. We separately estimate the banks' loan demands in credit markets for 2007 and 2009, because the economic downturn that began in 2008 dampened the performance of loan markets. We recover the distribution of the bad debt fraction for each bank's loan portfolio before and after the policy reform and calculate the corresponding implied default risk.

Using our model estimates, we explore the implications of the new policy by solving the market equilibrium, that is, consumers' optimal financial decisions and banks' optimal deposit interest rates and risk caps, under the old deposit-insurance regime and the new one. Comparing the equilibrium market discipline and banks' moral hazard in these two scenarios, we find banks reduce their deposit interest rates and increase their risk caps after the deposit-insurance coverage expands. This finding somehow contradicts the policy makers' original good intention. We further examine this moral hazard under different market structures, and our counterfactual experiments show market competition amplifies banks' moral hazard caused by the deposit-insurance expansion. In other words, banks further reduce their deposit interest rates and increase their risk caps after the deposit-insurance coverage expands when markets become competitive. Meanwhile, we calculate the consumer welfare from the market equilibrium and disentangle it into two parts: the welfare gain from the additional deposit-insurance coverage and the welfare loss from the banks' increased moral hazard. The policy experiment shows the latter dominates the former, and the depositors' welfare loss is equivalent to at least a 3.27% drop in the deposit interest rates in a duopoly market and an even higher drop in an oligopoly market. Furthermore, market competition may account for 59% of the depositors' welfare loss.

1.1. Related Literature

This paper lies at the intersection of several subjects. First, it contributes to the small but growing literature on structural estimation of bank demand. Adams et al. (2007) and Dick (2008) adopt the random coefficient discrete-choice approach to study the demand in the markets of retail deposits. They use the number of bank accounts to calculate banks' market shares. Ho and Ishii (2011) point out this approach may produce misleading market shares, because in the deposit markets, banks compete for funds rather than depositors. They introduce exogenous consumer savings to the bank-choice problem and construct market shares based on dollar deposits. We extend their work by endogenizing the consumer's saving decision and nesting it into the bank-choice problem. In our model, deposit interest rates not only affect the probability that a consumer patronizes a bank but also the amount of funds she will deposit at that bank. The latter does not appear in these papers and is crucial to our analysis. In fact, the recent financial crisis significantly changed banks' deposit interest rates and failure rates, both of which affected depositors' saving decisions.

Second, this paper is related to the literature on whether the proactive mandatory policies or programs the policy makers or some advocacy groups often support could benefit the predesignated agents and prevent market failure. Previous research offers mixed results. Jin and Leslie (2003, 2009) conclude that both mandatory and nonmandatory (market-induced) posting policies of hygiene grade cards indeed benefit (at least some) consumers. Luchs et al. (2010) conclude the well-intentioned Robinson–Patman Act favored larger businesses instead of smaller ones over time, a trend that challenges the notion that the act protects small businesses, which was its original purpose. Jiang et al. (2014), however, find a mandatory high ethical standard in the credence service market may lower market efficiency. As for deposit insurance specifically, Diamond and Dybvig (1983) consider banks as financial intermediaries in their seminal work and show deposit insurance smooths the coordination frictions among depositors and prevents panic-based bank runs. Matutes and Vives (1996) extend the theory of intermediation to imperfect competition and suggest that fairly priced deposit insurance is desirable when banks are local monopolies. Empirical works (Keeley 1990, Chernykh and Cole 2011), however, find the downside of deposit insurance and confirm that the introduction of deposit insurance weakens market discipline and encourages banks to pursue riskier investments. By contrast to the reduced-form analyses, our work contributes to the literature by presenting a structural framework that quantifies the effects of deposit insurance on market discipline and their implications for banks' risky loans and depositors' welfare. Furthermore, we find that deposit insurance induces larger banks' moral hazard when the market is competitive.

Third, this paper links to the literature on corporate default. To predict the probability of corporate default, past works usually either select a set of exogenous covariates and estimate their correlations with actual defaults (Brown and Dinç 2011) or assume the value of the underlying firm following some exogenous dynamic stochastic process and compute the likelihood that the firm's value drops below some threshold at some time in the future (Crosbie and Bohn 2002). Contrary to conventional wisdom, we derive a bank's failure rate from its market conduct, so the probability of default is endogenous and depends on the interactions with rival banks. Thus, our paper provides a microfoundation for bank failure and empirically estimates the bank's default rate during the recent financial crisis.

Finally, this paper presents an application of the indirect inference approach (Gourieroux et al. 1993, Keane and Smith 2003). Indirect inference is a simulation-based method that is able to tackle many estimation problems for which the criterion function (e.g., likelihood function) is analytically intractable or expensive to evaluate. Indirect inference is feasible as long as the economic model can be simulated given its structural parameters. Intuitively, indirect inference views the empirical data and the simulated data through the windows characterized by some auxiliary model and chooses the structural parameters in such a way that both "views" look the same from this window (Collard-Wexler 2013). We apply this idea in our estimation and demonstrate its advantage when the model complexity prohibits the direct derivation of moment conditions.

The remainder of this paper is organized as follows. Section 2 describes the background of deposit insurance and the data and provides some reduced-form analysis. Sections 3 and 4 present our model and estimation methodology, respectively. Sections 5 and 6 discuss results and a counterfactual analysis, respectively. Section 7 concludes.

2. Institutional Setting and Data

Deposit insurance is a mechanism to insure deposits and protect depositors from losses resulting from a bank failure, provided by the FDIC, established under the Banking Act of 1933. During the recent financial crisis, the FDIC closed 168 banks. When a bank failure occurs, the FDIC takes over the insolvent bank and guarantees the payback of deposits up to the insurance limit to all customers of this bank.

The FDIC set the initial deposit-insurance limit at $2,500 and gradually increased it over time. The deposit-insurance limit reached $100,000 after the passage of the Depository Institutions Deregulation and Monetary Control Act of 1980. Because of the recent financial crisis, the FDIC temporarily raised the deposit-insurance limit to $250,000 in 2008. This increase became permanent after July 21, 2010, when the Dodd–Frank Wall Street Reform and Consumer Protection Act was signed. The current deposit-insurance policy covers all deposit accounts including checking accounts, saving accounts, money market accounts, and certificates of deposit (CDs). The coverage limit is $250,000 per depositor for every account-ownership category, including individuals, firms, and governments, at each insured bank.

2.1. Data

We compile a two-year (2007 and 2009) repeated cross-sectional data set from several sources. We collect the data on bank characteristics from the Federal Reserve Board's financial statements of call reports, and information about branch-level bank deposits from the FDIC's Summary of Deposits surveys. We collect the data on households' financial status and demographic information from the 2007 and 2009 Survey of Consumer Finances. We use household income data from the 2006 and 2008 censuses to generate the local income distributions for each MSA in the United States. These distributions help us generate corresponding local distributions of demographics.

2.1.1. Banks: Deposit Markets. A market is defined geographically by an MSA, and the product is dollar deposit, including checking, savings, and CDs. To calculate the market share, we use the dollar amount of funds that a bank collects in a market. Table 1 describes the market concentration in deposit markets. Market structure seems to have been quite stable in the deposit markets during the recent financial crisis. On average, each market has 6 banks, ranging from 2 to 10, and the largest bank's market share is around 24%.

Table 2 summarizes bank characteristics in deposit markets. We compute the deposit interest rate by dividing a bank's deposit interest expense over its total deposits. Because this rate is a six-month rate,[2] we compound it to get the annual deposit interest rate. The average deposit interest rate was 2.81% in 2007 and dropped to 1.34% in 2009. Banks offered lower interest rates to depositors after the deposit-insurance coverage expanded in 2008. This first inspection seems to be consistent with the story that deposit insurance may weaken market discipline and reduce deposit interest rates. Branch density is the number of branches a bank has in a market. It describes how conveniently depositors can access a bank's deposit services. Depositors may find using a bank's deposit services convenient if the bank opens many branches in a market. Branch density did not change much during the recent financial crisis. The average branch density is 17, whereas the median branch density is 7. This finding implies

Table 1. Market Summary Statistics

	Year 2007			Year 2009			
	Mean	Median	S.D.	Mean	Median	S.D.	Definition
Bank number	5.785	6	1.491	6.033	6	1.483	The number of active banks in a market
C(1)	0.2441	0.2304	0.0865	0.2431	0.2259	0.0876	The market share of the largest bank in a market
HHI	1,263	1,157	604.7	1,273	1,174	592.1	The Herfindahl–Hirschman Index of a market
Number of markets	365			364			The number of markets in our data

Notes. C(1) is the one-firm concentration ratio, that is, the largest bank's market share. The HHI is calculated by summing the square of market shares and then multiplying by 10,000.

that in deposit markets, many small banks compete for funds with some large banks. The single market indicator describes a bank's geographic focus, that is, whether a bank operates its major business in a given market. This indicator is bank-market specific, and is 1 if the bank collects more than 85% of its deposits from the market[3] and is zero otherwise.

We drop observations that have zero deposits, zero expense of premise, and missing values. We also drop observations whose market share is less than 5%. The remaining data set contains 741 banks and 1,950 bank-market observations in 2007, and 729 banks and 2,027 bank-market observations in 2009.

2.1.2. Banks: Credit Markets. This section introduces banks' characteristics in credit markets, summarized in Table 3. Loan return is the ratio of a bank's loan income to its total loans. Similar to the deposit interest rate, we annualize it in our analysis. The average loan return dropped from 7.75% in 2007 to 5.96% in 2009. Loan loss is a bank's actual charge-offs normalized by its total loans. The average loan loss increased from 0.26% in 2007 to 1.2% in 2009. Both loan returns and loan losses changed in such a way that shows the recent financial crisis deteriorated the loan business in credit markets.

The ratio of allowance for loan and lease losses (ALLL) to total loans measures a bank's expected loan-loss percentage. It proxies the default risk of a bank's loan portfolio. This ratio, on average, increased from 2.47% in 2007 to 3.58% in 2009. The ratio of equity capital to total assets captures a bank's risk-management strategy in credit markets. A high equity capital-to-total assets ratio means a bank operates conservatively and may not be enthusiastic about seeking high loan returns. This ratio, on average, dropped from 0.1 in 2007 to 0.084 in 2009. At first glance, the changes in both ALLL and the equity capital-to-total assets ratio seem to be consistent with the story that deposit insurance provides a moral hazard for excessive risk taking.

2.1.3. Depositors. In this section, we introduce the depositor's characteristics. A depositor's bank deposits include her checking, savings, and CDs. Her portfolio size is the amount of her liquid assets, including bank deposits, bonds, stocks, mutual funds, and investment in brokerage accounts. Her portfolio income is the total of her interest income, dividend income, and capital gains (losses). The risk-free rate is the annualized return of a three-month Treasury bill, and the market return is the weighted average of the bond market return and the stock market return, whose weights are determined by the relative market size of both markets.

We compute bond market returns and stock market returns from the BofA Merrill Lynch U.S. Corp Master Total Return Index Value and the S&P 500 Index, respectively. We drop observations that have missing values. Table 4 presents the summary statistics of depositors' characteristics. The sample distributions

Table 2. Bank Characteristics: Deposit Market

	Year 2007			Year 2009			
	Mean	Median	S.D.	Mean	Median	S.D.	Definition
Deposit rate	0.0281	0.0278	0.0058	0.0134	0.0130	0.0060	The deposit interest of a bank
Bank age	102.2	103	50.66	105.5	105	51.86	The number of years a bank has been active
Branch density	16.86	7	35.72	17.15	7	40.20	The number of branches a bank has in a market
Single market bank	0.1677	0	0.3737	0.1524	0	0.3595	Indicates whether a bank collects more than 85% of its deposits in a market
Bank obs.	741			729			The number of bank-level observations in our data
Bank-market obs.	1,950			2,027			The number of bank-market-level observations in our data

Table 3. Bank Characteristics: Credit Market

	Year 2007			Year 2009			
	Mean	Median	S.D.	Mean	Median	S.D.	Definition
Loan return	0.0775	0.0766	0.0118	0.0596	0.0589	0.0089	The loan return of a bank
Loan loss	0.0026	0.0017	0.0062	0.0120	0.0057	0.0172	The amount of default loans of a bank
ALLL	0.0247	0.0234	0.0104	0.0358	0.0299	0.0203	The allowance for loan and lease losses (normalized by total loans) of a bank
$\log(TA)$	13.74	13.35	1.580	13.79	13.46	1.582	The log of bank size
EC/TA	0.1002	0.0924	0.0305	0.0840	0.0788	0.0286	The equity capital-to-total asset ratio of a bank
Failed banks[a]	1			24			The number of failed banks

Note. log(TA), log(total assets); EC/TA, equity capital/total assets.
[a]We consider only the banks whose market shares are at least 5% in 2007 or 2009.

of portfolio size, bank deposits, and portfolio income are highly skewed, because the Survey of Consumer Finances oversamples rich people.

2.2. Reduced-Form Analysis

Our data show that, on average, banks decreased their deposit interest rates and increased their loan-portfolio default risks after the FDIC expanded the deposit-insurance coverage to $250,000 in 2008. These observations raise the following questions: Does the new policy regime weaken market discipline? If so, how strong is the effect?

We confront a major difficulty when identifying the policy effect, because our data does not have a control group for this policy change. The new policy regime takes effect nationwide and applies to all banks in our data. Thus, perfect collinearity exists between the time effect and the policy treatment effect in our regression if we include both in the reduced-form analysis.

To overcome this difficulty, we consider the interaction of the bank size and the time effect, and assume it to be a reasonable proxy for the policy effect. The bank size captures the effect of deposit insurance on market discipline. Large banks are more likely to absorb large deposits in deposit markets. These deposits usually are not fully insured by deposit insurance, so large banks are more likely to have large proportions of uninsured deposits. This result is consistent with the findings in Maechler and McDill (2006) and is confirmed by our data. We regress the proportion of uninsured deposits of a bank on the bank size and find the bank size has a positive and significant effect on the proportion of uninsured deposits of a bank. The regression results are shown in Table 5.

The depositors' security concerns about these partially insured deposits create market discipline, which prevents the bank from taking excessive risk. When the deposit-insurance coverage increases, these partially insured deposits become safer, and their owners have less incentive to discipline the bank. Therefore, we expect the policy effect on the bank's default risk (deposit interest rate) to be positive (negative), and to be greater for larger banks than small banks. The interaction of the bank size and the time effect measures the difference in the policy effects among banks of different sizes. If its effect on the bank's default risk (deposit interest rate) is positive (negative), our reduced-form analysis provides indirect evidence that the new policy regime weakens market discipline and encourages banks to behave opportunistically.

Table 4. Depositors' Characteristics, Summary Statistics

	Year 2007			Year 2009			
	Mean	Median	S.D.	Mean	Median	S.D.	Definition
Portfolio size	9,322	761	33,800	7,498	593	30,100	The size of a consumer's financial portfolio
Bank deposits	753	79	3,599	673	85	2,432	The amount of bank deposits a consumer has in her portfolio
Portfolio income	938	21	4,864	442	7	2,845	The income of a consumer's financial portfolio
Risk-free rate	0.0435			0.0015			Annualized return of the three-month Treasury bill
Market return	0.0440		0.0886	0.1833		0.2550	The return of the market portfolio, which is a weighted average of the bond market return and the stock market return
Obs.	1,454						The number of consumer observations in our data

Note. Portfolio size, bank deposits, and portfolio income are measured in thousands of dollars.

Table 5. Regression of the Proportion of Uninsured Deposits on Bank Size

Variable	Mean	S.E.
log(*Bank Size*)	0.0176*	0.0049
Year 2009	0.0451**	0.0176
Bank Age	−0.000099	0.0001
Employees per Branch	0.000017*	0.000004
Average Wage	0.0023*	0.0004
Fixed Cost Normalized by Bank Size	3.8536	5.7520
Constant	−0.0593	0.0701

Note. *Bank Size* is measured by the bank's total assets.
*Significant at the 1% level; **significant at the 5% level.

The left-hand panel of Table 6 (loan portfolio default risk) presents the results of regressing the bank's loan portfolio default risk on the policy-effect proxy (i.e., the interaction of the bank size and the time effect). The new policy regime has a positive and significant effect on the bank's loan portfolio default risk. This finding is consistent with our conjecture and indirectly confirms that the new policy regime provides banks with incentives to take more risks.[4] Interestingly, the time effect is negative and significant. The financial crisis dampens the performance of the credit market, so taking risks is less rewarding for banks. As a result, banks are less willing to lend to risky borrowers.

The right-hand panel of Table 6 (deposit interest rate) displays the results of regressing the bank's deposit interest rate on the policy-effect proxy. The effect of the new policy regime on the bank's deposit interest rate is negative and significant. This finding also aligns with our claim and indirectly supports the result that the new policy regime weakens market discipline. Indeed, after the deposit-insurance coverage increases, consumers whose deposits are not fully insured demand fewer risk premiums from the banks, which allows the banks to reduce their deposit interest rates.

In summary, we present some preliminary reduced-form analyses and indirectly show the new policy regime weakens market discipline and provides banks with incentives to take excessive risks. The effect is significant, as shown in Table 6. We realize our reduced-form analysis is not able to directly estimate the policy effect, because our data do not have any control group for the policy change. We resolve this problem by adopting the structural approach to perform some policy experiments.

Table 6. Reduced-form Analysis of Policy Effect

	Dependent variable			
	Loan portfolio default risk		Deposit interest rate	
Variable	Mean	S.E.	Mean	S.E.
Single Market Bank	0.0021	0.0009	−0.000018	0.0004
log(*Bank Size*)	0.0003	0.0004	−0.0003	0.0002
Year 2009	−0.0571*	0.0069	−0.0038	0.0029
log(*Bank Size*) × *Year* 2009	0.0049*	0.0005	−0.0007*	0.0002
Constant	0.0197*	0.0053	0.0349*	0.0022

*Significant at the 1% level.

3. Model

We develop a model of the banking industry to study the interactions between consumers and banks in deposit markets and banks' loan-portfolio choices in credit markets. Consumers are risk averse and maximize their expected utility in a two-stage decision process. First, they make their banking choices, that is, whether to deposit at a bank and, if so, at which bank. Then they optimize their portfolios that consist of their bank deposits and outside investment options.

Banks act as financial intermediaries and maximize their expected profits by simultaneously choosing their optimal instruments in both deposit markets and credit markets. In deposit markets, banks use deposit interest rates and bank-failure rates to compete for funds. In credit markets, we assume each bank operates as a portfolio manager that trades off default risk and expected returns when optimizing her loan portfolio. We explicitly model the bank's loan-portfolio choice from its optimal decision of instruments in both deposit markets and credit markets.

3.1. Consumers

This section explores consumers' demand for depository services and their portfolio-optimization decisions during the recent financial crisis. At the beginning of date t, consumer i in market m is endowed with a package of money w_{imt} and an outside investment option I_{i0mt}. This outside option summarizes the possible investments consumer i can undertake at date t, such as public stocks and corporate bonds. We denote the return of this outside option as $r_{i0mt} = \beta_{imt} r_{mt} + (1-\beta_{imt}) r_{ft}$, where r_{ft} and r_{mt} are the risk-free rate and the market return at date t, respectively, and β_{imt} describes the asset position of consumer i's outside investment option at date t.[5] We parameterize this asset position as $\beta_{imt} = \theta_{mt1} + \theta_{mt2}\log(w_{imt})$. The asset position is heterogeneous over time and across consumers, so it captures the effects of the financial turbulence and the portfolio size on a consumer's investment alternative.

The expected return of the outside investment option I_{i0mt} is $E[r_{i0mt}] = \beta_{imt} E[r_{mt}] + (1-\beta_{imt}) r_{ft}$. The risk-free rate is deterministic, so the variance of the outside investment option I_{i0mt} depends on the asset position of consumer i's outside investment option and the variance of the market return $\mathrm{Var}[r_{i0mt}] = \beta_{imt}^2 \mathrm{Var}[r_{mt}]$.

Consumer i receives utility from saving at bank j in two ways. First, she receives pecuniary returns from her deposits at bank j. In general, this return comes from bank j's deposit interest payment. However, if bank j fails, the return may be less than bank j's deposit interest rate, depending on the amount of principal and deposit interest bank j owes consumer i.

Second, consumer i receives deposit services from bank j. High-quality deposit services can help consumer i smooth her daily transactions, so consumer i prefers a bank that provides convenient deposit services. We decompose consumer i's valuation of bank j's deposit services into three parts. First, this valuation may depend on bank j's observable (to the econometrician) characteristics in market m, denoted by the vector X_{jmt}, such as the bank's geographic focus, branch density, and age. These characteristics describe bank j's deposit-service capacity and operation experience, which directly affect consumer i's valuation of bank j's deposit services. Second, the valuation may depend on bank j's unobservable (to the econometrician) characteristics in market m, such as staff members' communication skills. We denote them as ξ_{jmt}. Finally, the valuation may depend on consumer i's taste parameter ϵ_{ijmt}. We assume it follows type 1 extreme value distribution and is independently and identically distributed across consumers, banks, markets, and time.

Then, consumer i's utility for depositing at bank j is

$$u_{ijmt} = \underbrace{\lambda v_{ijmt}}_{\substack{\text{utility from}\\ \text{pecuniary return}}} + \underbrace{X_{jmt}\theta^D_{imt} + \xi_{jmt} + \varepsilon_{ijmt}}_{\substack{\text{utility from}\\ \text{deposit services}}}, \tag{1}$$

where v_{ijmt} denotes consumer i's utility from her portfolio return when saving at bank j, and λ is the price-utility scalar. When consumer i chooses not to use deposit services, her utility is

$$u_{i0mt} = \underbrace{\lambda v_{i0mt}}_{\substack{\text{utility from}\\ \text{pecuniary return}}} + \underbrace{\varepsilon_{i0mt}}_{\substack{\text{random}\\ \text{utility shock}}}. \tag{2}$$

Consumer i's portfolio return is the weighted average of her deposit return and the return of her outside option. Her date-t deposit return depends on the amount of funds she places at bank j, because bank j may fail and the deposit insurance is limited to the current coverage limit l_t. Let p_{jmt} be bank j's failure rate (to be derived below). Then, consumer i's date-t deposit return at bank j is

$$R_{ijmt} = \begin{cases} r_{jmt}, & \text{if } s_{ijmt} \le l_t/(1+r_{jmt}), \\ l_t/s_{ijmt} - 1, & \text{with probability } p_{jmt}, \\ & \quad \text{if } s_{ijmt} > l_t/(1+r_{jmt}), \\ r_{jmt}, & \text{with probability } 1 - p_{jmt}, \\ & \quad \text{if } s_{ijmt} > l_t/(1+r_{jmt}), \end{cases} \tag{3}$$

where r_{jmt} is bank j's date-t deposit interest rate, and s_{ijmt} is consumer i's deposits at bank j in market m at date t. Consumer i's portfolio return is therefore

$$\underbrace{(s_{ijmt}/w_{imt})R_{ijmt}}_{\substack{\text{return from}\\ \text{bank } j\text{'s deposits}}} + \underbrace{(1 - s_{ijmt}/w_{imt})r_{i0mt}}_{\substack{\text{return from consumer } i\text{'s}\\ \text{outside option}}}.$$

We assume consumer i is risk averse, and her risk preference is characterized by the mean-variance utility function. Let a_{imt} denote consumer i's risk coefficient, drawn from the exponential distribution with mean θ_{at}. Consumer i maximizes her utility from her portfolio investments by choosing the optimal level of deposits at bank j. Then consumer i's utility from her pecuniary return when saving at bank j is

$$\begin{aligned} v_{ijmt} = \max_{0 \le s_{ijmt} \le w_{imt}} & w_{imt} \\ & \cdot \Bigg(\underbrace{E\left[\frac{s_{ijmt}}{w_{imt}} R_{ijmt} + \left(1 - \frac{s_{ijmt}}{w_{imt}}\right) r_{i0mt}\right]}_{\text{consumer } i\text{'s portfolio return}} \\ & - \frac{a_{imt}}{2} \mathrm{Var}\left[\frac{s_{ijmt}}{w_{imt}} R_{ijmt} + \left(1 - \frac{s_{ijmt}}{w_{imt}}\right) r_{i0mt}\right]\Bigg). \end{aligned} \tag{4}$$

When consumer i chooses not to use deposit services, she invests all her money in her outside option I_{i0mt}. The utility from her portfolio return becomes

$$v_{i0mt} = w_{imt}\left(E[r_{i0mt}] - \frac{a_{imt}}{2}\mathrm{Var}[r_{i0mt}]\right). \tag{5}$$

Now we can compute the market share for each bank. Following Dick (2008) and Ho and Ishii (2011), we assume every consumer only chooses one bank at which to deposit.[6] Suppose the random coefficient θ^D_{imt} can be decomposed as

$$\theta^D_{imt} = \theta^D + \nu^D_{imt}, \quad \nu^D_{imt} \sim N(0, \Sigma),$$

where Σ is a diagonal matrix, and the individual preference shock ν^D_{imt} is independent across markets and time. The probability that consumer i chooses bank j is

$$\frac{\exp(\delta_{jmt} + \mu_{ijmt})}{\sum_k \exp(\delta_{kmt} + \mu_{ikmt})},$$

where $\delta_{jmt} = \lambda E[v_{ijmt}] + X_{jmt}\theta^D + \xi_{jmt}$ is the part of utility that does not vary with consumer characteristics, and $\mu_{ijmt} = \lambda(v_{ijmt} - E[v_{ijmt}]) + X_{jmt}\nu_{imt}$ is the interaction term.

We define the market share by the dollar amount of deposit funds, so bank j's market share in market m is

$$ms_{jmt} = \frac{\iint s^*_{ijmt} \frac{\exp(\delta_{jmt}+\mu_{ijmt})}{\sum_k \exp(\delta_{kmt}+\mu_{ikmt})} dF(\nu^D_{imt}) dF(a_{imt}) dF(w_{imt})}{\sum_l \iint s^*_{ilmt} \frac{\exp(\delta_{lmt}+\mu_{ilmt})}{\sum_k \exp(\delta_{kmt}+\mu_{ikmt})} dF(\nu^D_{imt}) dF(a_{imt}) dF(w_{imt})}. \tag{6}$$

3.2. Banks

This section examines the bank's profit-maximization problem. We consider banks as financial intermediaries that transfer funds raised in deposit markets into loans in credit markets. All banks simultaneously choose their deposit interest rates and risk caps to maximize their expected profits. We use a bank's deposit interest rate and risk cap to characterize its loan portfolio, from which we derive the bank's default risk. We incorporate limited liability into the bank's expected profit, so the bank's payoff is zero when it defaults.

3.2.1. Loan Portfolio. At the beginning of date t, bank j is endowed with a set of loan demands. We assume each loan demand has the same size and is characterized by a pair (K, ρ), where K is the expected loan return and ρ is the default risk.

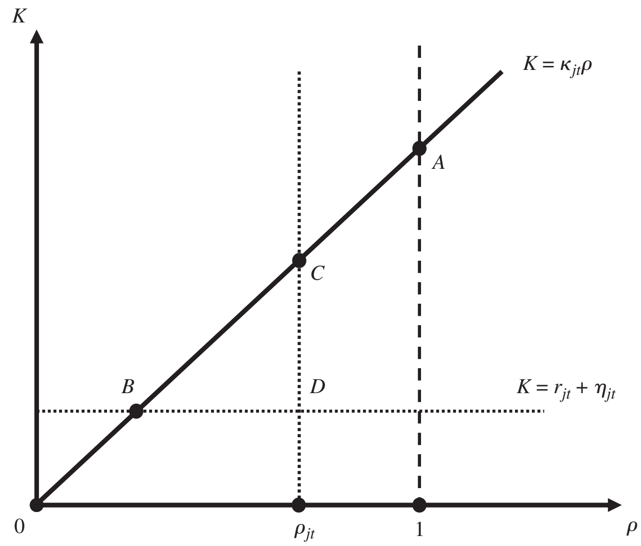
To keep our problem tractable, we assume banks receive no repayment when borrowers default. Therefore, the return of the loan (K, ρ) is $(1+K)/(1-\rho)$ with probability $1-\rho$, and -1 with probability ρ. Suppose bank j's loan demands are uniformly distributed[7] over the triangle bounded by the horizontal axis, the vertical line $\rho = 1$, and the line $K = \kappa_{jt}\rho$. The slope κ_{jt} measures bank j's loan profitability at each default risk level in the sense of stochastic dominance. In other words, fixing the default risk level ρ, bank j's loans are more likely to have high returns when the slope κ_{jt} is large. We parameterize κ_{jt} by

$$\kappa_{jt} = \exp(X_{jt}^L \phi + \omega_{jt}), \tag{7}$$

where X_{jt}^L is a vector of bank j's observable (to the econometrician) characteristics that affect its loan profitability in credit markets, including the log of bank size and the equity capital-to-total assets ratio. The bank size proxies bank j's screening methodology in credit markets. Large banks usually use hard information[8] to screen borrowers, whereas small banks often rely on soft information,[9] such as personal networks (Stein 2002). Thus, large banks are more likely than small banks to screen out good borrowers who cannot provide documents as evidence to verify themselves. The equity capital-to-total assets ratio describes bank j's risk-management strategy in credit markets. A high equity capital-to-total assets ratio implies bank j operates conservatively and may not be enthusiastic about seeking high loan returns. The error term ω_{jt} captures the effect of bank j's unobservable (to the econometrician) characteristics, such as special business campaigns, on its loan profitability in credit markets. We assume this error term is a random variable and is independently and identically distributed across banks and time. We further assume this error term has zero mean conditional on the bank's observable characteristics

$$E[\omega_{jt} \mid X_{jt}^L] = 0 \quad \forall\, j, t. \tag{8}$$

Figure 1. Bank j's Loan Portfolio



The probability density function of bank j's loan demands is

$$f(K, \rho) = \frac{2}{\kappa_{jt}}, \tag{9}$$

where $0 \le K \le \kappa_{jt}\rho$ and $0 \le \rho \le 1$.

Figure 1 illustrates that in Equation (9) bank j's loan demands are uniformly distributed in the triangle $0A1$. Bank j constructs its loan portfolio within this triangle, trading off the default risk and the expected return. Let r_{jt} and η_{jt} denote bank j's deposit interest rate and operation cost,[10] respectively; then, bank j's cost of capital is $r_{jt} + \eta_{jt}$. Bank j refuses to offer unprofitable loans, so bank j's loan portfolio does not contain loans below the line $K = r_{jt} + \eta_{jt}$. Meanwhile, bank j wants to avoid bank failure, so it may decline loan applications whose default risks are sufficiently high. We assume bank j only accepts loans whose default risks do not exceed its risk cap ρ_{jt}. Then bank j's loan portfolio is given by the triangle BCD in Figure 1.

The probability density function of loans in bank j's loan portfolio BCD is

$$g(K, \rho \mid r_{jt}, \rho_{jt}) = \frac{2\kappa_{jt}}{(\rho_{jt}\kappa_{jt} - (r_{jt} + \eta_{jt}))^2}, \tag{10}$$

where $r_{jt} + \eta_{jt} \le K \le \rho\kappa_{jt}$ and $(r_{jt} + \eta_{jt})/\kappa_{jt} \le \rho \le \rho_{jt}$.

3.2.2. Default Risk. We follow two steps to derive bank j's failure rate from its loan portfolio. First, we consider the fraction of bad loans in bank j's loan portfolio and derive the distribution of this fraction. Then we calculate the probability that this fraction exceeds some bank-failure threshold and link it to bank j's default risk. The bank-failure threshold varies across banks and time, because banks are heterogeneous in their buffers against defaults and are more likely to fail in financial crises.

Recall bank j's loan portfolio BCD derived in Section 3.1. We consider the loans whose default risk is ρ. Let $\tau(\rho)$ denote the fraction of these loans that are uncollectible. Then, for each possible default risk level ρ in bank j's loan portfolio, $\tau(\rho)$ is a random variable distributed over the unit interval and has mean ρ conditional on the given default risk level

$$E[\tau(\rho) \mid \rho] = \rho.$$

We assume $\tau(\rho) = H^{-1}(z \mid \rho, \theta_\tau)$, where $H(\cdot \mid \rho, \theta_\tau)$ is the cumulative distribution function of a beta random variable with parameters $\theta_\tau \rho$ and $\theta_\tau(1-\rho)$, and z is the standard uniform random variable. The fraction of bad loans in bank j's loan portfolio is therefore

$$\bar{\tau}_{jt}(r_{jt}, \rho_{jt}) = \int \underbrace{H^{-1}(z \mid \rho, \theta_\tau)}_{\substack{\text{fraction of bad loans}\\ \text{for loans whose}\\ \text{default risk is } \rho}} \, d\underbrace{G_\rho(\rho \mid r_{jt}, \rho_{jt})}_{\substack{\text{marginal distribution}\\ \text{of } \rho \text{ of bank } j\text{'s}\\ \text{loan portfolio}}}. \quad (11)$$

Clearly, the fraction $\bar{\tau}_{jt}(r_{jt}, \rho_{jt})$ from Equation (11) is also a random variable distributed over the unit interval. Let $\bar{H}(\bar{\tau}_{jt}(r_{jt}, \rho_{jt}) \mid r_{jt}, \rho_{jt})$ be its cumulative distribution function. Because $H(\cdot \mid \rho, \theta_\tau)$ is monotonically increasing in z, for every $\bar{\tau}_{jt} \in [0,1]$, a unique

$$z^* = z^*(\bar{\tau}_{jt}) \in [0,1]$$

exists, solving Equation (11). Then the cumulative distribution function of $\bar{\tau}_{jt}$ is

$$\begin{aligned}\bar{H}(a \mid r_{jt}, \rho_{jt}) &= \Pr(\bar{\tau}_{jt} \le a) = \Pr(z^*(\bar{\tau}_{jt}) \le z^*(a)) \\ &= \Pr(z^* \le z^*(a)) = z^*(a), \quad \forall\, a \in [0,1]. \end{aligned} \quad (12)$$

A bank fails when a substantial number of its loans become uncollectible. We parameterize the bank-failure threshold by $\Phi(X_{jt}^F \theta^F)$, where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal random variable, and X_{jt}^F is a vector of bank j's characteristics that describe bank j's buffers against defaults. The characteristics include the log of bank size and the financial-crisis indicator, because both help determine whether a bank is vulnerable to defaults. We assume bank j becomes insolvent if

$$\bar{\tau}_{jt}(r_{jt}, \rho_{jt}) \ge \Phi(X_{jt}^F \theta^F).$$

Then bank j's default risk is

$$p_{jt} = 1 - \bar{H}(\Phi(X_{jt}^F \theta^F) \mid r_{jt}, \rho_{jt}). \quad (13)$$

3.2.3. Profit Maximization. This section completes the bank's profit-maximization problem. Bank j's loan-portfolio return depends on the fraction of its loans that are impaired, so we have to bridge the gap between them.

Suppose a fraction $\bar{\tau}_{jt}(r_{jt}, \rho_{jt})$ of bank j's loan portfolio becomes uncollectible; by Equation (11), the proportion of loans of default risk ρ being impaired is $H^{-1}(z^*(\bar{\tau}_{jt}(r_{jt}, \rho_{jt})) \mid \rho, \theta_\tau)$. Then, conditional on the fraction $\bar{\tau}_{jt}(r_{jt}, \rho_{jt})$, bank j's loan portfolio return is

$$\begin{aligned}&\bar{K}(\bar{\tau}_{jt}(r_{jt}, \rho_{jt}) \mid r_{jt}, \rho_{jt}) \\ &= \int\!\!\int \Bigg[\underbrace{(1 - H^{-1}(z^*(\bar{\tau}_{jt}(r_{jt}, \rho_{jt})) \mid \rho, \theta_\tau))\left(\frac{1+K}{1-\rho} - 1\right)}_{\text{profits from loan repayments}} \\ &\quad + \underbrace{H^{-1}(z^*(\bar{\tau}_{jt}(r_{jt}, \rho_{jt})) \mid \rho, \theta_\tau)(-1)}_{\text{bad debt losses}}\Bigg] g(K, \rho \mid r_{jt}, \rho_{jt})\, dK\, d\rho. \end{aligned} \quad (14)$$

We assume bank j has limited liability to its debt obligations, so bank j's payoff is zero when it fails. Therefore, bank j's profit-maximization problem is to choose its deposit interest rate r_{jt} and loan-risk cap ρ_{jt} to maximize its expected profit

$$\begin{aligned}\max_{\{r_{jt}, \rho_{jt}\}} \sum_{m \in M(j)} \int_0^{\Phi(X_{jt}^F \theta^F)} &[\bar{K}(\bar{\tau}_{jt}(r_{jt}, \rho_{jt}) \mid r_{jt}, \rho_{jt}) - (r_{jt} + \eta_{jt})] \\ &\cdot D_{jmt}\, d\bar{H}(\bar{\tau}_{jt}(r_{jt}, \rho_{jt}) \mid r_{jt}, \rho_{jt}), \end{aligned} \quad (15)$$

where $M(j)$ is the set of markets in which bank j operates, and D_{jmt} is the amount of deposits it collects in market m.

3.2.4. Discussion of the Assumption that Banks Are Myopic. In our model, banks are assumed to be myopic, which is not only a parsimonious characterization of their behaviors but also a reasonable approximation to the reality. Dallas (2011) provides some empirical evidence suggesting banks' myopic decisions lead to financial crisis. Table 7 shows the number of bank failures in the United States between 2007 and 2012 based on the FDIC data.[11] The crisis severely affected the banking industry, as evidenced by many banks' failures throughout the years. Widespread bank failures may trigger market panic, which makes investors impatient (Bruner and Carr 2009). Previous research (Stein 1988) suggests impatient shareholders tend to undervalue and sell their shares when firms perform poorly in current earnings. However, bank managers have incentives to boost current profits to either costly signal the prospects of their banks or simply keep their jobs (Stein 1988). This managerial myopia provides a

Table 7. Number of Failed Banks

Year	2007	2008	2009	2010	2011	2012
Number of failed banks	3	25	140	157	92	51

rationale for bank managers' myopic behaviors in 2009 when the crisis heavily influenced the banking market.

If banks ultimately learn from their mistakes, they might be forward looking about the deposit interest rate and loan demands. Furthermore, they might be forward-looking about the possible financial crisis caused by the moral hazard (default risk). If banks are forward-looking and rationally expect the policy change during the crisis, they should find engaging in the risky behaviors later (in the crisis) to be less expensive as the higher deposit-insurance coverage weakens the market discipline. Thus, an intertemporal tradeoff might exist in the risk-taking behaviors, and these forward-looking banks might generate larger moral hazard effects.

4. Estimation

We use the general method of simulated moments to estimate our model. Our model has five sets of moment conditions coming from the interactions between banks and their customers in deposit markets and credit markets. We face a major difficulty in estimating our parameters in the depositor's optimal-savings problem,[12] because we do not have individual-level data about the depositors' deposit returns. Fortunately, we know the distribution of deposit interest rates from our bank-side data, so we integrate over the deposit interest rates and derive the aggregate-level optimal savings for depositors. The model complexity of these optimal savings prevents us from directly deriving the moment conditions, so we adopt the indirect inference approach (Gourieroux et al. 1993) to estimate our savings parameters.

4.1. Deposit Market

This section provides the estimates of depositors' preferences for banks' depository services $\{\theta^D, \lambda, \Sigma\}$, depositors' risk preferences θ_{at}, and the systematic risk of depositors' outside investment options $\{\theta_{mt1}, \theta_{mt2}\}$. We use two sets of moments to identify these parameters. First, we follow Berry et al. (1995) to derive the moment conditions for the depositors' preferences for banks' depository services[13]

$$E[\xi_{jmt} \mid Z_{jmt}] = 0. \tag{16}$$

This moment condition comes from the fact that bank j's unobserved demand shock ξ_{jmt} has zero mean conditional on its instruments Z_{jmt}. We use two types of instruments to tackle the endogeneity of bank j's deposit interest rate. As Berry et al. (1995) and Sudhir (2001) argue, in oligopoly competition, competitors' characteristics correlate with the bank's market share but not with its unobserved demand shock. Our first set of instruments is the average of competitors' characteristics, such as branch density and bank age. Our second type of instrument is the cost shifters from the bank side, such as wage and expenses of premises and fixed assets.[14]

The second set of moments comes from the following identity of the depositor's investment return:[15]

$$\underbrace{\frac{\text{inc}_{imt}}{w_{imt}}}_{\substack{\text{consumer } i\text{'s}\\ \text{investment}\\ \text{return}}} = \underbrace{\frac{s^*_{ijmt}}{w_{imt}} R_{ijmt}}_{\substack{\text{bank deposit}\\ \text{return}}} + \underbrace{\left(1 - \frac{s^*_{ijmt}}{w_{imt}}\right) r_{i0mt}}_{\substack{\text{outside option}\\ \text{investment return}}}, \tag{17}$$

where inc_{imt} is consumer i's portfolio income, including her income from interest-earning assets, stock dividends, and capital gains. As we mentioned previously, we do not observe consumer i's deposit return R_{ijmt}, because neither her bank affiliation nor her deposit-interest income is available in our data. Fortunately, our data contain the deposit interest rates for all banks and the list of failed banks, so we can get around this problem by examining Equation (17) at the aggregate level. We take the expected value of both sides of Equation (17) conditional only on consumer i's portfolio size w_{imt}

$$E\left[\frac{\text{inc}_{imt}}{w_{imt}} \middle| w_{imt}\right] = E\left[\frac{s^*_{ijmt}}{w_{imt}} R_{ijmt} + \left(1 - \frac{s^*_{ijmt}}{w_{imt}}\right) r_{i0mt} \middle| w_{imt}\right]. \tag{18}$$

The conditional return on the left-hand side of Equation (18) is available in our data, and we calculate the one on the right-hand side of Equation (18) from our model. Recall that $\beta_{imt} = \theta_{mt,1} + \theta_{mt,2} \log(w_{imt})$, the expected return of consumer i's outside investment option conditional on her portfolio size w_{imt} is

$$E[r_{i0mt} \mid w_{imt}] = r_{ft} + (\theta_{mt,1} + \theta_{mt,2} w_{imt})(E[r_{mt}] - r_{ft}). \tag{19}$$

Let $\gamma(w_{imt}, j, m)$ denote the model-implied choice probability[16] that consumer i with portfolio size w_{imt} deposits at bank j in market m. Then we can calculate our target conditional expected return by integrating over consumer i's risk preference and all banks

$$\begin{aligned} &E\left[\frac{s^*_{ijmt}}{w_{imt}} R_{ijmt} + \left(1 - \frac{s^*_{ijmt}}{w_{imt}}\right) r_{i0mt} \middle| w_{imt}\right] \\ &= E_m\Bigg[\sum_{j \in M(j) \cup \{0\}} \gamma(w_{imt}, j, m) \\ &\quad \cdot \underbrace{E_{a_{imt}}\left[\frac{s^*_{ijmt}}{w_{imt}} R_{ijmt} + \left(1 - \frac{s^*_{ijmt}}{w_{imt}}\right) E[r_{i0mt} \mid w_{imt}] \middle| w_{imt}, j, m\right]}_{\substack{\text{consumer's average conditional}\\ \text{portfolio return when}\\ \text{depositing at bank } j \text{ in market } m}}\Bigg], \end{aligned} \tag{20}$$

where $M(j)$ is the set of markets in which bank j operates. By Equations (19) and (20), we rewrite the consumer's conditional expected portfolio return in Equation (18) as

$$E\left[\frac{\mathrm{inc}_{imt}}{w_{imt}}\middle| w_{imt}\right] = E_m\left[\sum_{j\in M(j)\cup\{0\}} \gamma(w_{imt}, j, m) E_{a_{imt}}\right.$$
$$\left.\cdot\left[\frac{s^*_{ijmt}}{w_{imt}} R_{ijmt} + \left(1-\frac{s^*_{ijmt}}{w_{imt}}\right) E[r_{i0mt}\mid w_{imt}]\middle| w_{imt}, j, m\right]\right]. \quad (21)$$

Equation (21) shows consumer i's portfolio size w_{imt} has a multifaceted effect on consumer i's conditional expected portfolio return, which comes from several sources, namely, consumer i's outside investment option I_{i0mt}, consumer i's return from her bank deposits R_{ijmt}, and consumer i's banking-choice probability $\gamma(w_{imt}, j, m)$. This (net) effect consists of two parts: the base effect and the scale effect. The former does not depend on $\log(w_{imt})$, whereas the latter does. To explore the latter, we examine the marginal effect of the consumers' portfolio sizes on the conditional expected portfolio return. By Equation (21), the marginal effect is not a constant, so we consider both its constant part and its variable part. In summary, we decompose the effect of the consumers' portfolio sizes on the conditional expected portfolio return into three components: the base effect, the constant part of the marginal effect, and the variable part of the marginal effect. These three effects jointly identify the three structural parameters in the optimal-savings problem.

The model complexity of these effects prevents us from directly constructing moment conditions for our model primitives, so we adopt the indirect inference approach to derive the moment conditions. Following our identification strategy, we choose the data projection onto the space spanned by 1, $\log(w_{imt})$, and $\log^2(w_{imt})$ as our auxiliary model.

The left-hand side of Equation (21) is the consumer's conditional expected portfolio return exhibited in our data, and the right-hand side is the corresponding conditional return implied by our model. Thus, under the true parameters, if we project both sides of Equation (21) onto the space spanned by 1, $\log(w_{imt})$, and $\log^2(w_{imt})$, we will get the same projections in expectation. Let $\hat{\pi}_0$, $\hat{\pi}_1$, and $\hat{\pi}_2$ be the coefficients from regressing $E[\mathrm{inc}_{imt}/w_{imt}\mid w_{imt}]$ on 1, $\log(w_{imt})$, and $\log^2(w_{imt})$, respectively. Similarly, we regress $E_m[\sum_{j\in M(j)\cup\{0\}}\gamma(w_{imt}, j, m)E_{a_{imt}}[(s^*_{ijmt}/w_{imt})R_{ijmt} + (1 - s^*_{ijmt}/w_{imt})E[r_{i0mt}\mid w_{imt}]\mid w_{imt}, j, m]]$ on 1, $\log(w_{imt})$, and $\log^2(w_{imt})$ and get coefficients $\tilde{\pi}_0$, $\tilde{\pi}_1$, and $\tilde{\pi}_2$. Then the following moment conditions identify $\theta_{mt,1}$, $\theta_{mt,2}$, and θ_{at}:[17]

$$E[\hat{\pi}_k - \tilde{\pi}_k] = 0, \quad k = 0, 1, 2. \quad (22)$$

4.2. Credit Market

In this section, we estimate our bank-side parameters $\{\phi, \theta_\tau, \theta^F\}$ from three sets of moment conditions. First, we use bank j's loan profitability κ_{jt} to identify ϕ. According to the generally accepted accounting principles, ALLL is an estimate of a bank's expected credit losses

$$\text{bank } j\text{'s ALLL} = \text{bank } j\text{'s total loans} \cdot \underbrace{E[\rho\mid r_{jt}, \rho_{jt}]}_{\substack{\text{credit risk of}\\ \text{bank } j\text{'s loan portfolio}}}. \quad (23)$$

Meanwhile, our data contain bank j's loan return and the fraction of its loan portfolio that is uncollectible (i.e., $\bar{\tau}_{jt}$). By Equation (14), we have

$$\text{bank } j\text{'s loan return} = \bar{K}(\bar{\tau}_{jt}\mid r_{jt}, \rho_{jt}). \quad (24)$$

Using Equations (23) and (24), we solve for bank j's loan profitability κ_{jt} and risk cap ρ_{jt}. Once we know κ_{jt}, by Equation (8), we use the following moment condition to estimate ϕ:

$$E[\log(\kappa_{jt}) - X^L_{jt}\phi \mid X^L_{jt}] = 0. \quad (25)$$

Second, we use the interaction between the bank's deposit interest rate and the fraction of its loan portfolio being impaired to identify θ_τ.

Our model-implied interaction is[18]

$$E[r_{jt}\bar{\tau}_{jt}] = E_{\rho_{jt}}[E_{r_{jt}}[E[r_{jt}\bar{\tau}_{jt}(r_{jt}, \rho_{jt})\mid r_{jt}, \rho_{jt}]]].$$

Let $\widehat{E[r_{jt}\bar{\tau}_{jt}]}$ denote the empirical interaction from our data. Under the true parameter, both interactions must be the same in expectation, thus giving the following moment condition:

$$E[E[r_{jt}\bar{\tau}_{jt}] - \widehat{E[r_{jt}\bar{\tau}_{jt}]}] = 0. \quad (26)$$

Finally, we use the interaction between the bank's characteristics X^F_{jt} and its failure event to estimate θ^F. Define bank j's failure event at date t as 1_{jt}. This event indicator is equal to 1 if bank j fails at date t, and is zero otherwise. By Equation (13), bank j fails with probability p_{jt}, so its failure event 1_{jt} is a Bernoulli random variable with parameter p_{jt}. Then our model-implied interaction is

$$E[X^F_{jt}\cdot 1_{jt}] = E_{r_{jt},\rho_{jt}}[E[X^F_{jt}(1-\bar{H}(\Phi(X^F_{jt}\theta^F)\mid r_{jt}, \rho_{jt}))\mid r_{jt}, \rho_{jt}]].$$

Let $E\widehat{[X^F_{jt}\cdot 1_{jt}]}$ denote the empirical interaction from our data. Under the true parameter, both interactions must be the same in expectation, giving the following moment condition:

$$E[E[X^F_{jt}\cdot 1_{jt}] - E\widehat{[X^F_{jt}\cdot 1_{jt}]}] = 0. \quad (27)$$

5. Estimation Results

We present our parameter estimates in Table 8. In deposit markets, both branch density and bank age have positive and significant effects on demand. Branch density measures the scope of a bank's network in a market. When a bank maintains a large banking network in a market, consumers may find using the bank's services to be convenient. Bank age describes a bank's business experiences and its knowledge of customer service, so a bank with a long history is more likely to provide high-quality services. The negative and significant coefficients of $\theta_{2009,1} - \theta_{2007,1}$ and $\theta_{2009,2} - \theta_{2007,2}$ indicate consumers undertook less risky investments during the financial crisis. Using the demand-side estimates, our model predicts the systematic risk of a median[19] consumer's outside investment option was 1.03 in 2007 and 0.72 in 2009. Clearly, consumers have less incentive to invest in assets that are highly correlated with the market portfolio as the market portfolio becomes more risky. Our estimates of consumers' risk preferences show consumers became more risk averse during the financial crisis. This finding is consistent with the findings in Barberis et al. (2001) and Guiso et al. (2016) that the financial crisis dampened the performance of individuals' investments, causing them to become more reluctant to take risks. Our model-implied required return for a consumer of mean risk aversion to participate in the market portfolio is 1.80% before the crisis and 16.85% thereafter. Both of them are less than the corresponding expected market return in our data, so the consumer with mean risk aversion would prefer the market portfolio to no investment in both 2007 and 2009.

Table 8. Estimation Results

Deposit market			
Banking choice (mean)		Optimal saving (θ_t): Asset position and risk preference	
Branch	1.3079** (0.0383)	$\theta_{2007,1}$	0.9765**
Age	0.0643* (0.0303)	$\theta_{2007,2}$	0.0040**
Single	−12.0334** (4.2129)	$\theta_{2009,1} - \theta_{2007,1}$	−0.0020*
Banking choice (S.E.)			
Branch	0.4998** (0.0009)	$\theta_{2009,2} - \theta_{2007,2}$	−0.0229**
Age	1.0633** (0.0040)	$\theta_{2007,a}$	4.5811**
Single	1.4238** (0.2899)	$\theta_{2009,a}$	5.1820**
Credit market			
Loan portfolio (ϕ)		Bad loans distribution (θ_τ)	
Year 2009	−0.6507** (0.0272)	θ_τ	0.9465**
log(*TA*)	−0.0709** (0.0083)	Bank failure threshold (θ^F)	
		Year 2009	0.0111 (0.5238)
EC/TA	−1.3375** (0.4443)	log(*TA*)	0.0169* (0.0078)

Note. TA, Total assets; EC, equity capital.
*Significant at the 5% level; **significant at the 1% level.

In loan markets, the recent financial crisis (i.e., *Year* 2009) has had a negative and significant effect on banks' profitability in credit markets (i.e., κ_{jt}). Bank size negatively affects a bank's loan profitability. Large banks usually have many organizational hierarchies, so they rely heavily on hard information to process loan applications. As a result, they may reject profitable loans whose profitability cannot be justified by hard information, such as loans from small entrepreneurs who are hardworking but cannot provide required financial statements. The capital asset-to-total asset ratio has negative and significant effects on a bank's loan profitability as well. This ratio describes a bank's risk preference for market operations. A high capital asset-to-total asset ratio means a bank operates conservatively and may not be enthusiastic about seeking high-return loans. Using our estimated θ_τ, the fraction of bad loans of the moderately risky bank's loan portfolio[20] in 2007 has a mean of 0.0042 and standard deviation of 0.0190. The mean and standard deviation increase to 0.0095 and 0.0424, respectively, in 2009, so the recent financial crisis has raised the likelihood of defaults and the probability of insolvency. Finally, the bank size has a positive and significant effect on a bank's buffer against bankruptcy.

Using the estimated parameters, our model predicts the average loan return is 0.0844 in 2007 and 0.0705 in 2009, both of which are close to the corresponding average loan returns in the data.[21] Moreover, our prediction of the average bank's failure rate is 0.0139 in 2007 and 0.0202 two years later, both of which are also close to the corresponding actual probabilities of bankruptcy.[22] Our model clearly performs fairly well in capturing the key aspects of the retail banking industry.

6. Counterfactual Analysis

In this section, we perform policy simulation to examine the effects of the recent change in deposit-insurance coverage on market discipline and consumer welfare. We decompose the policy effects into several components and analyze them separately. We compare the policy effects across consumers and different market structures.

We carry out the policy experiments in 16 markets detailed in Appendix A, including the choices of the markets. For the sake of brevity, we present our counterfactual analysis of two markets, one a duopoly (Market 1) and the other an oligopoly (Market 2), in Tables 9(A)–11(B). We have similar results when performing our counterfactual analysis in the other 14 markets.

6.1. Policy Effect

The policy effect has two components. One is the direct welfare effect from the higher deposit-insurance coverage, and the other is the indirect welfare effect from the banks' reoptimizations under the new policy regime. We separately compute these two components and examine the overall policy effect.

Using the estimated consumer preferences and market conditions in 2009, we solve for the market equilibrium and compute consumer welfare for each of the following three scenarios:[23]

S1. Deposit-insurance coverage is $100,000.

S2. Deposit-insurance coverage is $250,000, and banks do not reoptimize (i.e., their deposit interest rates and risk caps are the same as those in S1).

S3. Deposit-insurance coverage is $250,000, and banks reoptimize.

S1 is our benchmark scenario, describing the market discipline and the consumer welfare under the old policy regime. The second scenario keeps the market discipline unchanged and raises the deposit-insurance coverage to $250,000, so factors other than the change in market discipline affect consumer welfare. S3 completes the market description under the new policy regime. Banks in S3 reoptimize their deposit interest rates and risk caps under the new policy regime, so in addition to the change in the deposit-insurance coverage, the change in market discipline influences consumer welfare. The welfare implication of the new policy regime depends on the consumer's portfolio size. We calculate the interest-rate measure of equivalent variation[24] for consumers with different portfolio sizes and use this measure to compare the welfare effects of the new policy regime on different consumers. The deposit interest rate is the price of deposits, so our interest-rate measure is consistent with the conventional wisdom of equivalent variation and is a reasonable tool for our welfare comparison.

We calculate the market discipline and the welfare effects and present them in Table 9(A) (duopoly) and Table 9(B) (oligopoly). We mainly discuss the results in Table 9(A), because the results in Table 9(B) tell a similar story. Under the old policy regime (S1), bank A's equilibrium deposit interest rate and risk cap are 0.0350 and 0.0862, respectively. After the ceiling of insured deposits increases to $250,000 (S3), bank A decreases its deposit interest rate to 0.0025 and increases its risk cap to 0.1165. Similar results hold for bank B. The new policy regime clearly weakens the market discipline and increases banks' moral hazard, both of which make banks behave less favorably toward consumers. Indeed, when the deposit-insurance coverage

Table 9(A). Policy Effect (Market 1)

	Market discipline (%)		Welfare effect	
	Deposit interest rate	Risk cap		Average consumer welfare
Bank A (S1)	3.50	8.62	Direct effect	3,083
Bank A (S3)	0.25	11.65	Indirect effect	−4,152
Bank B (S1)	2.89	7.60	Total effect	−1,069
Bank B (S3)	0.15	11.60	Equivalent rate	−3.27%

Table 9(B). Policy Effect (Market 2)

	Market discipline (%)		Welfare effect	
	Deposit interest rate	Risk cap		Average consumer welfare
Bank A (S1)	3.29	4.68	Direct effect	2,813
Bank A (S3)	0.99	13.69	Indirect effect	−4,578
Bank B (S1)	2.75	9.68	Total effect	−1,765
Bank B (S3)	0.95	16.68	Equivalent rate	−3.83%
Bank C (S1)	0.59	5.80		
Bank C (S3)	0.24	14.80		
Bank D (S1)	3.74	6.95		
Bank D (S3)	0.94	14.02		

increases, consumers have less incentive to discipline the bank's opportunistic behaviors, so the bank's cost of taking risks falls. This shift distorts the original trade-off between risk and return when the bank optimizes its loan portfolio, and encourages the bank to take more risks in the end. On the other hand, when the FDIC expands the deposit-insurance coverage, consumers, on average, demand less risk premium for their bank deposits.[25] As a result, the bank offers a lower deposit interest rate, which implies its cost of capital falls, and therefore the benefit of granting risky loans rises. In summary, the extension of the deposit-insurance coverage increases the bank's benefit of taking risks and decreases its cost of doing so, both of which provide the bank with incentives to behave opportunistically.

These opportunistic behaviors of banks may decrease consumer welfare, which the welfare effects displayed in Table 9(A) confirm. A quick inspection of the welfare effects tells us the new policy regime hurts depositors as the losses from the weakened market discipline (i.e., indirect effect) dominate the benefits from the additional deposit-insurance coverage (i.e., direct effect). The loss of consumer welfare on average is equivalent to a 3.27% drop in the deposit interest rates for all banks in the market.

6.2. The Effect of Portfolio Size

The previous experiment explores the overall consumer welfare effects of the policy change. In general, the welfare effects are heterogeneous across consumers, depending on the consumers' portfolio sizes. In this section, we explore this heterogeneity of the welfare effects across consumers and examine its relationship with the consumers' portfolio sizes.

We compute the welfare effects for the consumers whose portfolio sizes are \$50,000, \$200,000, \$300,000, and \$3,000,000 and present them in Tables 10(A) and 10(B). We first discuss the results in Table 10(A). The first column provides an example that consumers derive no benefit from the new policy regime. These consumers' portfolio sizes are so small that the original policy regime is sufficient to protect their bank deposits from any possible bank failure. Thus, the new policy regime only brings them a welfare drop caused by the weakened market discipline. Their welfare loss is equivalent to a 3.03% drop in the deposit interest rates for all banks in the market, which is the largest among the four cases. The remaining columns display the cases in which consumers gain from the extended deposit-insurance coverage, although the gain cannot compensate for the loss from the weakened market discipline. In general, consumers with large portfolio sizes are more likely to benefit from the higher insurance coverage, because they usually deposit more than the coverage limit specified by the old regime. The new policy regime may cause less harm to these consumers. Table 10(A) confirms this hypothesis. Comparing the interest-rate measure of equivalent variation (i.e., equivalent rate) across consumers, we can see the new policy regime causes less harm to consumers who have large portfolios. When the consumer's portfolio size is \$3,000,000, her welfare loss from the new policy regime is equivalent to a 0.02% drop in deposit interest rates for all banks in the market.

However, Table 10(A) tells only one side of the story, and Table 10(B) refutes this hypothesis.[26] In fact, the other side of the story is that consumers with large portfolio sizes may suffer more from the weakened market discipline, because they may have more bank deposits. Therefore, the total effect depends on the relative strength of these two forces (i.e., direct effect and indirect effect), so it may not be monotonic in the consumer's portfolio size. Table 10(B) shows the new policy regime benefits consumers with moderate portfolios and harms consumers who have either small or large portfolios. Among the four portfolio sizes shown in Table 10(B), consumers whose portfolio sizes are \$300,000 benefit the most from the new policy regime, which is equivalent to a 1.68% jump in deposit interest rates for all banks in the market. Intuitively, the benefit from the higher insurance coverage is bounded, whereas the loss from the weakened market discipline may not be. The new insurance coverage is \$250,000, so the maximal benefit from the higher insurance coverage (i.e., direct effect) is the benefit of the \$150,000 extra deposit-insurance coverage. On the other hand, the loss from the weakened market discipline (i.e., indirect effect) depends on the amount of the consumers' bank deposits, which may be positively related to their portfolio sizes. Thus, in principle, this loss may not be bounded above as the consumers' portfolio sizes grow. Altogether, consumers with moderate portfolios might gain more under the new policy regime than consumers with large portfolios.

In summary, the new policy regime causes heterogeneous welfare effects for consumers. Consumers with small portfolios always lose under the new policy regime because they cannot benefit from the higher insurance coverage. Moreover, the new policy regime may benefit consumers whose portfolio sizes are moderate and harm consumers whose portfolio sizes are large.

Table 10(A). Portfolio Size and Welfare Effect (Market 1)

	Size = 50,000	Size = 200,000	Size = 300,000	Size = 3,000,000
Direct effect	0	1,174	4,106	14,006.9
Indirect effect	−728	−2,820	−4,173	−14,007
Total effect	−728	−1,646	−67	−0.1
Equivalent rate (%)	−3.03	−2.18	−0.08	−0.0002

Table 10(B). Portfolio Size and Welfare Effect (Market 2)

	Size = 50,000	Size = 200,000	Size = 300,000	Size = 3,000,000
Direct effect	0	1,178	4,223	14,750
Indirect effect	−473	−1,834	−2,716	−15,383
Total effect	−473	−656	1,507	−633
Equivalent rate (%)	−1.93	−0.86	1.68	−0.68

6.3. The Effect of Market Competition

This section examines the relationship between market competition and the welfare effect of the new policy regime. A direct comparison between Tables 9(A) and 9(B) shows market competition magnifies the negative effects of the policy change and makes the new policy even more unfavorable to consumers. This result may not be robust, because the comparison ignores the market heterogeneity across the markets. To control the market heterogeneity, we fix the market in each experiment and focus on the simulated variation in competition in this market.

Similar to Section 6.1, we mainly discuss the results in Table 11(A), because the results in Table 11(B) tell a similar story. We repeat the first experiment but allow only one bank to be active in the market. We perform the policy experiment twice, because two banks are in the market.[27] Table 11(A) compares the welfare effects from the policy experiments with those when both banks are active.

Table 11(A). Competition and Welfare Effect (Market 1)

	Market	Bank A only	Bank B only
Direct effect	3,083	2,507	1,905
Indirect effect	−4,152	−2,527	−2,002
Total effect	−1,069	−20	−97
Equivalent rate (%)	−3.27	−0.06	−0.37

Table 11(B). Competition and Welfare Effect (Market 2)

	Market	Bank A only	Bank B only	Bank C only	Bank D only
Direct effect	2,873	1,382	2,605	1,019	1,471
Indirect effect	−4,578	−2,554	−3,008	−2,646	−1,692
Total effect	−1,765	−1,172	−403	−1,627	−221
Equivalent rate	−3.83	−1.54	−0.99	−1.57	−0.51

In Table 11(A), the first column denotes the welfare effect when the market is competitive, and the second and third columns display the welfare effects when market competition disappears. Market competition clearly exaggerates the welfare effect of the new policy regime. When the market is competitive, the average welfare loss from the new regime is equivalent to a 3.27% drop in deposit interest rates for all banks in the market. The corresponding interest-rate measure of equivalent variation drops to 0.09% or 0.37%,[28] when only bank A or bank B is active, respectively.

In general, market competition increases banks' moral hazard to take excessive risks and makes bank deposits more risky, in which case the deposit insurance has a greater impact on market discipline. When banks optimize their loan portfolios, they trade off loan returns and default risks. The bank's opportunity cost of taking additional risk is the increment of its probability of bankruptcy, in which case the bank loses all its profits. Because the bank's profit decreases as the market becomes more competitive, the bank's cost of behaving opportunistically drops when the market is competitive (Villas-Boas and Schmidt-Mohr 1999). As a result, market competition provides banks with incentives to take excessive risks in credit markets. These risks are eventually passed to consumers because banks are financial intermediaries that transfer funds in the deposit markets to loans in the credit markets. Thus, market competition creates moral hazard for banks and makes bank deposits more risky.

When consumers are concerned about the security of their money at banks, the banks' opportunistic behaviors could generate the market discipline. This market discipline is stronger in more competitive markets, because market competition induces banks to behave more opportunistically. On the other hand, deposit insurance protects consumers from losses caused by bank failures, so it substantially alleviates consumers' security concerns about their bank deposits and therefore weakens the strong market discipline coming from the market competition. Thus, the depreciation of the market discipline is greater in more competitive markets. In summary, market competition gives banks incentives to take excessive risks, which is the source that magnifies the negative effects of deposit insurance on market discipline.

7. Discussion and Conclusion

This paper explores the policy implications of the recent change in deposit-insurance coverage. We focus on the effect of the new policy regime on market discipline and consumer welfare. We develop and estimate a stylized model of the retail banking industry, in which banks are considered financial intermediaries that transfer funds in deposit markets to loans in credit markets.

Our counterfactual analysis shows several interesting findings. First, the new policy regime could weaken market discipline and harm consumers. When the deposit-insurance coverage increases, banks offer lower deposit interest rates and grant more risky loans, both of which disfavor consumers. Second, the new policy regime hurts consumers with small portfolios more, because the interest-rate measure of equivalent variation decreases[29] in the consumer's portfolio size. In general, consumers who have moderate portfolios may be more likely to benefit from the extended insurance coverage, so they are less resistant to the new policy regime. Third, market competition exaggerates the bank's moral hazard caused by the deposit insurance and further weakens market discipline, which makes the new policy regime even less appealing to consumers.

Our work highlights the economic impact of deposit insurance. In our model, we focus on the bank's default risk, so an exploration of the effect of the new policy regime on banks' moral hazard and market discipline along alternative dimensions, such as the bank's liquidity risk, will be interesting. The deposit insurance creates a buffer against liquidity shocks for banks, so banks may have incentives to undertake more illiquid investments. Furthermore, as we discussed before, the myopic characterization of banks' behaviors may be parsimonious, because banks could be forward looking in deciding risk caps and deposit interest rates. Such a forward-looking banking sector might make the moral hazard effect even larger, not smaller. Nevertheless, a dynamic empirical framework is needed to investigate these issues, especially the market discipline and banks' moral hazard when banks decide their portfolio liquidity.

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Appendix A. Algorithm of Counterfactual Experiments

Step 1. Select the markets for the counterfactual analysis. We separately sort and group the markets in year 2007 and year 2009 based on the ascending order of the number of active banks in each market. We drop the markets in which either only one bank is active or the banks active in year 2007 are not the same as the banks active in year 2009. Then we randomly choose two markets from each group (e.g., within a group, each market has the same number of active banks) and form the pool of markets for our counterfactual analysis. We consider the groups in which the market has 2 to 9 active banks, and choose 16 markets in total.

Step 2. Solve for the market equilibrium. First, we compute the bank's default risk following Section 3.2.2. Given a bank's deposit interest rate r_{jt} and risk cap ρ_{jt}, its default risk is given by Equation (13), where $\bar{H}(\cdot \mid r_{jt}, \rho_{jt})$ is defined in Equation (12).

Second, we compute the bank's demand in deposit markets following Section 3.1. We draw 1,000 consumers in each market and compute consumer i's utility of saving at bank j as defined in Equations (4) and (5) for all consumers. Then we compute bank j's deposit demand from the numerator of Equation (6).[30]

Third, we compute bank j's profit function following Section 3.2.3. We assume all banks operate in no more than one market, so they maximize their profits based on the conditions of the market in which they operate. In other words, we do not consider the multimarket effect in the bank's profit maximization. Bank j's profit-maximization problem is given by Equation (15).

Fourth, we derive the first-order conditions from the bank's profit-maximization problem for all banks and solve for the market equilibrium (i.e., deposit rates and risk caps).

Step 3. Compute the policy effect. We use the same (1,000) consumer draws and the market equilibrium computed in Step 2 to compute the policy effect.

Experiment 1: Welfare Effect

We use the market conditions (e.g., consumers and banks) in 2009 to perform this experiment. Following Step 2, we compute the market equilibrium under the old deposit-insurance regime (i.e., insurance coverage is \$100,000) and then compute the corresponding consumer welfare W_1. The consumer's welfare is defined as the sum of the utilities of all consumers in the market. For example, by (1) and (2), the consumer welfare W_1 is

$$W_1 = \textstyle\sum_{i,j} \hat{u}_{ijmt} \quad \text{where}$$
$$\hat{u}_{ijmt} = \begin{cases} \hat{\lambda}\hat{v}_{ijmt} + X_{jmt}\hat{\theta}^D_{imt} + \hat{\xi}_{jmt} + \hat{\varepsilon}_{ijmt}, & \text{if } j \neq 0, \\ \hat{\lambda}\hat{v}_{i0mt} + \bar{\varepsilon}_{i0mt}, & \text{if } j = 0. \end{cases} \tag{A.1}$$

Then we fix this market equilibrium and compute consumer welfare W_2 under the new deposit-insurance regime (i.e., insurance coverage is \$250,000). The difference between these two consumer welfares is the direct effect (i.e., pure insurance coverage effect) of the policy reform

$$\text{Direct effect} = W_2 - W_1. \tag{A.2}$$

Finally, we solve the market equilibrium when banks can reoptimize under the new policy regime and compute consumer welfare W_3. The difference between W_2 and W_3 is the indirect effect (i.e., moral hazard)

$$\text{Indirect effect} = W_3 - W_2. \tag{A.3}$$

The total policy effect is the sum of the direct effect and the indirect effect

$$\text{Total effect} = \text{direct effect} + \text{indirect effect} = W_3 - W_1. \tag{A.4}$$

Experiment 2: The Impact of Consumers' Financial Portfolio Size on Welfare

We consider four portfolio sizes: \$50,000, \$200,000, \$300,000, and \$3,000,000. For each portfolio size, we use (A.1) to compute the consumer welfare in all three scenarios (i.e., S1, S2, and S3). In each scenario, we use the corresponding market equilibrium computed in Experiment 1 to compute consumer welfare. For example, in the first scenario with the portfolio size \$50,000, we set $w_{imt} = 50{,}000$ for all (1,000) consumers and use the market equilibrium of this scenario computed in Experiment 1 to calculate consumer welfare. After we get all consumer welfares, we use (A.2)–(A.4) to compute the direct effect, the indirect effect, and the total effect, respectively, in a similar manner.

Experiment 3: The Impact of Market Competition on Welfare

We separately sort the banks in each market based on the ascending order of the bank's FDIC certificate number. In each market, we keep the first bank (i.e., the bank with the smallest FDIC certificate number in the market) that is active and shut down all other banks. Then we perform similar welfare calculations as in Experiment 1.

We use the market conditions (e.g., consumers and banks) in 2009 to perform this experiment. First, we compute the market equilibrium under the old deposit-insurance regime (i.e., insurance coverage is \$100,000) and then compute the corresponding consumer welfare W_7. Then we fix this market equilibrium and compute consumer welfare W_8 under the new deposit-insurance regime (i.e., insurance coverage is \$250,000). Finally, we solve the market equilibrium when banks can reoptimize under the new policy regime and compute consumer welfare W_9. We use (A.1) when computing these consumer welfares. By (A.2)–(A.4), we compute the direct effect, the indirect effect, and the total effect, respectively.

Now we fix a market and compare the policy effects (i.e., direct effect, indirect effect, and total effect) in Experiment 1 with those in this experiment. For example, in Market 1, we compare the direct effect in this experiment (i.e., $W_8 - W_7$) with that in Experiment 1 (i.e., $W_2 - W_1$), from which we learn the impact of market competition on the policy's direct effect. Then we compare the indirect effect in this experiment (i.e., $W_9 - W_8$) with that in Experiment 1 (i.e., $W_3 - W_2$), from which we learn the impact of market competition on the policy's indirect effect. Finally, we compare the total effect in this experiment (i.e., $W_9 - W_7$) with that in Experiment 1 (i.e., $W_3 - W_1$), from which we learn the impact of market competition on the policy's total effect.

We perform this comparison for all 16 markets in our counterfactual analysis and then derive the implication of the market competition on the policy effect.

Experiment 4: The Impact of the Credit Market on Welfare

We use the market conditions (e.g., consumers and banks) in 2009 to perform this experiment. Following Step 2, we compute the market equilibrium under the old deposit-insurance regime (i.e., insurance coverage is $100,000). In equilibrium, the set of borrowers taking loans is the triangle BCD in Figure 1. Then the population of borrowers taking loans is the area of the triangle BCD. Given bank j's equilibrium deposit interest rate r^*_{jt} and risk cap ρ^*_{jt}, the base of this triangle (i.e., the length of BD) is $\rho^*_{jt} - (r^*_{jt} + \eta_{jt})/\hat{\kappa}_{jt}$, where η_{jt} is bank j's noninterest expense from the data, and $\hat{\kappa}_{jt}$ is the estimated slope of bank j. The height of this triangle (i.e., the length of CD) is $\hat{\kappa}_{jt}\rho^*_{jt} - (r^*_{jt} + \eta_{jt})$. Thus, the area of the triangle BCD is

$$\text{Area of } \Delta BCD = \frac{1}{2}\left(\rho^*_{jt} - \frac{r^*_{jt} + \eta_{jt}}{\hat{\kappa}_{jt}}\right)(\hat{\kappa}_{jt}\rho^*_{jt} - (r^*_{jt} + \eta_{jt})). \quad \text{(A.5)}$$

We denote this area calculated using the old policy regime as the area of ΔBCD_{2007}.

We perform the same computation for the new policy regime, under which the insurance coverage is $250,000. We denote the area of the triangle BCD in this computation as the area of ΔBCD_{2009}. Then the percentage change of the borrowers taking loans at bank j is

$$\frac{\text{Area of } \Delta BCD_{2009} - \text{Area of } \Delta BCD_{2007}}{\text{Area of } \Delta BCD_{2007}}. \quad \text{(A.6)}$$

We calculate this percentage change for all banks in our counterfactual analysis.

Appendix B. Derivation of Equation (22)

We start with Equation (21). The left-hand side of Equation (21) is the empirical consumer's conditional expected portfolio return, and the right-hand side of Equation (21) is our model-implied consumer's conditional expected portfolio return. We view our model-implied consumer's conditional expected portfolio returns as the simulated data generated by our structural model given parameters $\theta_{mt,1}$, $\theta_{mt,2}$, and θ_{at}. The fundamental idea of indirect inference is to view the empirical data and the simulated data along the dimension defined by an auxiliary model characterized by some auxiliary parameters. The number of auxiliary parameters has to be equal to or greater than the number of parameters in the structural model. The indirect inference approach chooses the auxiliary parameters in such a way that both the empirical data and the simulated data look similar when viewing them along the dimension defined by the auxiliary model.

Our auxiliary model is a quadratic function of $\log(w_{imt})$ with the white noise χ_{imt}

$$\begin{aligned}&\text{Conditional Expected Return}_{imt}\\ &\quad = \pi_0 + \pi_1 \log(w_{imt}) + \pi_0 \log^2(w_{imt}) + \chi_{imt}. \quad \text{(B.1)}\end{aligned}$$

Then our auxiliary parameters are π_0, π_1, and π_2. Clearly, the number of our auxiliary parameters is equal to the number of structural parameters, satisfying the modeling condition imposed by the indirect inference approach.

We estimate the auxiliary model using the empirical data and get the corresponding estimates. In other words, we run the regression

$$E\left[\frac{\text{inc}_{imt}}{w_{imt}}\middle| w_{imt}\right] = \pi_0 + \pi_1 \log(w_{imt}) + \pi_0 \log^2(w_{imt}) + \chi_{imt} \quad \text{(B.2)}$$

and get the estimated coefficients $\hat{\pi}_0$, $\hat{\pi}_1$, and $\hat{\pi}_2$. These coefficients are the "view" of the empirical data along the dimension defined by our auxiliary model (B.1).

On the other hand, we estimate the auxiliary model using the simulated data and get the corresponding estimates. The estimation process is the following. First, we fix our structural parameters $(\theta_{mt,1}, \theta_{mt,2}, \theta_{at})$ and simulate the model-implied consumer's conditional expected portfolio return

$$\begin{aligned}y_{imt} = E_m\Bigg[&\sum_{j\in M(j)\cup\{0\}} \gamma(w_{imt}, j, m)\\ &\cdot E_{a_{imt}}\left[\frac{s^*_{ijmt}}{w_{imt}} R_{ijmt} + \left(1 - \frac{s^*_{ijmt}}{w_{imt}}\right) E[r_{i0mt} \mid w_{imt}]\middle| w_{imt}, j, m\right]\Bigg].\end{aligned}$$

Second, we run the regression

$$y_{imt} = \pi_0 + \pi_1 \log(w_{imt}) + \pi_0 \log^2(w_{imt}) + \chi_{imt} \quad \text{(B.3)}$$

and get the estimated coefficients $\tilde{\pi}_0$, $\tilde{\pi}_1$, and $\tilde{\pi}_2$. These coefficients are the "view" of the simulated data along the dimension defined by our auxiliary model (B.1).

We repeat our estimation of $\tilde{\pi}_0$, $\tilde{\pi}_1$, and $\tilde{\pi}_2$ 100 times and denote the estimated coefficients of the Hth estimation as $\tilde{\pi}^H_0$, $\tilde{\pi}^H_1$, and $\tilde{\pi}^H_2$. Then we compute the sample estimate of the "binding function" (Gourieroux et al. 1993, p. S88) as follows:

$$\frac{1}{100}\sum_H \tilde{\pi}^H_k(\theta_{mt,1}, \theta_{mt,2}, \theta_{at}), \quad k \in \{0, 1, 2\}. \quad \text{(B.4)}$$

According to the indirect inference, when the structural parameters $(\theta_{mt,1}, \theta_{mt,2}, \theta_{at})$ take their true values, both $\hat{\pi}_k$ and $(1/100)\sum_H \tilde{\pi}^H_k(\theta_{mt,1}, \theta_{mt,2}, \theta_{at})$ converge to the same "pseudo" true value π_k, $k \in \{0, 1, 2\}$, as the sample size goes to infinity.[31] Therefore, we have the following moment condition for the structural parameters $\theta_{mt,1}$, $\theta_{mt,2}$, and θ_{at}:

$$E[\hat{\pi}_k - \tilde{\pi}_k] = 0, \quad k = 0, 1, 2,$$

as shown in (22).

Endnotes

[1] During the 2008 financial crisis, depositors believed bank deposits were risky and withdrew their deposits electronically. As a result, many banks faced silent bank runs.

[2] We calculate our deposit interest rates based on the financial statements of the second quarter call report.

[3] This definition is consistent with that in Ho and Ishii (2011) and Cohen and Mazzeo (2007), except the former's threshold is 90% and the latter's is 80%.

[4] Another possible alternative explanation is that the crisis affected large banks more heavily than small banks, because large banks are usually national banks operating in many different markets, whereas small banks are local banks with more flexibility. As a result, compared with small banks, large banks have to offer lower interest rates and higher risk caps to deal with the heavy losses. However, in fact, at the per-dollar deposit level, the crisis may not have affected large banks more heavily than small banks, because multimarket operations allow large banks to pool the loss at a per-dollar deposit level across markets, and therefore protect them from extreme hits. When a crisis casts heterogeneous effects across markets, the effect on small banks at a per-dollar deposit level may be either greater or smaller than that on large banks, depending on the markets in which small banks operate. Thus, compared with small banks, large banks may not necessarily offer lower deposit interest rates and higher risk caps to deal with the losses. We thank an anonymous reviewer for the insightful suggestion.

[5] The asset position β_{imt} can be any real number, because a short sale is possible in the market. For example, if β_{imt} is greater than 1, consumer i has a short position in risk-free assets.

[6] Amel and Starr-McCluer (2002) find consumers tend to cluster their purchases of deposit services with their primary financial institution. This assumption that every consumer chooses either one bank at which to deposit or not to deposit is standard in the banking literature. The 2010 Survey of Consumer Finances also reveals the average number of savings accounts is 1 if including consumers who do not have any savings account, and 1.8 otherwise. Furthermore, over 80% of consumers who have large deposits do not fully utilize their deposit-insurance coverage. All of this anecdotal evidence suggests the single-account assumption is not so restrictive.

[7] This assumption implies that, conditional on the default risk, the number of high-return loans is about the same as the number of low-return loans. Thus, more high-risk loans than low-risk loans are along the risk dimension, and more low-return loans than high-return loans are along the return dimension. These implications are consistent with the practice in the loan market.

[8] Hard information is defined as the information a third party can verify, such as financial statements and tax statements.

[9] Soft information is defined as the information only the person who produces it can verify. For example, a loan manager personally knows the entrepreneur is smart and hardworking.

[10] The operation cost is defined as the bank's noninterest expense normalized by its bank size.

[11] We retrieved the data from the Federal Deposit Insurance Corporation website: https://www5.fdic.gov/hsob/HSOBSummaryRpt.asp?BegYear=2007&EndYear=2012&State=1&Header=0 (accessed June 2013).

[12] Our data do not include the depositor's banking choice, so we are not able to learn the depositor's deposit return from our bank-side data. On the other hand, our data about the depositor's interest income do not distinguish her deposit-interest income from her income coming from other interest-earning instruments. Thus, we are unable to learn the depositor's deposit return from our depositor-side data either.

[13] The parameters of depositors' preferences for bank depository services are identified by the variations of the bank deposits observed in our bank-side data (i.e., data described in Tables 2 and 3).

[14] We follow Ho and Ishii (2011) and use the cost shifters as a set of instrument variables. The commercial banking service as an industry is rather mature and has had well-established service standards for a long time. Specifically, we divide the bank's labor expense over its number of equivalent full-time employees to get the wage, and normalize the expenses of premises and fixed assets by the bank's assets.

[15] We use the variations of the consumers' financial portfolio returns in our consumer-side data (i.e., data described in Table 4) to estimate the parameters of the consumers' optimal-savings problem.

[16] This probability comes from our demand model.

[17] In Appendix B, we further detail the derivation of these moment conditions, namely, Equation (22).

[18] We use the empirical distributions of r_{jt} and ρ_{jt} to calculate the corresponding expected value.

[19] We do not use the mean consumer here, because the distribution of the consumer's portfolio size is highly skewed to the right.

[20] We define the moderately risky bank as the bank whose expected loan loss $E[\rho \mid r_{jt}, \rho_{jt}]$ is the mean of ALLL.

[21] Table 3 shows the average loan return was 0.0775 in 2007 and 0.0596 in 2009.

[22] The actual probability of bankruptcy is the ratio of the number of failed banks to the total number of banks. From Table 3, the actual probability of bankruptcy was 0.0013 in 2007 and 0.0329 in 2009.

[23] We take 1,000 draws when calculating the consumer welfare.

[24] The interest-rate measure of equivalent variation is defined as the deposit interest rate that the consumer is willing to pay to avert the policy change.

[25] Consumers demand risk premium for their bank deposits as they are aware of the possibility of bank failures and the limited deposit-insurance coverage offered by the FDIC.

[26] The difference between Tables 10(A) and 10(B) comes from the market-competition effect described in Section 6.3. The income effect has two parts: the direct effect and the indirect effect. The former increases in the consumer's portfolio size and is bounded above, whereas the latter decreases in the consumer's portfolio size and is not bounded. Thus, some critical level of the portfolio size exists, beyond which the income effect decreases in the consumer's portfolio size. The market-competition effect magnifies the indirect effect, so it reduces the critical level of the portfolio size. As a result, we are more likely to observe the "moderate"-level portfolio size (i.e., the critical level of the portfolio size) when the market becomes more competitive (e.g., Table 10(B)).

[27] We perform the policy experiment four times in Table 11(B) because four banks are in the market.

[28] Both interest-rate measures of equivalent variations are negative because the new policy regime reduces consumer welfare. Because our focus is the magnitude of the welfare effect, we do not include the negative sign here.

[29] We focus on the magnitude of the interest-rate measure of equivalent variation, so we ignore the negative sign in our comparison here.

[30] The numerator of Equation (6) is the amount of deposits bank j collects in the market, and the denominator is the total amount of deposits in the market.

[31] The sample size is the number of observations in our consumer data set, which is 1,454, shown in Table 4.

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