Competition between single-market and multimarket banks: Evidence from the U.S. banking industry*

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Abstract

This paper estimates a dynamic model of local entry for the U.S. banking industry which considers two types of competitors: Single-market and Multimarket banks. Banking deregulation started a process were Single-market banks, once a majority heavily protected by both intrastate and interstate laws are being continuously replaced by multimarket banks.

The econometric model allows for differences between single-market and multimarket banks in competitive effects, sell-off values, and sunk costs of entry. The contribution of the paper is twofold. First, it discusses the coexistence of firms with such a different geographic scope in an industry. Second, it provides evidence of the viability of single-market banks in the U.S. banking industry. Results suggest that single-market banks have profit advantages over multimarket banks, but single-market banks pay a sunk cost of entry which is 25 percent higher. These higher barriers to entry can be linked to start-up costs, advertisement, and hiring costs for management positions.

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1. Introduction

After a long history of branching restrictions, the market structure in the U.S. banking industry presents direct competition between different organizational forms in the same geographic market: *single-market* and *multimarket banks*. For example, in the city of Boston there is competition between Bank of America and Meetinghouse Bank. Bank of America owns 4,896 offices located in 35 different states and has 1,600 billions of $ in assets; Meetinghouse Bank owns 2 offices located in Boston and has 126 millions of $ in assets.

How can such different firms coexist in the same market? A plausible explanation is that single-market banks have a niche market where they enjoy a comparative advantage over multimarket banks. Who are the clients in this niche market? Previous work suggest that borrowers with projects whose profitability depends crucially on the borrower's reputation.[1] Importantly this reputation can only be learned by the lender through personal interaction and cannot be truthfully transmitted within a hierarchical organization. These loans are usually called "soft information" loans. On the other hand, multimarket banks have a comparative advantage when the borrower reputation can be learned using "hard information" like financial statements, credit history, credit scoring, etc.

In this paper I look for evidence consistent with the relationship lending explanation for the comparative advantage of single-market banks. To do that, I estimate differences in profitability between single-market and multimarket banks in small geographic markets. I focus on small geographic markets because in these markets firms are smaller and less sophisticated thus more likely to be good candidates for a relationship loan. Moreover, in smaller markets it is more likely that the branch manager has information about the community that is difficult to transmit within a hierarchical organization. The results of the paper show that single-market banks have a comparative advantage in small markets controlling for market structure, market size variables and time-invariant market unobservables.

A better understanding of the differences between single-market and multimarket is a

[1] See, for example, Petersen and Rajan (1994) and Stein (2002).

relevant economic question for the U.S. banking industry due to recent regulatory changes in the industry. Historically the banking industry in the United States was subject to strict regulation from the state and federal governments. There were particularly stringent restrictions to opening branches in different geographic markets in the same state and across different states. In the period 1970-1990 the states relaxed the branching restrictions within the state, and the Riegle-Neal Interstate Banking and Branching Efficiency Act enacted in 1994 eliminated almost all remaining branching restrictions between states. The welfare effects of the Riegle-Neal may be important. On the one hand, some economists stress that the act lowers barriers to entry that can increase competition at the local market level, and it can allow banks to exploit economies of scale and risk diversification strategies. On the other hand, a change in the distribution of banks may imply a change in the access to or the cost of credit for agents traditionally served for single-market banks. If there is compelling evidence that single-market banks have a comparative advantage with some agents, we may learn that a pro-competition policy may have some unexpected distributional consequences that policy makers might want to consider when designing new policies.

After the Riegle-Neal Act the U.S. banking industry shows a slow but continuous process of structural change in the market structure of the industry. In the sample of small markets, the average market structure changed from three single-market banks and two multimarket banks in 1994 to two single-market banks and four multimarket banks in 2007. What is a reasonable explanation behind this change in the market structure? A potential suspect is the expansion cost of single-market banks. Although this cost is unobservable for the researcher, Pakes, Ostrovsky, and Berry (2007)(POB) propose to infer the entry costs of firms using data on entry and exit decisions, the evolution of the market structure and the firm's profit function. I apply POB approach to estimate the entry costs for single-market and multimarket banks. The results show that single-market banks face higher entry costs than multimarket banks. These results can explain the finding in Aguirregabiria, Clark, and Wang (2015) that the Riegle-Neal Act opened the door for potential gains due to risk diversification for banks, but these gains remained largely unexploited for small banks. This paper offers a plausible explanation: the expansion costs for small banks are too large so it is not profitable for small banks to follow a risk diversification strategy.

This paper relates with several empirical papers that study agency problems in soft information loans in the banking industry. In a seminal paper Petersen and Rajan (1994) find that a solid relationship between a bank and a small firm has a positive effect on the availability of funds for the creditor. In this paper I study a related but different question: whether the geographic scope of a bank creates an informational advantage with small firms. Brickley, Linck, and Smith Jr. (2003) using data from Texas in 1998, estimate the probability that a large bank owns a branch conditional on the type of local market: large urban market, small urban market, or rural market. They find that the probability that a large bank owns a branch decreases significantly in a rural market. Their findings are consistent with the results is this paper, but the identification strategy is different. This paper exploits the panel data structure of the data while Brickley, Linck, and Smith Jr. (2003) exploit the cross-section variation in the data. Finally, Berger, Miller, Petersen, Rajan, and Stein (2005) using bank-firm matched data find evidence consistent with small bank specialization in soft information loans. In particular, they find that large banks lend to less opaque borrowers, at a greater distance between firm and bank headquarters, with less personal interaction with the borrower, and they form shorter and less exclusive relationships. A difference with Berger, Miller, Petersen, Rajan, and Stein (2005) is that in this paper the relevant difference between banks is not size but geographic scope. Moreover, geographic scope seems a feature more suitable for the soft information story.

A related literature studies the effect of the banking market structure on small firms. Sapienza (2002) measures the effect of bank mergers on loan interest rates and credit supply for Italy. Sapienza finds evidence that, after a large bank acquires a small bank, small borrowers of the target bank are less likely to borrow from the consolidated bank. This evidence is consistent with small banks having a comparative advantage in small business loans. In a recent paper, Canales and Nanda (2012) evaluate whether the presence of decentralized banks – banks where branch managers have greater autonomy over lending decisions – is beneficial for small firms in Mexico. Interestingly, they find that the result is ambiguous and it depends on the level of competition: only in a more competitive environment a greater presence of decentralized banks implies lower loan interest rates for small firms.

Finally, there are some papers that analyze the effects of the Riegle-Neal Act. In a sample of large urban markets (MSA) Dick (2007) finds that banking markets became less concentrated and banks became more efficient after the Riegle-Neal Act. Rice and Strahan (2010) find that small firms are more likely to borrow from banks and at a lower interest rate after the Riegle-Neal Act. These results do not necessarily contradict the findings in this paper because their sample consists mainly of large urban markets. Finally, Aguirregabiria, Clark, and Wang (2015) seek to measure efficiency effects due to the Riegle-Neal Act. They find that the act expanded substantially the potential gains in risk diversification due to the possibility of expanding to other states. However, few small banks took advantage of these risk diversification possibilities.

The rest of the paper is structured as follows. The next section reviews the history of the U.S. banking stressing recent changes in market structure. The data used to estimate the model are described in section 3. Section 4 presents the entry/exit model used in the structural estimation. Section 5 describes the two-stage procedure used in the estimation. Section 6 reports and discusses the main results of the estimation. Final remarks and conclusions are presented in section 7.

2. Industry background

The U.S. banking industry has a remarkable feature compared with the banking industry in other countries: 75 percent of U.S. banking institutions have presence in only one local market, and these banks make around 40 percent of all banking loans to small businesses and farms.

This feature of the U.S. banking industry is not random but the consequence of restrictions on the geographic expansion of banks that have a long history in the United States. Because the U.S. Constitution prevented states from issuing fiat money and from taxing interstate trade, the states used their power to grant bank charters to generate a substantial part of state revenues. A state received no charter fees from banks incorporated in other states, so states prohibited out-of-state banks from operating in their territories. These were called *interstate branching restrictions*. States would grant a charter for a specific location or limit bank branches to that city or county. By adopting branching restrictions, states created a series of local monopolies from which they could extract part of the rents. These were called *intrastate branching restrictions*.

In the period 1970-1994, states started to deregulate these geographic restrictions. There were different stages of deregulation. First, states relaxed intrastate branching restrictions. Second, states signed bilateral agreements allowing banks chartered in one state to open branches in the other state and vice versa. Though the deregulation phenomenon was quite extended, different states showed different timing and intensity in their deregulation. See Kroszner and Strahan (1999) for a political economy explanation of the different speed in the deregulation across states.

In 1994, the Congress passed the Riegle-Neal Interstate Banking and Branching Efficiency Act that effectively permitted banks and holding companies to enter any state. Until 1997 the states had the option to opt-in or opt-out some of the provisions in the act, but most of the states decided to opt-in in 1994.

In part as a consequence of such regulatory changes, the industry became more concentrated. Figure 1 shows that the number of banks halved between 1979 and 2007 and decreased 25 percent between 1994 and 2007.

Aggregate industry trends may differ with the trends at the local market level. Table 1 shows the evolution of concentration and market structure at the aggregate level and at the local market level. Local markets are classified as large urban markets, small urban markets and rural markets. A large urban market is defined as a Metropolitan Statistical Area, an urban area with a core of more than 50,000 inhabitants and contiguous counties. A small urban market is defined as a Micropolitan Statistical Area, an urban area with a core of more than 10,000 inhabitants but less than 50,000 inhabitants and contiguous counties. A rural market is a county not classified as a Metropolitan or Micropolitan Statistical Area.[2] Interestingly, concentration indexes at the local market level remained steady even when aggregate concentration increased.

The market structure changed after the deregulation. Figure 1 shows that the number of multimarket banks increased a 27 percent in the period 1994-2007 and the number of single-market banks decreased more than 40 percent in the same period. Looking at the numbers in terms of branches is even more striking as shown in figure 2. Table 1 reports the evolution of the market structure for local markets. The mean market structure in a large urban market changed from 19 single-market banks (SM banks) and 9 multimarket banks (MM banks) in 1994 to 14 SM banks and 15 MM banks in 2007; the mean market structure in a small urban and rural market changed from 3 SM banks and 2 MM banks in 1994 to 2 SM banks and 4 MM banks in 2007.

Tables 2 and 3 show the sources of variation in the number of single-market and multimarket branches. The dynamics in the number of branches is decomposed in the contribution of branch openings, branch closings, mergers at the bank level, and switching in the bank type (a SM bank becoming a MM bank). Branch opening and closing explain an important part of the variation in the number of branches. Bank mergers are important in the sample period. However most of the mergers during this period were out-of-market mergers and this type of merger do not affect the market structure at the local market level. In the rest of the paper, I consider that merger decisions are exogenous from the point of view of the local market. This assumption is a reasonable approximation to the problem at hand given the difficulty to model merger decisions taken at the bank level using a model at the level of a local market.

[2] Metropolitan Statistical Areas and Micropolitan Statistical Areas are geographic areas defined by the U.S. Office of Management and Budget and used by the Census Bureau and other federal government agencies for statistical purposes.

3. Data

3.A. Data sources

The data set consists of yearly data for nearly all commercial banks and thrifts in United States and socioeconomic data at the market level for the period 1994-2007. The bank data were obtained from four sources: the Summary of Deposits (SOD) and the Institution Directory from the Federal Deposit Insurance Corporation (FDIC), the Reports on Condition and Income (Call Reports) from the Federal Reserve Bank of Chicago (FED), and the Thrift Financial Reports from the Office of Thrift Supervision (OTS).

The Summary of Deposits is a yearly survey conducted by the FDIC, a government corporation that insures deposits, examines and supervises financial institutions, and manages receiverships. The FDIC requests all FDIC-insured banks to submit a form with the amount of deposits in each branch at June, 30th each year. The Summary of Deposits includes deposits, branch's location, and branch's ownership information. The Summary of Deposits data are used to construct the number of SM incumbents, the number of MM incumbents, and entry and exit variables.

To identify mergers I complemented the data in the SOD with the FDIC's Institution Directory. The Institution Directory lists structural changes in bank institutions: the date a bank began operations, the date a bank finished operations, and the reasons for finishing operations. In case a bank merges with another bank, the Institution Directory includes the bank code of the acquirer.

Call Reports are available for all commercial banks regulated by the FED, FDIC, and the Comptroller of the Currency. The Call Reports contain balance sheet information collected on a quarterly basis. I use the Call Reports data to construct deposit interest rates, loan interest rates, default rates, wage expenditures, and other costs. I use the second quarter information to make it comparable with the SOD information. Thrift Financial Reports provide the same information for thrifts.

Demographic data at the local market level come from the U.S. Census Bureau, the

Bureau of Economic Analysis (BEA), and the Bureau of Labor Statistics (BLS). Population, income per capita, number of employees, and average wage come from the BEA's Local Area Personal Income, number of establishments comes from the U.S. Census Bureau' County Business Patterns, and consumer price indexes come from the BLS's CPI.

3.B. Variable definitions

Local market definition. A local market definition should balance two contradictory objectives. On the one hand, it should be large enough so that households and firms in the local market do not use banking services from banks outside the local market. On the other hand, it should be small enough so that there are no distinct or overlapping submarkets within the local market.

To satisfy those requirements I selected: (i) Small urban markets and rural markets, (ii) with less than 100,000 inhabitants, and (iii) with less than 8 single-market and 8 multimarket incumbent banks in the period 1994-2007.

As mentioned above, a small urban market is a Micropolitan Statistical Areas, a set of counties with at least one urban cluster of at least 10,000 but less than 50,000 population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties. A rural market is a county not classified as Micropolitan or Metropolitan Statistical Areas.[3]

I dropped large urban areas and markets with more than 100,000 inhabitants to avoid the presence of distinct and overlapping submarkets. I dropped markets with more than 8 single-market and 8 multimarket incumbent banks for computational reasons. The computational time of the estimation increases exponentially in the number of incumbents so there are practical limits to number of incumbents that the estimation can handle. I relaxed the selection rule slightly to check that the results are robust to small changes in the maximum number of incumbents.

The final sample consists of 1,691 local markets. The sample includes small urban

[3]A Metropolitan Statistical Area is a set of counties with at least one urbanized area of 50,000 or more population.

and rural markets and it covers 12 percent of the total population in the United States. Figure 3 shows a map of the United States with large urban markets in grey, small urban markets in black, and rural counties in white. The map shows that the sample is more representative of the Midwest and South regions rather than the West and Northeast regions. For example, the sample represents 30 percent of the population in the East South Central Division (Alabama, Kentucky, Mississippi, Tennessee) and West North Central Division (Iowa, Nebraska, Kansas, North Dakota, Minnesota, South Dakota, Missouri), but around 5 percent of the Middle Atlantic Division (New Jersey, New York, Pennsylvania) and Pacific Division (Alaska, California, Hawaii, Oregon, Washington).

The selection of the sample reflects the fact that it is difficult to properly identify a relevant market in large urban areas for retail activities. To deal with this problem, empirical researchers select markets where a relevant market is clearly defined. For example, Bresnahan and Reiss (1991)'s seminal paper selected 202 isolated markets at least 20 miles from the nearest town of 1,000 people or more, Mazzeo (2002) selected 492 markets excluding MSA and counties with more than 15 firms, and Seim (2006) selected 151 markets which consisted in cities with population between 40,000 and 150,000.

Table 4 shows descriptive statistics for the sample of local markets. The median market has a population of 15,000 inhabitants, an income per capita of $21,000, and 343 business establishments. This shows that local markets in the sample are relatively small. However there is enough variability in the sample in population, employees, establishments, and population density that can be exploited in the estimation. As usual the distribution of population, business employees, and business establishments per market is asymmetric with a right tail.

Single-market and multimarket banks. The empirical definition of a single-market is a bank that holds more than 80 percent of its total deposits in a single local market. Otherwise the bank is classified as a multimarket bank.

Table 5 shows differences in observable characteristics between single-market and multi-market banks. I compute statistics at the bank-market level and at the bank level. For the variables at the bank-market level I calculate a simple mean, for the variables at the bank level I calculate a mean weighted by the number of branches.

Single-market and multimarket banks differ in geographic scope, size, ownership structure, and lending practices. The average SM bank was active in 2 local markets and 1 state in 2007 while the average MM bank was active in 73 local markets and 5 states. Also the average SM bank owned 6 branches in 2007 while the average MM bank owned 570 branches in 2007. These differences in geographic scope and size have increased since 1994 as a result of deregulation and consolidation in the banking industry. Regarding ownership structure, 25 percent of SM banks were owned by a multibank holding company in 2007 while 58 percent of MM banks were owned by a multibank holding company in 2007.

More relevant are differences in lending practices. In 2007, the average SM bank lent 86 percent of its business loans to small businesses while the average MM bank lent 59 percent of its business loans to small businesses. Also, the average SM bank lent 83 percent of its farm loans to small farms while the average MM bank lent 65 percent of its farm loans to small farms.[4] Such ratios show some evidence of SM banks having a comparative advantage in the provision of loans to small businesses and small farms.

There are differences between SM and MM banks in average interest rates paid on deposits and average interest rates charged on loans. The average SM bank paid a higher interest rate on deposits and charged a higher interest rate on loans than the average MM bank. The higher interest rate paid on deposits by a SM bank may be evidence that a SM bank has to offer a higher return to attract depositors. The higher interest rate paid on loans by a SM bank may be evidence of SM banks exploiting an informational advantage when lending to more opaque lenders or may be evidence of SM lending to riskier lenders. It can also be the case that MM banks charge lower loan interest rates because they can exploit some economies of scale.

There are also differences in the ratio of equity to assets and non-performing loans to

[4] Loans to businesses includes loans secured by nonfarm nonresidential property and commercial and industrial loans, and loans to farms includes loans secured by farmland and loans to finance agricultural production and other loans to farmers. Loans to small businesses are loans to businesses with amounts smaller than \$ 1,000,000, and loans to small farms are loans to farms with amounts smaller than \$ 500,000.

loans. The average SM bank had a higher equity-assets ratio and a higher non-performing loans-loans ratio. These might highlight that a MM bank can decrease the risk in their portfolio through diversification in different geographic markets.

Finally, there does not exist observable differences in the number of branches per market of an incumbent bank of the SM or MM type. Both type of incumbents owned approximately 2 branches. This statistic is useful to rule out a possible interpretation for the differences in entry costs between the 2 types: they are not driven by differences in the number of branches.

To sum up, the average SM bank has less geographic scope, is smaller, and has a simpler ownership structure. Hence a SM bank cannot enjoy economies of scale, economies of scope, or geographic risk diversification but it may be able to exploit informational advantages in relationship lending.

There is a caveat to the descriptive statistics reported in table 5. Given that most of the statistics are computed at the bank level, a mean at the bank level for a MM bank includes the lending practices in other local markets where those banks are incumbents while a mean at the bank level for a SM bank includes the lending practices in the local markets in the sample. Thus part of the observed differences for SM and MM banks might be explained by different lending practices across local markets that affect the means reported by MM banks. The descriptive statistics should be interpreted with such limitation in mind.

Table 6 shows the distribution of market structures in the final sample. Each cell reports the percentage of times that such market structure is observed in the data. The most observed market structure is a local market with 2 SM banks and 1 MM bank. The local markets in the final sample are concentrated markets: 75 percent of the observed markets had less than 4 incumbents of each type. It does not exist a clear pattern between banks types and market concentration that can drive the results such as SM banks being incumbents in more concentrated markets or vice versa. For example, a SM monopolist is observed 2.7 percent of the time and a MM monopolist is observed 3.8 percent of the time.

Potential entrants. I use 2 different definitions to capture potential entrants. For the first definition I assume one potential entrant of each type, and I drop a few markets that experience multiple entries. For the second definition I compute the maximum number of SM incumbents in each market across time, and I define the number of SM potential entrants in period t as the difference between that maximum and the number of SM incumbents in a period t. I apply the same procedure the number of MM potential entrants. The rationale behind this definition is that in each geographic market we observe all potential entrants being active at some point in time. Dunne, Klimek, Roberts, and Xu (2013) use a similar definition but for a model with homogenous firms. To check the sensitivity of the estimates to the definition of potential entrants, I estimate the model using the 2 different pools of entrants.

Exit and entry definition. I matched branches over time using 7 variables: branch's FDIC code, bank's FDIC code, bank holding company's FED code, address, city reported, ZIP code, state, and county.[5] I use exact merge and fuzzy merge with different subsets of these variables. The exact merge matched 95 percent of the branch-year observations and the fuzzy merge matched an additional 1.5 percent-2 percent of the unmatched branch-year observations.

The longitudinal data set at the branch level allows me to identify opening and closing of branches: a new branch in the data set is an opening, and a branch that drops from the data set is an closing. I use the branch code and branch's address to differentiate true opening and closing of branches from changes of ownership, i.e. a bank acquired by another bank or a bank selling some branches to another bank.

Finally, I identified that a bank enters in a local market when a bank is not an incumbent in $t-1$ but is an incumbent in t and all its branches are opened in t. I identified that a bank exits from a local market when a bank is an incumbent in $t-1$ but is not an incumbent in t and all its branches are closed in $t-1$. I do not consider an entry or an exit those situations where there is a change in ownership: when a bank acquired another bank or when a bank enters in a local market by buying branches from another bank.

I clean some cases from the data to avoid measurement error issues. Specifically, I do not

[5] I use multiple variables for the matching because the branch code in the SOD has 10 percent of missing values and it does not change in a consistent manner.

consider as an entry or exit: a bank that enters and exit more than once in the same local market, and an entry/exit using the bank code but not the branch code. I also drop banks without deposits, and branches in Hawaii, Alaska, Puerto Rico or American Islands.

In table 7 I computed some entry and exit statistics for the different number of incumbents in the local market. I observe that both entries and exits increased in absolute terms with the number of incumbents but the number of entries increases less than proportionally with the number of incumbent and the number of exits increases proportionally with the number of incumbents. Dunne, Klimek, Roberts, and Xu (2013) find a similar evidence for a sample of doctors and chiropractors. Without a structural model it is difficult to interpret whether this observation is driven by differences in the number of potential entrants, entry costs, or profitability. I also observe that the entry proportion is larger than the exit rate. This is evidence of the geographic expansion of banks after the deregulation and a quite profitable period for the banking industry. Also, the saving and loans crisis of the 80's and early 90's caused the more inefficient banks to exit the industry, and this contributed to the lower exit rate afterwards.

More relevant for this paper are differences between SM and MM banks. I observe that the entry proportion is larger for SM than for MM banks, and the exit rate is slightly smaller for SM than MM banks. This evidence shows that the decrease in the number of SM branches was due either to SM banks downsizing, SM expanding to new local markets and becoming MM banks, or a MM banks acquiring a SM banks. But it is also true that SM banks were active players in the industry during this period. It is not clear whether SM banks continue to open branches because they face low entry costs than compensate demand or production cost disadvantages with respect to MM banks, or SM banks face higher entry costs that were compensated by informational advantages with respect to MM banks.

The structural model introduced in the next section tries to identified such differences in entry costs, demand, and production costs between SM and MM banks.

4. Model

The model is an oligopolistic model of entry/exit with imperfect information similar to POB. There are incumbent and potential entrant banks competing in geographic markets. Each period a bank observes a private information shock. An incumbent bank decides whether to continue or exit, and a potential entrant bank decides whether to enter or not. Banks choose optimal actions based on their beliefs about their competitors' behavior. In equilibrium, those beliefs are correct. The model departs from POB framework by allowing heterogeneity between banks based on their geographic scope: single-market and multimarket banks.

Both single-market and multimarket banks take entry/exit decisions separately in each market based on the market profitability. Such an assumption is reasonable for identification of heterogeneity between single-market and multimarket banks in several dimensions: preferences, technology, sell-off value, and entry costs.

There are $m \in \{1, 2, \ldots, M\}$ geographic markets and infinite periods $t \in \{1, 2, \ldots, \infty\}$. Banks are indexed by $i \in \mathcal{N}$, where the set of banks $\mathcal{N}$ can be partitioned in the set of single-market banks and the set of multimarket banks.

Bank's profitability depends on common knowledge and private information state variables. Common knowledge state variables are number of incumbents of type $\tau \in \{1, 2\}$, n^{τ}_{mt}, and market state variables, z_{mt}. The private information state variable for the incumbent is its sell-off value ϕ^{τ}_{imt}, and for the potential entrant is its entry cost κ^{τ}_{imt}.

The timing of the game is as follows. First, a bank observes the number of incumbents, the market state, and its private information realization. Second, banks simultaneously choose actions. Third, entrants pay the entry cost and incumbents earn current profits. Finally, at the end of the period, banks that exit earn the sell-off value, entrants become incumbents, and the market evolves to a new state. The timing is summarized in figure 4.

The incumbent's current payoff is

$$\Pi^{\tau}_{imt} = \begin{cases} \pi^{\tau}(n^1_{mt}, n^2_{mt}, z_{mt}; \theta^{\tau}_P) & \text{if } a^{\tau}_{imt} = 1, \\ \pi^{\tau}(n^1_{mt}, n^2_{mt}, z_{mt}; \theta^{\tau}_P) + \beta\, \phi^{\tau}_{imt} & \text{if } a^{\tau}_{imt} = 0, \end{cases}$$

where $\pi^{\tau}(.; \theta^{\tau}_P)$ is the bank profit function parameterized by θ^{τ}_P, β is the intertemporal discount factor, and a^{τ}_{imt} is the action continue/exit for the type τ incumbent or enter/not enter for the type τ potential entrant. The current payoff is consistent with the timing of the game: incumbents earn current profits, and, at the end of the period, exiters receive the sell-off value.

The potential entrant's current payoff is

$$\Pi^{\tau}_{imt} = \begin{cases} -\kappa^{\tau}_{imt} & \text{if } a^{\tau}_{imt} = 1, \\ 0 & \text{if } a^{\tau}_{imt} = 0. \end{cases}$$

I assume that potential entrants are short-lived to avoid timing of entry issues. Entrants pay the entry cost this period but become incumbents next period, not entrants receive a zero payoff.

Private information shocks are IID over banks, markets, and time with CDFs,

$$\phi^{\tau}_{imt} \sim F(.; \theta^{\tau}_X),$$
$$\kappa^{\tau}_{imt} \sim G(.; \theta^{\tau}_E).$$

θ^{τ}_X and θ^{τ}_E are the parameters of the sell-off value CDF and entry cost CDF. Although the entry costs and sell-off values are private information, their CDF is common knowledge.

To simplify notation the set of parameters is denoted by $\theta = (\theta^{\tau}_P, \theta^{\tau}_X, \theta^{\tau}_E)^2_{\tau=1}$, the set of common knowledge variables is denoted by $s = (n^1, n^2, z)$, and the private information shock is denoted generically by ν_i.

Each bank maximizes the discounted expected value of future payoffs,

$$\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\pi_i(a_{imt}, s_{mt}, \nu_{imt})|s_{m0}, \nu_{im0}\right],$$

where the expectation is taken over beliefs about its competitors' actions and the evolution of the market state variables.

I focus on Markov Perfect Equilibria (MPE) of the game. A MPE is a Subgame Perfect equilibrium in payoff relevant strategies or Markov strategies. Formally, a Markov strategy is a mapping $\sigma_i(s,\nu_i) \mapsto \{0,1\}$ which assigns an action to each possible realization of the state variables. A Markov strategy profile $\sigma = (\sigma_1, \dots, \sigma_N)$ assigns an action to each player. Then a Markov strategy is a MPE if and only if for all s, ν_i, i, and alternative strategies σ_i',

$$V_i(s,\nu_i|\sigma_i,\sigma_{-i}) \geq V_i(s,\nu_i|\sigma_i',\sigma_{-i}),$$

where $V_i()$ is the value function of bank i associated to the corresponding strategy profile. I focus on symmetric MPE. Therefore a Markov strategy for an incumbent and a potential entrant of each type completely characterize the equilibrium.

The integrated value function is the value function with the private information shock integrated out. Under an IID assumption for the private information shock there is no loss of generality in working with the integrated value function.

The integrated value function for the incumbent can be written as the solution of a functional equation:

$$V_{in}^{\tau}(s;\theta) = \pi^{\tau}(s;\theta_P^{\tau}) + \beta\int\left[\max\{\phi_i^{\tau}, VC^{\tau}(s;\theta)\}\right]dF(\phi_i^{\tau};\theta_X^{\tau}), \tag{1}$$

$$VC^{\tau}(s;\theta) = \sum_{s'} V_{in}^{\tau}(s';\theta)P_{in}^{\tau}(s'|s, a_i^{\tau}=1). \tag{2}$$

$VC^{\tau}()$ is the continuation value, i.e. the expected value function in $t+1$ conditional on the state in t and the bank continuing. $P_{in}^{\tau}()$ is the transition probability for the state variables conditional on continuing and it embodies the beliefs about its competitors' strategies.

Equations (1) and (2) can be solved for the integrated value function or the continuation value, but it is straightforward to write optimal policies in terms of the continuation value.

The optimal choice for a type τ incumbent is to exit if $\phi_i^\tau > VC^\tau()$, otherwise to continue. The exit probability of a type τ bank i is the expected behavior of the bank before the realization of the private information shock,

$$\begin{aligned} Pr(\tau\, exits|s;\theta) &= Pr(\phi_i^\tau > VC^\tau(s;\theta)), \\ &= 1 - F(VC^\tau(s;\theta);\theta_X^\tau). \end{aligned} \tag{3}$$

Given arbitrary beliefs on rivals strategies equation (3) is the expected best response of type τ bank, but it is the expected behavior of bank i if other firms are playing equilibrium strategies.

The integrated value function for the potential entrant can be obtained as the solution of the following equation

$$V_{en}^\tau(s;\theta) = \max\{0, -\kappa_i^\tau + \beta VE^\tau(s;\theta)\}, \tag{4}$$

$$VE^\tau(s;\theta) = \sum_{s'} V_{in}^\tau(s';\theta) P_{en}^\tau(s'|s, a_i^\tau = 1). \tag{5}$$

$VE^\tau()$ is the entry value or expected value of a potential bank next period conditional on entry, and $P_{en}^\tau()$ is the transition probability of the state variables conditional on entry. The entry value is a function of the continuation value through the incumbent value function.

The optimal choice for a type τ potential entrant is to enter if $\kappa_i^\tau < \beta VE^\tau()$, otherwise not entering is optimal. The entry probability of a type τ bank is

$$\begin{aligned} Pr(\tau\, enters|s;\theta) &= Pr(\kappa_i^\tau \leq \beta VE^\tau(s;\theta)), \\ &= G(\beta VE^\tau(s;\theta);\theta_E^\tau). \end{aligned} \tag{6}$$

The econometric implementation rests on the theoretical exit probability in equation (3) and the theoretical entry probability in equation (6). The estimation strategy is based on finding parameter values that minimize the distance between theoretical and observed exit and entry probabilities. Under similar observed entry probabilities for SM and MM banks can lay heterogeneity in different economic primitives: profitability, sell-off values, or entry costs. I impose the economic structure, and use the data to identify the parameters that affects the entry/exit behavior of SM and MM banks.

5. Empirical implementation

I estimate the parameters of the model using a 2-stage procedure. In the first stage I obtain an estimation of VC and VE based on profit, exit probability, and transition probability estimates. In the second stage I use the estimated continuation value $\widehat{VC}$ and entry value $\widehat{VE}$ to compute theoretical exit and entry probabilities that depend on θ. Then the parameter estimates are those values that minimize a distance between theoretical and observed probabilities.

I assume that sell-off values follow an exponential distribution, and entry costs follow a logistic distribution. The exponential assumptions allows me to obtain an explicit expression for $\widehat{VC}$, but it can be replaced by another parametric distribution at the cost of complicating the computation of $\widehat{VC}$. The exponential probability has also the nice property of restricting sell-off values to be positive.

In theory the CDF for entry costs is non-parametrically identified, in practice data constraints require to assume a parametric distribution. I choose the logistic distribution because is similar to the normal distribution and its CDF has an analytical expression which decreases computational time in the estimation. Notice that the independent of irrelevant alternatives critique of the logistic does not apply here because there are only 2 choices: continue/exit for incumbents or entry/no entry for potential entrants.

Assumption 1. *Distribution of entry costs and sell-off values.*

1. *The sell-off values follow an exponential distribution with mean and variance θ_X^τ,*

$$F(\phi;\theta_X^\tau) = 1 - \exp\left(\frac{\phi}{\theta_X^\tau}\right) \ \textit{with}\ \phi \in (0,\infty). \tag{7}$$

2. The entry costs follow a logistic distribution with mean θ_E^τ and variance $\pi^2/3$,

$$G(\kappa;\theta_E^\tau) = \frac{\exp(\kappa-\theta_E^\tau)}{1+\exp(\kappa-\theta_E^\tau)} \text{ with } \kappa \in \mathbb{R}. \tag{8}$$

I fixed the variance of the entry costs to be $\pi^2/3$ [6] and estimate the mean of the distribution θ_E^τ. θ_E^τ might depend on market size so the mean entry cost changes with market size. Moreover, the effect of market size on entry costs might be different for SM and MM banks. In the estimation I explore these different alternatives.

I assume that z follows an exogenous Markov process. This assumption helps to alleviate the curse of dimensionality when estimating transition matrices non-parametrically.

Assumption 2. *Exogenous Markov process for z. z follows an exogenous first order Markov process, $Pr(z'|n^1,n^2,z,a) = Pr(z'|z)$.*

For an exponential distributed random variable, $\mathbb{E}[\phi_i^\tau|\phi_i^\tau > VC^\tau] = \theta_X^\tau + VC^\tau$ holds.[7] Then the VC can be written as,

$$VC^\tau(s;\theta) = \sum_{s'} \{\pi^\tau(s';\theta_P^\tau) + \beta\, P_{exit}^\tau(s')\,\theta_X^\tau + \beta\, VC^\tau(s';\theta)\}\, P_{in}^\tau(s'|s,a_i^\tau=1),$$

where $P_{exit}^\tau(s)$ is the reduced form exit probability in state s. Such a functional equation can be solved for the continuation value in matrix form as

$$VC^\tau(\theta) = [I-\beta M_{in}^\tau]^{-1} M_{in}^\tau[\pi^\tau(\theta_P^\tau) + \beta P_{exit}^\tau\,\theta_X^\tau], \tag{9}$$

where VC^τ,π^τ,P_{exit}^τ are vectors that stack the continuation value, profit function, and exit probability in each state, M_{in}^τ is a matrix with the transition probability between states conditional on the incumbent continuing, and I is the identity matrix. Analogously the entry

[6] $\pi^2/3$ is the variance of a standard logistic random variable

[7] Due to this property of the exponential distribution the continuation value has an explicit expression, otherwise the continuation value is a fixed point in a functional equation. Then the exponential assumption avoids solving a functional equation for each parameter value tried in the estimation.

value can be written in matrix form as

$$VE^{\tau}(\theta) = M_{en}^{\tau}[I + \beta(I - \beta M_{in}^{\tau})^{-1} M_{in}^{\tau}][\pi^{\tau}(\theta_P^{\tau}) + \beta P_{exit}^{\tau}\, \theta_X^{\tau}], \tag{10}$$

where M_{en}^{τ} is a matrix with the transition probability between states conditional on entering in the market.

The first stage estimates the profit function, the transition probability for market state, exit and entry probabilities, and transition probabilities. With these estimates, continuation and entry values are estimated.

5.A. First stage estimation

Profit function. The parameters of the profit function can be estimated with profit and covariates data without imposing the dynamic model.

Unfortunately I cannot observe bank's profits at the market level, but I observe the deposits held in a bank in a market and I can compute average interest rates, average tax rates, wage expenditure, and other expenses at the bank level. Using the available data I compute a measure of bank's current profits using

$$\pi_{imt} = (1 - tax_{it}) \left(q_{imt} \left(r_{it}^{L} - r_{it}^{D} \right) - wages_{imt} - other_{imt} \right),$$

where q_{imt} are deposits held by bank i in market m, r_{it}^{D} is the bank's average deposit interest rate, r_{it}^{L} is the bank's average loan interest rate (adjusted by expected loan losses), tax_{it} is the average tax rate paid by the bank, $wages_{imt}$ is the wage expenditure in the market, and $other_{imt}$ includes other costs incurred by the bank in the market. I computed average deposit interest rate as the ratio of interest expense on deposits net of service charges on deposit accounts to total deposits. Average loan interest rate are interest and fee income on loans and income from lease financing receivables to total loans and lease financing receivables. To adjust the loan interest rate for different risks on the bank's loans, I subtract from the average loan interest rate the ratio of allowances for loans and lease losses to total loans and lease financing receivables. Average tax rate paid by the bank is the ratio of applicable income taxes to income before income taxes. Wage expenditure in the market is expenses on salaries and employees benefits allocated to the market using market deposits. Other costs include expenses of premises and fixed assets allocated to the market using market deposits.

The measure of profits is reasonable because loans and deposits are the main retail activities carried out by banks. Measurement error in average interest rates measured at the bank level rather than the bank-market level is a minor concern since empirical evidence supports MM banks charging uniform prices at the state level.[8] The estimating equation for the profit function is,

$$\pi^{\tau}_{imt} = \sum_{\tau=1}^{2} \mathbf{1}(i \in \tau)\, g^{\tau}(n^1_{mt}, n^2_{mt}; \theta^{\tau}_N) + \theta'_Z\, z_{mt} + \eta_m + u_{imt}, \tag{11}$$

where

$$\begin{aligned} g^{\tau}(n^1_{mt}, n^2_{mt}; \theta^{\tau}_N) =& \theta^{\tau}_{N,0} + \theta^{\tau}_{N,1} \times \text{presence of first type } \tau \text{ competitor} \\ &+ \theta^{\tau}_{N,2} \times \text{presence of second type } \tau \text{ competitor} \\ &+ \theta^{\tau}_{N,3} \times \text{additional type } \tau \text{ competitors} \\ &+ \theta^{\tau}_{N,4} \times \text{presence of first type } \tau' \text{ competitor} \\ &+ \theta^{\tau}_{N,5} \times \text{presence of second type } \tau' \text{ competitor} \\ &+ \theta^{\tau}_{N,6} \times \text{additional type } \tau' \text{ competitors,} \end{aligned}$$

where η_m is a market fixed effect, and z_{mt} includes population, income per capita, number of business establishments, and number of business employees in the market. Controlling for unobserved market profitability is important for two reasons. First, an unobserved variable positively correlated with both own profitability and rival's presence creates a positive bias in the estimates. Second, the estimated market fixed effects are used as unobserved

[8] Some papers showing empirical evidence of uniform pricing are Biehl (2002) and Heitfield and Prager (2004).

correlated state variables in the dynamic game.[9] I estimate equation (11) by OLS with variance-covariance matrix robust to heteroscedasticity, and time series and within market correlation.

Transition probability for market state variables. To apply a non-parametric estimator I discretize the market state variables. First, I construct $\hat{z}_{mt} = \hat{\theta}'_Z z_{mt} + \eta_m$ to reduce the dimensionality of z. Then, I choose 10 group specific bins for $\hat{z}_{mt}$ such that they contain the same number of observations and I assign the mean value of $\hat{z}_{mt}$ to each bin. Finally, I estimate separate transition probabilities for each market type $\widehat{M}_z$ using a non-parametric estimator:

$$\widehat{M}_z(i,j) = \frac{\sum_{(m,t)\in T(z_i)} \mathbf{1}(z_{m,t+1} = z_j)}{\#T(z_i)}.$$

$M_z(i,j)$ is the estimated probability of being in state z_j tomorrow give the market is in state z_i, $T(z)$ is the set of observations with market state z, and $\#T(z)$ is the number of observations in $T(z)$.

Exit and entry probability. The exit probability of a type τ bank is estimated as the mean of observed exit probabilities. Let $T(n^1, n^2, z) = \{(m,t) : (n^1_{mt}, n^2_{mt}, z_{mt}) = (n^1, n^2, z)\}$ be the set of observations satisfying a given state configuration. Then the estimated exit probability is

$$\widehat{P}^{\tau}_{exit}(s) = \frac{1}{\#T(n^1,n^2,z)} \sum_{(m,t)\in T(n^1,n^2,z)} \frac{x^{\tau}_{mt}}{n^{\tau}},$$

where x^{τ}_{mt} is the number of type τ banks that exit the market.

The entry probability of a type τ bank is estimated as the mean of observed entry probabilities:

$$\widehat{P}^{\tau}_{entry}(s) = \frac{1}{\#T(n^1,n^2,z)} \sum_{(m,t)\in T(n^1,n^2,z)} \frac{e^{\tau}_{mt}}{E^{\tau}_{mt}},$$

[9] Dunne, Klimek, Roberts, and Xu (2013) follow a similar procedure in their paper about dentists and chiropractors.

where e^τ_{mt} is the number of type τ entrants, and $E^\tau_{mt}$is the number of type τ potential entrants. In general is difficult to identify potential entrants so I follow different approaches. I estimate the maximum number of type τ banks in a market as $N^\tau_m = \max_t(n^\tau_{mt})$, so the number of potential entrants is $E^\tau_{mt} = N^\tau_m - n^\tau_{mt}$. Another approach is to assume one potential entrant of each type per market. Though both approaches are imperfect, the estimation results are robust to the chosen potential entrant definition.

Incumbent and potential entrant transition probability. Transition probability estimates are weighted non-parametric estimators with weights given by the number of incumbents that continue or the number of entrants. The probability of n^1_j, n^2_j conditional on being in n^1_i, n^2_i, z_i and the type τ incumbent continuing is estimated by

$$\widehat{M}^\tau_{in,n}(i,j) = \frac{\sum_{(m,t)\in T(n^1_i,n^2_i,z_i)}(n^\tau_i - x^\tau_{mt})\mathbf{1}((n^1_{m,t+1}, n^2_{m,t+1}) = (n^1_j, n^2_j))}{\sum_{(m,t)\in T(n^1_i,n^2_i,z_i)}(n^\tau_i - x^\tau_{mt})}.$$

The probability of n^1_j, n^2_j conditional on being in n^1_i, n^2_i, z_i and the type τ bank entering is estimated by

$$\widehat{M}^\tau_{en,n}(i,j) = \frac{\sum_{(m,t)\in T(n^1_i,n^2_i,z_i)} e^\tau_{mt}\mathbf{1}((n^1_{m,t+1}, n^2_{m,t+1}) = (n^1_j, n^2_j))}{\sum_{(m,t)\in T(n^1_i,n^2_i,z_i)} e^\tau_{mt}}.$$

Estimation of the type τ incumbent transition probability matrix $\widehat{M}^\tau_{in}$ derives directly from $\widehat{M}^\tau_{in,n}$ and $\widehat{M}_z$, and similarly for the type τ entrant transition probability matrix $\widehat{M}^\tau_{en}$.

Estimation of continuation and entry values. Plugging $\widehat{\pi}^\tau$, $\widehat{P}^\tau_{exit}$, and $\widehat{M}^\tau_{in}$ in equation (9) we obtain an estimation of the continuation value

$$\widehat{VC}^\tau(\theta) = \widehat{W}^\tau_{in,0}\,\widehat{\pi}^\tau + \widehat{W}^\tau_{in,1}\,\theta^\tau_X, \tag{12}$$

where $\widehat{W}^{\tau}_{in,0} = [I - \beta \widehat{M}^{\tau}_{in}]^{-1} \widehat{M}^{\tau}_{in}$, and $\widehat{W}^{\tau}_{in,1} = \widehat{W}^{\tau}_{in,0} \beta \widehat{P}^{\tau}_{exit}$. Similarly, plugging $\widehat{\pi}^{\tau}$, $\widehat{P}^{\tau}_{exit}$, $\widehat{M}^{\tau}_{in}$, and $\widehat{M}^{\tau}_{en}$ in equation (10) we obtain an estimation of the entry value

$$\widehat{VE}^{\tau}(\theta) = \widehat{W}^{\tau}_{en,0}\, \widehat{\pi}^{\tau} + \widehat{W}^{\tau}_{en,1}\, \theta^{\tau}_{X}, \tag{13}$$

where $\widehat{W}^{\tau}_{en,0} = \widehat{M}^{\tau}_{en}[I + \beta(I - \beta \widehat{M}^{\tau}_{in})^{-1} \widehat{M}^{\tau}_{in}]$, and $\widehat{W}^{\tau}_{en,1} = \widehat{W}^{\tau}_{en,0} \beta \widehat{P}^{\tau}_{exit}$. Estimated continuation and entry value are linear functions of the parameters of interest.

5.B. Second stage estimation

In the second stage, the estimated continuation and entry value are used to construct theoretical probabilities that depend on the parameters. The estimates are those parameter values than minimize a distance between theoretical and observed probabilities.

Plugging the estimated continuation value in equation (9) in the exit probability in equation (3) and using the distributional assumption, the theoretical exit probability is

$$Pr(\tau\, exit|s; \theta, \widehat{P}) = \exp\left\{ -\frac{1}{\theta^{\tau}_{X}} [\widehat{W}^{\tau}_{in,0}(s)\, \widehat{\pi}^{\tau}(s) + \widehat{W}^{\tau}_{in,1}(s)\, \theta^{\tau}_{X}] \right\}. \tag{14}$$

$\widehat{P}$ denotes the exit and transition probabilities used to estimate the continuation value. Plugging the estimated entry value in equation (10) in the entry probability in equation (6) and using the distributional assumption, the theoretical entry probability is

$$Pr(\tau\, entry|s; \theta, \widehat{P}) = \frac{\exp\left\{ \beta[\widehat{W}^{\tau}_{en,0}(s)\, \widehat{\pi}^{\tau}(s) + \widehat{W}^{\tau}_{en,1}(s)\, \theta^{\tau}_{X}] - \theta^{\tau}_{E} \right\}}{1 + \exp\left\{ \beta[\widehat{W}^{\tau}_{en,0}(s)\, \widehat{\pi}^{\tau}(s) + \widehat{W}^{\tau}_{en,1}(s)\, \theta^{\tau}_{X}] - \theta^{\tau}_{E} \right\}}.$$

Finally, I apply a minimum distance estimator that minimize a metric in the difference between theoretical and observed probabilities,

$$\widehat{\theta} = \arg\max_{\theta \in \Theta} (\widehat{\pi} - \widehat{h}(\theta))' A_T (\widehat{\pi} - \widehat{h}(\theta)),$$

where $\widehat{\pi} = (\widehat{P}^{1\prime}_{X}, \widehat{P}^{2\prime}_{X}, \widehat{P}^{1\prime}_{E}, \widehat{P}^{2\prime}_{E})'$ is the vector that stacks the reduce form probabilities for each state, $\widehat{h}(\theta) = (Pr^1(exit;\theta,\widehat{P})', Pr^2(exit;\theta,\widehat{P})', Pr^1(entry;\theta,\widehat{P})', Pr^2(entry;\theta,\widehat{P})')'$ is the vector that stacks the theoretical probabilities for each state, and A_T is matrix that weights the different equalities.

The weighting matrix A_T is block diagonal with blocks

$$A_T(i,i) = \begin{pmatrix} \frac{\#T(s_1)^2}{T^2} & \frac{2\,\#T(s_1)\#T(s_2)}{T^2} & \cdots & \frac{2\,\#T(s_1)\#T(s_S)}{T^2} \\ \frac{2\,\#T(s_1)\#T(s_2)}{T^2} & \frac{\#T(s_2)^2}{T^2} & \cdots & \frac{2\,\#T(s_2)\#T(s_S)}{T^2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{2\,\#T(s_1)\#T(s_S)}{T^2} & \frac{2\,\#T(s_2)\#T(s_S)}{T^2} & \cdots & \frac{\#T(s_S)^2}{T^2} \end{pmatrix},$$

where $\#T(s)$ is the number of observation in state s, and T is the total number of observations. A_T is not the asymptotic optimal matrix but reduces the finite bias, and it is equivalent to the method of moments estimator proposed by POB. Pesendorfer and Schmidt-Dengler (2008) call this class of estimators asymptotic least square estimators and prove consistence and asymptotic normality. Usual standard errors are not valid due to the estimation error in the first stage thus standard errors are computed using a non-parametric bootstrap.

6. Empirical results

In this section I comment the results of the estimation. The main results are that a single-market bank has a profit advantage over a multimarket bank, but it pays a higher entry cost.

6.A. Profit function

The estimates of the profit function shown in table 8 have the expected sign, and are statistically significant. A single-market bank has an advantage in profits over a multimarket bank, increasing competition decreases profits, and a larger market size increases profits.

The single-market dummy is positive and significant at 1 percent: in mean the profits of a single-market monopolist bank is 0.2 million \$ higher than the profits of a multimarket monopolist bank. For the market configuration more common in the data with 1 SM and 2 MM banks the model predicts an average current profit for a SM bank of 1.1 million $ and for a MM bank of 0.96 million $. This result is robust to different specifications of the profit function and alternative profit definitions. A related result is obtained by Adams, Brevoort, and Kiser (2007) who estimate a deposit demand using a generalized extreme value model, and find that a SM bank faces a less elastic demand than a MM bank in both rural markets and MSAs.

A plausible explanation for this SM advantage is the soft vs hard-information story. The main idea is that there are different types of loans: transaction loans and relationship loans. Transaction loans are based on hard information like financial statements, collateral, covenants, credit scoring, etc. Relationship loans are based on soft information collected through repeated lender-borrower interactions. Soft information cannot flow easily within a formal organizational structure, and this creates an advantage for less hierarchical organizations like SM banks. It is natural to think on small businesses and farmers relying more in relationship lending.

Complementary evidence supporting this idea is provided by Berger, Bonime, Goldberg, and White (2004). Berger, Bonime, Goldberg, and White find an increase in entry of small banks after a large out-of-market bank acquires a small incumbent bank. The authors interpret their findings as small banks entering to supply credit to some relationship-dependent small businesses.

Another explanation is that the profit approximation includes the traditional retail banking activities: loans and deposits. A MM bank obtains a higher proportion of its profits from sources like brokerage fees, securitization, etc. which are not directly included in the profit approximation use in the empirical application. Then estimation results highlight that SM might have advantages in retail banking activities while MM may have advantages in non-traditional banking activities where economies of scale are more important.

The effect of increasing competition is negative, and almost all of the competition effects are statistically significant. When there exist 1 SM incumbent and 2 MM incumbents, the expected effect of an additional SM competitor is to decrease the profit of the SM incumbent in .086 million $ and to decrease the profit of a MM incumbent in .153 million $. While the expected effect of an additional MM competitor is to decrease the profit of the SM incumbent in .101 million $ and to decrease the profit of a MM incumbent in .087 million $.

The effect of increasing competition on profit is quantitatively similar for competitors of different types, and for the first, second, or additional competitors. Cohen and Mazzeo (2007) use data for banks and thrifts in 2001 and 2003, and exploit the cross-section variation in the number of competitors and market size to estimate a profit function for banks. They conclude that competition among banks of the same type is greater than competition among different types, and find decreasing effects of the number of competitors on profits. Adams, Brevoort, and Kiser (2007) also find higher cross price elasticities within types than between types.

The effect of average wage, number of business establishments, and number of employees in the geographic market have the expected positive sign while the effect of population and income per capita have an negative sign. These results are not surprising given that the market size regressors are highly collinear but I choose to keep all of them in the regression to capture more variability of profits. I tried alternatives functional forms: quadratic, logarithmic, interacted with income per capita. The estimates were robust to the different specifications I choose a more simple model with a linear functional form.

A possible concern for the second stage is the fit of the model to the data: the model explains 1.7 percent of the within profit variation. Although this is expected given such simple econometric model, it may signal the need of a richer model of firm heterogeneity to capture the variability observed in the profit data.

6.B. Market state variables

The methodology I apply for the estimation requires a discrete state space. Number of incumbents of each type is a discrete variable, but the market variables must be discretized. Following Dunne, Klimek, Roberts, and Xu (2013) to reduce the dimensionality of the market state variables I use the estimated coefficients to construct a new artificial variable that capture the effects of population and income per capita. I work with the market state variable $\hat{z}_{mt} = \hat{\theta}_Z z_{mt} + \eta_m$ where z_{mt} are market state variables, η_m is unobserved market profitability, and $\hat{\theta}_Z$ are the estimated coefficients of the market state variables in the first stage. Then, I choose 10 group specific bins for $\hat{z}_{mt}$ such that they contain the same number of observations and I assign the mean value of $\hat{z}_{mt}$ to each bin.

Table 9 shows descriptive statistics for each market state. More profitable markets tend to be larger and to have larger income per capita. This is the case despite the estimated coefficient of population and income per capita are negative in the profit estimation. The fixed effect captures differences that do not change over time between markets so it is capturing most of the variation in population and income per capita between markets. The average population is 2,496 inhabitants for the 1st group, and increases up to 55,000 for the 10th group. The increasing difference in average population between contiguous groups is due to the skewed population distribution.

As expected the number of banks, single-market banks, and multimarket banks are increasing in the market state. But the number of MM banks increases at a faster rate than the number of SM banks. It seems that MM banks presence is relatively greater in more profitable markets, while the SM presence is relatively greater in less profitable markets.

Population per bank and profit per bank are increasing in the market state. If we associate market state with population, the results are in line with Bresnahan and Reiss (1991)'s seminal paper. Increasing competition decreases markups, and a firm needs a larger demand to cover its fixed costs. Note that profit increases at the lower rate than population that seems to confirm the competition story.

6.C. Sell-off values and entry costs

I estimate the sell-off values and entry costs using a minimum distance estimator. I minimize the objective function using a Compass Search algorithm. The standard errors are computed using a non-parametric bootstrap.

The results of the sell-off value and entry cost estimation are in table 10. The sell-off estimates are basically zero that is not surprising given the low exit probability in the data. It is reasonable that banks do not close many branches in a period characterized by expansion in the number of branches. Likely many of the non-profitable branches were closed during the saving a loan crisis of the '80s. The reluctance of banks to close branches can be explained by brand concerns when closing branches.

The main result in the entry cost estimation is that SM banks face a higher entry costs than MM banks, and the cost of a bank which decides to enter in a new local market is around 10 million $ for a SM bank and 7 million $ for a MM bank. This paper is one of the first papers that attempt at measuring entry costs in the banking industry, and the results and interpretations should be consider as a first approach to the issue.[10]

The estimated differences in entry costs are driven by differences in profit: SM banks have a profit advantage, so they should face a higher entry cost if they enter in same proportion as MM banks. The result is robust to the pool of potential entrants used.

A SM bank should pay a entry costs which is around 3 million $ higher than a MM bank. In relative terms it is a 30 percent more expensive for a SM bank to enter in a new market than for a MM bank. There are some plausible explanations for the cost differential. In general, a SM bank that enters in a new market is a denovo bank and a denovo bank must pay start-up costs than a bank already operating avoid. Though, a MM bank that enter in a new state could face some red tape costs, it is reasonable to assume that are less important. Advertisement can be in part fixed at the bank, at in part fixed at the bank-market level. A MM bank has economies of scale advantages over the bank level or institutional advertisement. Another factor is hiring costs for management positions. A multimarket bank has many branches in different local markets, and could find it less costly to look for a manager for a new branch: directors can promote an employee to a manager position, or reallocate a manager from another branch. A single-market bank has to search for a manager in the job market that is more costly.

[10]Up to my knowledge, Aguirregabiria, Clark, and Wang (2015) is the another recent paper that also seeks to measure to the entry costs in the U.S. banking industry.

Finally, as expected entry costs are higher the higher the market size. But though this effect is higher for MM banks than SM banks does not close the gap between both types of banks in larger markets.

7. Conclusions

Historic restrictions to the geographic expansion of banks have greatly affected the market structure of the U.S. banking industry. Recent deregulation, the most important the Riegle-Neal Act in 1994, foster a structural change in the market structure in the industry. These two facts motivate trying to understand the differences between two types of business models that coexist in the banking industry: single-market and multimarket banks.

An important result of the paper is that single-market incumbents are more profitable than multimarket incumbents in small local markets. This profit advantage is consistent with single-market banks having a comparative advantage in loans to small business and farmers.

Another feature that can differentiate single-market and multimarket banks is expansion costs, the cost to enter in a new local market. Measuring expansion costs is particularly relevant after recent interstate branching deregulation (Riegle-Neal Act) because it can help explain why single-market banks did not exploit new efficiency opportunities after the deregulation. It can also help in understanding the dynamics of the industry and some unexpected welfare consequences of the deregulation.

The second important results of the paper is that a single-market bank paid an entry costs which is 30 percent higher than the entry cost for a multimarket bank. This higher entry costs can be linked to start up costs, or higher advertisement and recruitment costs faced by single-market banks.

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Appendix A: Construction of the data set

This appendix defines the relevant market for the U.S. banking industry, describes the data sources, and the construction of the entry/exit variables.

7.A. Definition of the relevant market

In this paper the relevant market for the U.S. banking industry is a geographic market: a Metropolitan Statistical Areas (MSA), a Micropolitan Statistical Area (MicroSA)[11], or a county outside a MSA or MicroSA. It is natural to relate MSAs to large urban markets, MicroSAs to small urban markets, and counties outside a MSA or MicroSA to rural markets.

Given the size of some geographic markets, distinct or overlapping submarkets might exist within a geographic market. In turn, this makes difficult to distinguish which banks are effectively competing with whom within the geographic market. For this reason I restrict the analysis to those markets with less than 100,000 inhabitants. This condition follows the selection criteria applied in Cohen and Mazzeo (2007).[12]

An example of a urban market in the sample is Bogalusa Micropolitan Statistical Area in Louisiana that had a population of 43,926 in 2000. Figure 5 shows the bank's branches located in Bogalusa. Almost all branches are located in the two biggest cities of the local market: Bogalusa and Franklinton.

The definition of a relevant market as a local geographic market seems appropriate for the U.S. banking industry. Indeed several papers present empirical evidence suggesting the relevant market for financial services is local.

A first strand of papers use survey data to document that households and small businesses use financial services from local institutions. Amel and Starr-McCluer (2002) using the 1998 Survey of Consumer Finances (SCF) find the median distance between a household and its

[11]Micropolitan Statistical Areas are defined by the U.S. Census Bureau and it consist on a urban center plus adjoining counties. A Micropolitan Statistical Areas (MicroSA) has a smaller population than a MSA.

[12]Cohen and Mazzeo (2007) use Labor market areas (LMAs) defined by Bureau of Labor Statistics. LMAs are MSA, MicroSA, or small labor market areas. In New England, small labor market areas are based on a geographic level not available in my data. Hence, outside MSA and MicroSA I decided to work with individual counties rather than excluding New England states.

depository institution is 3 miles, and for 75 percent of the households the distance is smaller than 10 miles. Moreover, 90 percent of checking accounts, savings accounts and certificates of deposits are acquired within 30 miles of home or workplace. Kwast, Starr-McCluer, and Wolken (1997) find similar results for small businesses. Using the 1993 Survey of Small Business Finances (SSBF) they find that more than 75 percent of small businesses did their banking business within 15 miles of their offices.

A second strand of papers estimate the demand of financial services by households, and the sensitivity of demand to changes in distance. Most of these studies use data on bank's branch locations (and branch characteristics), household locations (and household characteristics), market shares and prices to estimate a demand function. Ho and Ishii (2011) use data for MSA and counties in California, Oregon and Washington, and find the cross-price elasticities are very low for banks more than one mile away. Ishii (2005) use data for MSA in Massachusetts. Ishii finds that households are indifferent between a decrease in 1.1 miles in the distance to the nearest branch or an one standard deviation increase in the deposit interest rate. Finally, Wang (2009) use data on 132 isolated, middle-sized, U.S. geographic markets, and finds that a branch that is one mile closer is equivalent to a branch with one standard deviation higher deposit interest rate.

7.B. Data sources

The main data source is the Summary of Deposits (SOD) for the period 1994-2007 collected by the Federal Deposit Insurance Corporation (FDIC). The SOD contains data for all branches and offices owned by FDIC-insured institutions. The FDIC collects deposit balances for commercial and savings banks as of June 30 of each year, and the Office of Thrift Supervision (OTS) collects the same data for savings institutions. Data are collected annually. The SOD contains information about location, ownership, and amount of deposits at the branch level.

I complemented the SOD data with balance sheet data at the bank level. I used data for the period 1994-2007 from the Call Reports of the Federal Reserve Bank of Chicago (commercial banks) and the Thrift Financial Reports of the Office of Thrift Supervision (saving institutions). I used the balance sheet data to compute average deposit interest rates, average loan interest rates, and other financial ratios.

7.C. Construction of entry/exit variables

The SOD reports information for almost all depository institutions in the United States. But given that it is administrative data it required a lengthy cleaning process before the data is suitable for research purposes. In particular the construction of entry/exit variable is sensitive to measurement error problems. For example, missing information in a year can be interpreted as exit and subsequent entry, or consolidation of bank charters by a Multibanking Holding Company can be interpreted as bank exit and bank entry in several markets.

In the SOD there is a bank code (variable `cert`) and a branch code (variable `uninumbr`). The variable `uninumbr` can be used to build a panel data of branches, but such a variable presents some problems. First, if there is an ownership change of the branch, `uninumbr` usually changes for the same branch. Second, there are missing values for `uninumbr`. Missing values in `uninumbr` are more pervasive for savings institutions whose information is collected by the OTS.[13]

Given the above-mentioned problems with the branch code variable, I relied also on the information provided by other branch variables. I matched observations using the branch's code, address, city, ZIP code, state, county, bank code, and bank holding company code. I used a *fuzzy merge*[14] that links observations based on a matching algorithm. If the matching score is higher than a user given threshold, two observations are linked. I applied the fuzzy merge recursively to observations in t and $t+1$.

Once the panel was constructed at the branch level, I defined the relevant variables to study the market dynamics: entry, exit, and ownership changes. A branch entry refers to the opening of a new branch, and a branch exit refers to closing an existing branch. Hence, entry

[13] `uninumbr` is missing for 8.65 percent of the commercial banks and for 57.18 percent of the saving banks.
[14] I applied the fuzzy merge using the command `reclink` in Stata.

is defined as

$$entry_{mt} = active_{mt} \times (1 - active_{m,t-1}),$$

and exit is defined as,

$$exit_{mt} = (1 - active_{mt}) \times active_{m,t-1},$$

where $active_{mt}$ is an indicator function which equals 1 if the branch is active in market m at time t.

Part of the dynamics in the industry is due to changes in ownership. I considered a change in ownership when an active branch experiences a change in its bank charter (variable `cert`). There are several economic situations behind a change of ownership: a merger or acquisition of a bank, a bank holding company that consolidates the bank charters of its subsidiaries, or a bank which sells individual branches. I distinguished a change in ownership by merger or acquisition (M&A) from other reasons using data from the Federal Reserve Bank of Chicago about mergers. As expected most of the changes of ownership matched mergers at the bank level.

I dropped some observations from the final data set. First, I deleted a branch that satisfy at least one of the following conditions: (1) it does not have deposits in more than 75 percent of the observations, (2) it has only 1 observation with positive deposits, (3) it is active for only 1 period, or (4) it has less than 100,000 $ of deposits in average. Second, I consolidated branches with the same address and bank code. Third, I made linear interpolations for deposits in case there is a gap of one period in the observations of a branch.

Appendix B: Figures and tables

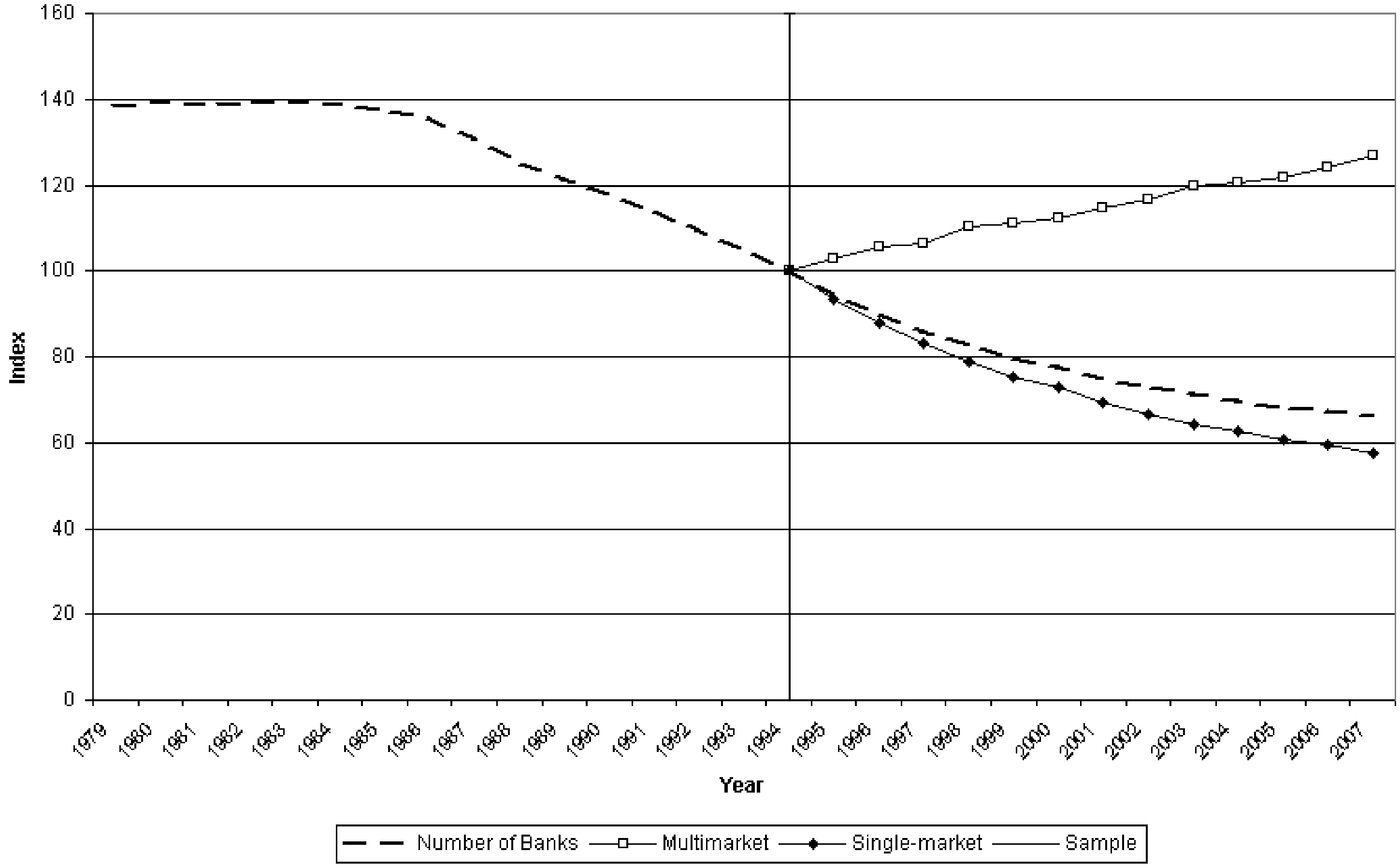

Figure 1: Number of banks. U.S. commercial and saving banks. 1979-2007. Index 1994=100.

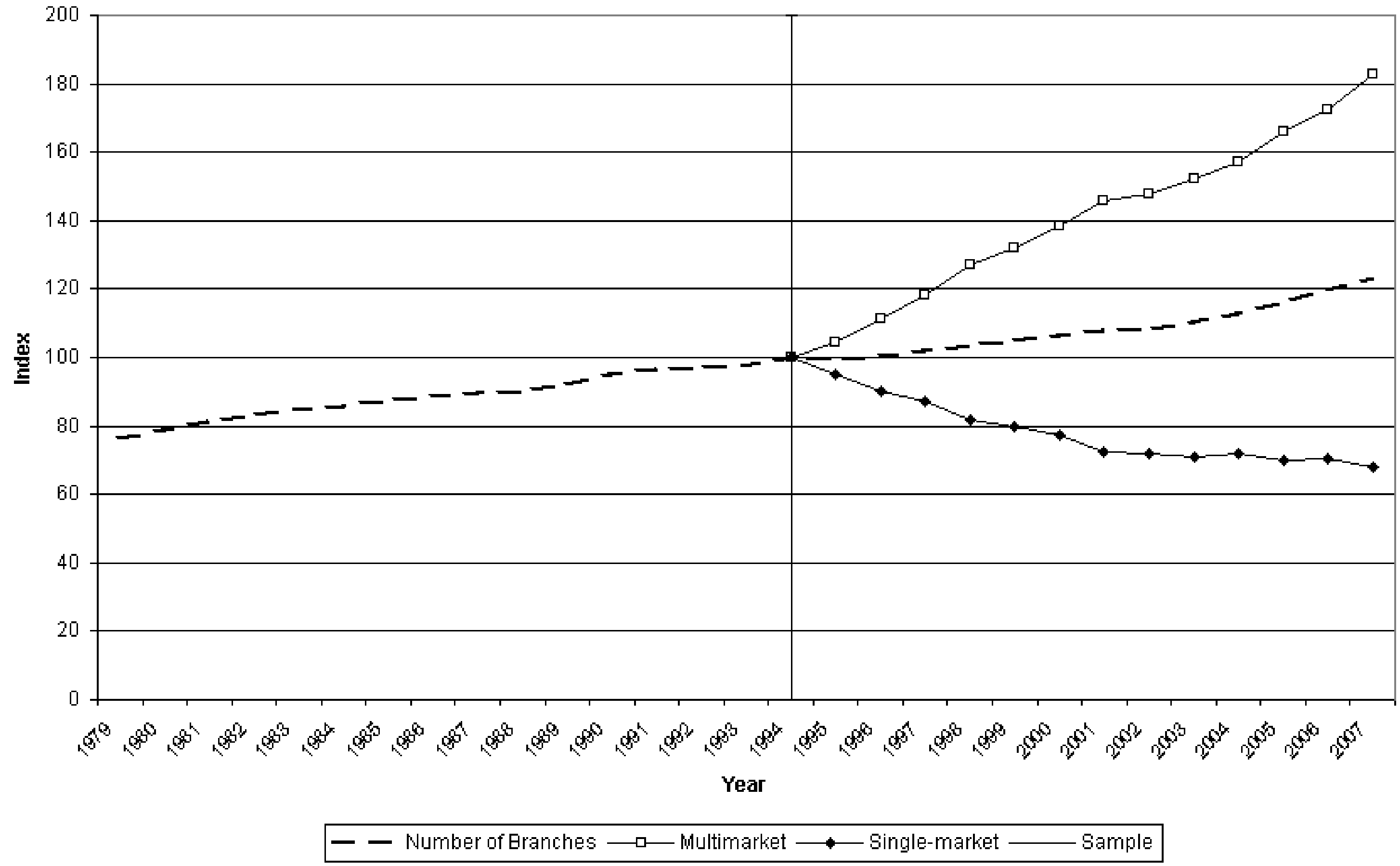

Figure 2: Number of branches. U.S. commercial and saving banks. 1979-2007. Index 1994=100.

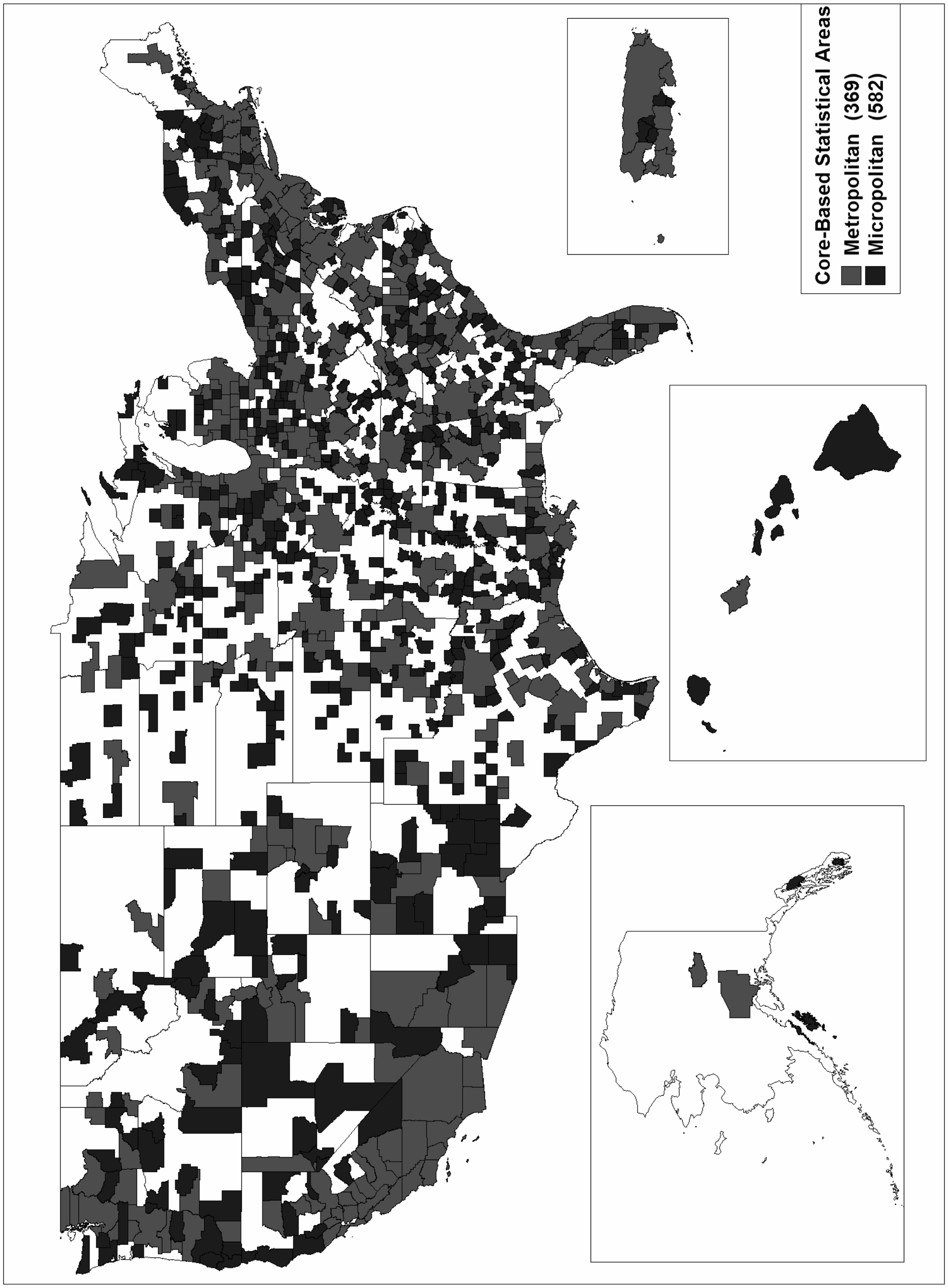

Figure 3: Metropolitan and Micropolitan Statistical Areas.

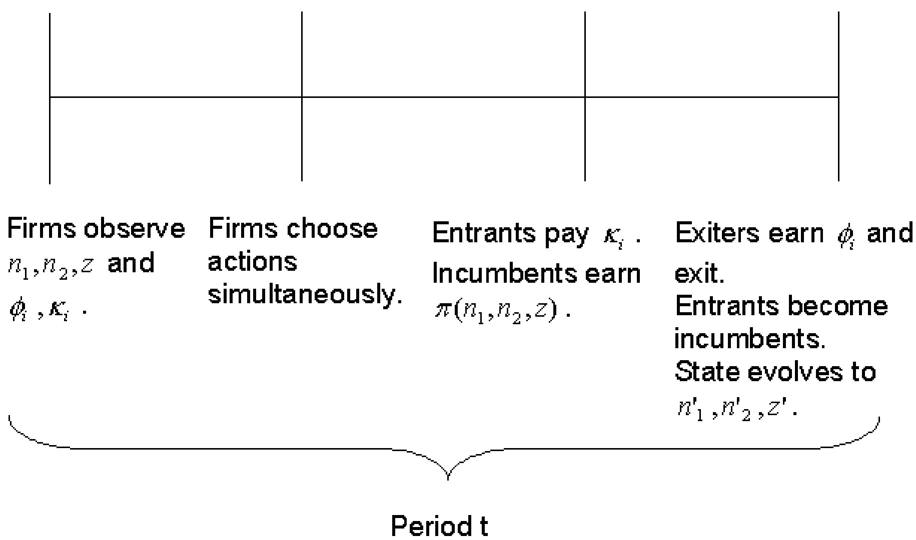

Figure 4: Timing of the game in period t.

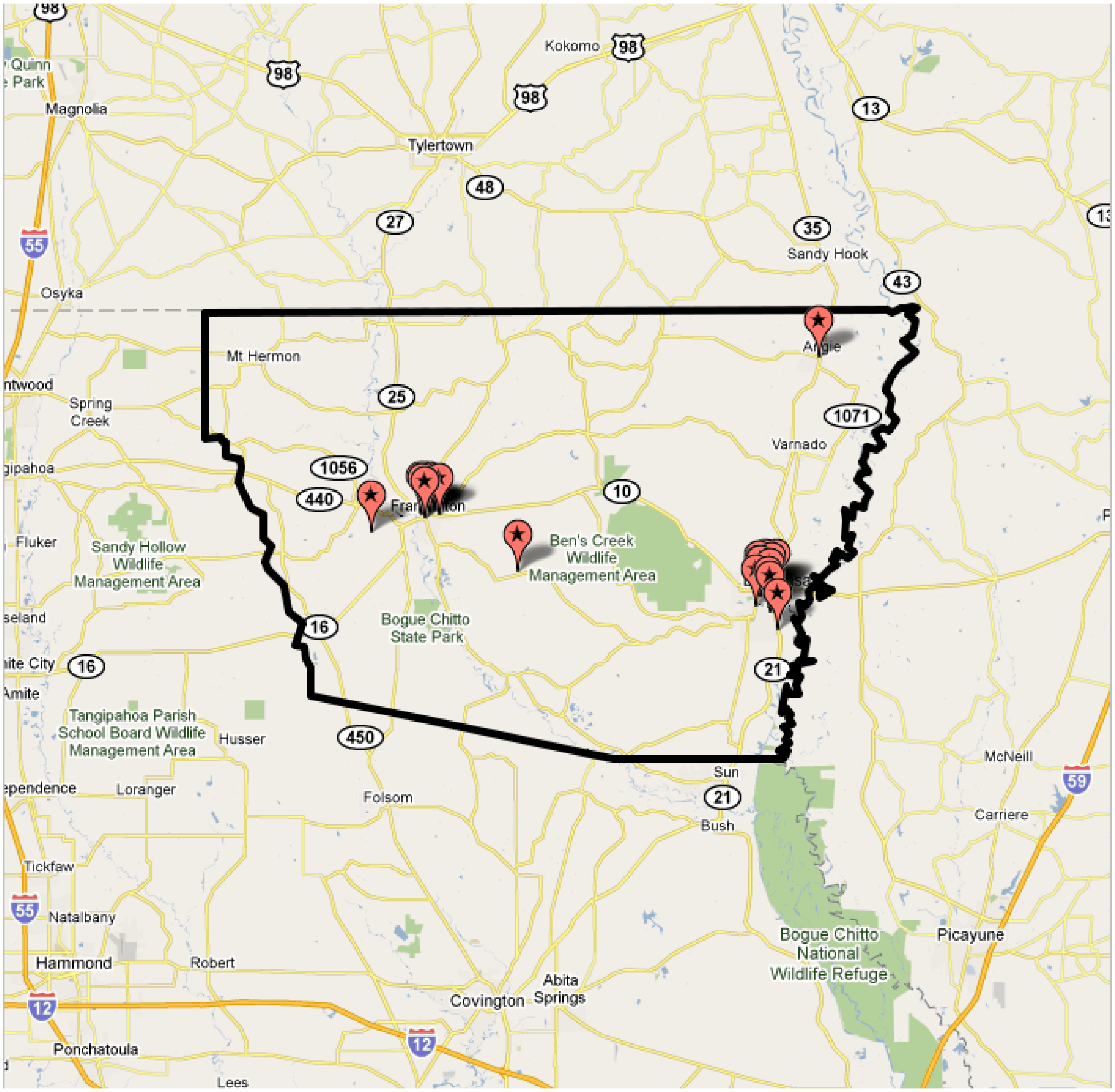

Figure 5: Bank's branch locations in Bogalusa Micropolitan Statistical Area, LA.

Table 1: Evolution of concentration and market structure in the banking industry, U.S., 1994-2007

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Aggregate level														
C4 (percentage)	8	7	8	10	13	14	15	16	17	18	21	26	25	26
HHI	33	32	36	53	71	78	107	114	126	137	157	221	210	215
Number of banks	12,928	12,221	11,630	11,125	10,677	10,288	10,060	9,703	9,433	9,219	9,034	8,825	8,733	8,567
Single-market	11,325	10,564	9,929	9,413	8,908	8,507	8,246	7,865	7,559	7,296	7,101	6,873	6,749	6,535
Multimarket	1,602	1,656	1,700	1,711	1,768	1,780	1,813	1,837	1,873	1,922	1,932	1,951	1,983	2,031
Number of branches	75,468	75,692	76,412	77,651	78,856	79,946	81,121	81,716	82,411	83,556	85,542	87,855	90,435	92,824
Single-market	39,155	37,389	35,541	34,258	32,252	31,498	30,327	28,460	28,215	27,847	28,230	27,350	27,652	26,455
Multimarket	36,300	38,290	40,858	43,379	46,589	48,434	50,780	53,242	54,181	55,694	57,297	60,489	62,766	66,353
Large urban markets[a]														
C1 (percentage)	25	25	26	26	26	26	26	26	26	26	26	27	26	26
HHI	1,440	1,461	1,491	1,498	1,519	1,512	1,507	1,505	1,505	1,503	1,518	1,538	1,514	1,505
Number of banks	29	28	27	27	27	27	27	27	27	27	27	27	28	29
Single-market	19	18	17	17	16	15	15	15	14	14	14	14	14	14
Multimarket	9	10	10	10	11	11	12	13	13	13	13	14	14	15
Small urban and rural markets[a]														
C1 (percentage)	45	45	45	45	45	45	45	45	45	45	45	45	45	45
HHI	3,585	3,567	3,555	3,549	3,537	3,532	3,517	3,500	3,494	3,495	3,488	3,471	3,438	3,437
Number of banks	5	5	5	5	6	6	6	6	6	6	6	6	6	6
Single-market	3	3	3	3	2	2	2	2	2	2	2	2	2	2
Multimarket	2	3	3	3	3	3	3	3	4	4	4	4	4	4

Notes: [i] Source: FDIC Summary of Deposits. [ii] C1 is the deposit market share of the largest bank in the market; C4 is the deposit market share of the four largest banks in the market; and HHI is the Herfindahl-Hirschman index computed with deposit market shares.
[iii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks. [iv] Large urban markets are Metropolitan Statistical Areas defined by the U.S. Census Bureau. Small urban and rural markets are Micropolitan Statistical Areas defined by the U.S. Census Bureau and rural counties. [a] Means over local markets.

Table 2: Sources of variation in the number of bank branches, Large urban markets, U.S., 1994-2006.

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
All banks													
Branch openings	3.5	4.0	5.5	5.0	4.7	4.2	3.9	3.6	3.9	4.8	5.0	5.0	4.9
Branch closings	-3.4	-3.1	-3.9	-3.5	-3.3	-2.6	-3.2	-2.6	-2.1	-1.8	-1.7	-1.5	-1.8
Net change	*0.2*	*0.9*	*1.6*	*1.6*	*1.4*	*1.6*	*0.7*	*1.0*	*1.7*	*3.0*	*3.3*	*3.5*	*3.1*
Single-market banks													
Branch openings	2.1	2.3	2.7	2.5	2.5	2.3	2.0	1.8	1.7	1.6	1.9	2.0	1.8
Branch closings	-1.6	-1.3	-1.5	-1.0	-0.9	-0.8	-0.7	-0.7	-0.6	-0.5	-0.5	-0.4	-0.4
Net bank change by M&A	-1.5	-2.1	-1.9	-1.9	-1.7	-2.2	-1.7	-0.8	-0.5	-0.9	-0.7	-0.6	-1.7
Net switch SM to MM	-1.3	-1.5	-0.9	-2.3	-0.5	-0.8	-1.9	-0.3	-0.8	0.6	-1.8	-0.4	-1.1
Net change	*-2.3*	*-2.7*	*-1.6*	*-2.7*	*-0.6*	*-1.5*	*-2.3*	*-0.1*	*-0.2*	*0.8*	*-1.1*	*0.6*	*-1.3*
Multimarket banks													
Branch openings	1.5	1.8	2.8	2.5	2.2	1.9	1.9	1.8	2.2	3.2	3.1	3.0	3.0
Branch closings	-1.8	-1.8	-2.4	-2.4	-2.4	-1.8	-2.4	-1.8	-1.5	-1.3	-1.2	-1.1	-1.4
Net bank change by M&A	1.5	2.1	1.9	1.9	1.7	2.2	1.7	0.8	0.5	0.9	0.7	0.6	1.7
Net switch SM to SM	1.3	1.5	0.9	2.3	0.5	0.8	1.9	0.3	0.8	-0.6	1.8	0.4	1.1
Net change	*2.4*	*3.6*	*3.2*	*4.3*	*2.0*	*3.1*	*3.1*	*1.1*	*2.0*	*2.1*	*4.4*	*2.8*	*4.4*

Notes: [i] Source: FDIC Summary of Deposits. [ii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks. [iii] Large urban markets are Metropolitan Statistical Areas defined by the U.S. Census Bureau. Small urban and rural markets are Micropolitan Statistical Areas defined by the U.S. Census Bureau and rural counties.
[iv] A branch opening means a denovo branch, a branch closing means a branch closed by a bank, a net bank change by M&A means branches owned by a different bank due to a bank merger, and a switch SM to MM means a single-market bank becoming a multimarket bank.
[v] Percentage over the number of incumbents.

Table 3: Sources of variation in the number of bank branches, Small urban and rural markets, U.S., 1994-2006.

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
All banks													
Branch openings	2.9	3.0	3.3	3.9	3.4	3.1	2.8	2.3	2.2	1.9	2.1	2.3	2.3
Branch closings	-2.1	-1.9	-1.6	-2.4	-2.1	-2.0	-2.0	-2.0	-1.8	-1.4	-1.2	-1.2	-1.2
Net change	*0.7*	*1.0*	*1.7*	*1.5*	*1.3*	*1.1*	*0.8*	*0.3*	*0.3*	*0.5*	*0.9*	*1.1*	*1.2*
Single-market banks													
Branch openings	1.6	1.8	1.9	1.9	1.7	1.6	1.3	1.1	1.1	0.9	0.9	0.9	1.1
Branch closings	-0.9	-0.8	-0.7	-0.9	-0.6	-0.6	-0.5	-0.5	-0.5	-0.3	-0.2	-0.3	-0.3
Net bank change by M&A	-1.7	-1.3	-1.4	-1.3	-1.8	-1.1	-1.4	-0.6	-0.5	-0.2	-0.5	-0.5	-0.8
Net switch SM to MM	-1.6	-1.3	-1.6	-1.9	-1.4	-1.2	-1.6	-1.0	-1.1	-1.0	-1.0	-0.8	-1.3
Net change	*-2.6*	*-1.6*	*-1.9*	*-2.2*	*-2.2*	*-1.3*	*-2.2*	*-1.0*	*-1.1*	*-0.7*	*-0.7*	*-0.7*	*-1.3*
Multimarket banks													
Branch openings	1.3	1.2	1.5	2.0	1.7	1.4	1.5	1.2	1.1	1.0	1.2	1.3	1.3
Branch closings	-1.3	-1.2	-0.8	-1.6	-1.4	-1.4	-1.5	-1.5	-1.3	-1.1	-1.0	-0.9	-0.9
Net bank change by M&A	1.7	1.3	1.4	1.3	1.8	1.1	1.4	0.6	0.5	0.2	0.5	0.5	0.8
Net switch SM to MM	1.6	1.3	1.6	1.9	1.4	1.2	1.6	1.0	1.1	1.0	1.0	0.8	1.3
Net change	*3.3*	*2.7*	*3.6*	*3.7*	*3.5*	*2.4*	*3.0*	*1.4*	*1.5*	*1.2*	*1.6*	*1.8*	*2.5*

Notes: [i] Source: FDIC Summary of Deposits. [ii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks. [iii] Large urban markets are Metropolitan Statistical Areas defined by the U.S. Census Bureau. Small urban and rural markets are Micropolitan Statistical Areas defined by the U.S. Census Bureau and rural counties.
[iv] A branch opening means a denovo branch, a branch closing means a branch closed by a bank, a net bank change by M&A means branches owned by a different bank due to a bank merger, and a switch SM to MM means a single-market bank becoming a multimarket bank.
[v] Percentage over the number of incumbents.

Table 4: Descriptive statistics for local markets, Selected local markets, U.S., 1994-2007.

Variable	Mean	s.d.	Median	Percentiles	
				1%	99%
Population	20,097	16,916	15,044	844	78,184
Population density (per squared mile)	37	90	23	1	169
Income per capita (2007 $)	21,545	4,381	21,164	13,234	34,387
Average wage (2007 $)	23,295	3,928	22,853	16,438	35,383
Number of business employees	7,633	7,221	5,172	290	33,834
Number of business establishments	470	418	343	17	1,951

Notes: [i] Source: Local Area Personal Income of the Bureau of Economic Analysis (population, income per capita, average wage, number of business employees), County of Business Patterns of the U.S. Census Bureau (number of business establishments), and Summary File 3 of the U.S. Census 2000 (land area).
[ii] Sample: Small urban and rural markets with less than 100,000 inhabitants, less than 8 SM incumbent banks, and less than 8 MM incumbent banks.

Table 5: Descriptive statistics for single-market and multimarket banks, U.S., 1994 and 2007.

	1994		2007	
	SM	MM	SM	MM
Bank level				
Number of markets	1	14	2	73
Number of states	1	2	1	5
Number of branches	4	60	6	570
Employees/branches	12	13	12	18
Multibank holding company	31	50	25	58
Loans & leases/assets	53	61	62	69
Real estate loans/loans & leases	50	58	62	65
Agricultural loans/loans & leases	20	11	13	8
Commercial & industrial loans/loans & leases	13	13	14	15
Loans to individuals/loans & leases	17	18	10	9
Loans to small businesses/loans & leases	23	22	26	20
Loans to small farms/loans & leases	29	16	21	12
Non-performing Loans/loans & leases	1.0	0.9	1.1	1.0
Equity/assets	10.0	8.1	11.4	10.3
Return on equity (ROE)	12.1	11.9	10.7	11.1
Return on assets (ROA)	1.2	0.9	1.1	1.1
Deposit interest rate	2.6	2.5	2.5	2.3
Loan interest rate	6.9	6.8	6.6	6.3
Bank-market level				
Number of branches	1.7	1.7	1.7	1.8
Deposits per branch	27,460	23,474	34,934	33,729

Notes: [i] Source: Reports of Condition and Income from Federal Reserve Bank of Chicago and Thrift Financial Reports from the Office of Thrift Supervision. [ii] Sample: Banks with branches in the selected local markets. [iii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks. [iv] Variables computed at the bank level are means weighted by the number of branches; variables computed at the bank-market level are simple means.

Table 6: Descriptive statistics for the market structure, Selected local markets, U.S, 1994-2007

		Number of multimarket banks									
		0	1	2	3	4	5	6	7	8	Total
Number of single-market banks	0	0.9	3.8	4.6	4.2	3.4	2.1	1.7	0.8	0.2	21.7
	1	2.7	4.7	5.8	4.4	3.2	2.6	1.4	0.8	0.2	25.8
	2	2.7	4.9	3.7	3.6	2.7	2.0	1.2	0.7	0.2	21.7
	3	1.7	2.4	2.8	3.0	1.9	1.2	0.9	0.3	0.1	14.4
	4	0.9	1.1	1.8	1.4	1.2	0.9	0.5	0.2	0.1	8.2
	5	0.4	0.7	0.8	0.8	0.7	0.5	0.3	0.1	0.1	4.3
	6	0.1	0.5	0.5	0.5	0.4	0.3	0.1	0.1	0.0	2.5
	7	0.1	0.2	0.2	0.2	0.3	0.2	0.0	0.0	0.0	1.1
	8	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.4
	Total	9.5	18.3	20.3	18.1	13.9	9.8	6.2	3.0	0.9	100.0

Notes: [i] Source: Summary of Deposits (FDIC). [ii] Sample: Small urban and rural markets with less than 100,000 inhabitants, less than 8 SM incumbent banks, and less than 8 MM incumbent banks.
[iii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks.
[iv] Percentage of total market-year observations.

Table 7: Entry and exit statistics, Selected local markets, U.S, 1994-2007

Number	Entry proportion (%)			Exit rate (%)		
of Incumbents	All	SM	MM	All	SM	MM
1	3.52	2.21	1.31	0.69	0.34	0.34
2	2.19	1.04	1.15	0.43	0.11	0.32
3	1.90	1.05	0.85	0.51	0.19	0.32
4	1.78	0.81	0.97	0.67	0.20	0.48
5	1.89	1.03	0.87	0.70	0.21	0.48
6	1.44	0.74	0.69	0.53	0.19	0.34
7	1.53	0.77	0.75	0.55	0.17	0.38
8	1.53	0.80	0.73	0.63	0.20	0.43
9	1.12	0.62	0.50	0.57	0.16	0.41
10 or +	0.01	0.01	0.00	0.01	0.00	0.00
Average	1.62	0.85	0.77	0.59	0.20	0.40

Notes: [i] Source: Summary of Deposits (FDIC). [ii] Sample: Small urban and rural markets with less than 100,000 inhabitants, less than 8 SM incumbent banks, and less than 8 MM incumbent banks.
[iii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks.
[iv] Entry proportion is the ratio of entrants to incumbents, and exit rate is the ratio of exits to incumbents.

Table 8: Estimation of the profit function

Dependent variable: bank-market profits (in million of 2007 $)	
Single-market bank dummy	0.205***
	(0.039)
Effects of competition on single-market banks	
First single-market competitor	-0.086**
	(0.036)
Second single-market competitor	-0.091
	(0.076)
Additional single-market competitors	-0.137***
	(0.014)
First multimarket competitor	-0.040
	(0.025)
Second multimarket competitor	-0.141***
	(0.025)
Additional multimarket competitors	-0.101**
	(0.042)
Effects of competition on multimarket banks	
First single-market competitor	-0.117***
	(0.034)
Second single-market competitor	-0.153***
	(0.016)
Additional single-market competitors	-0.081***
	(0.015)
First multimarket competitor	-0.072***
	(0.026)
Second multimarket competitor	-0.087**
	(0.036)
Additional multimarket competitors	-0.141***
	(0.016)
Market size controls	
Log(population)	-0.320***
	(0.103)
Log(income per capita)	-0.184**
	(0.072)
Log(wage)	0.042
	(0.072)
Log(n of establishments)	0.178**
	(0.073)
Log(n of employees)	0.369***
	(0.070)
Market fixed effects	Yes
Number of observations	111,484
Number of markets	1,678
Mean of dependent variable	0.703

Notes: [i] Sample: Small urban and rural markets with less than 100,000 inhabitants, less than 8 SM incumbent banks, and less than 8 MM incumbent banks.
[ii] Asymptotic standard errors robust to heteroscedasticity, and time series and within market correlation. [iii] Significance level: *** 1%, ** 5%, and * 10%.

Table 9: Descriptive statistics for the market state variable

Market state	N. of obs.	Population	Income per capita	N of banks	N of SM banks	N of MM banks	Pop. per bank	Profits per bank
1	2,367	2,496	20,479	1.55	0.73	0.82	1,795	0.258
2	2,367	5,189	21,254	2.73	1.24	1.49	2,404	0.363
3	2,368	8,096	20,609	3.32	1.56	1.76	2,998	0.439
4	2,367	10,675	20,676	3.85	1.71	2.14	3,390	0.503
5	2,367	13,307	21,230	4.65	2.04	2.61	3,474	0.522
6	2,368	17,154	21,435	5.06	2.12	2.94	3,927	0.612
7	2,367	21,933	21,540	5.35	2.21	3.15	4,572	0.723
8	2,368	28,423	21,694	6.14	2.40	3.74	5,166	0.767
9	2,367	38,165	22,172	7.04	2.58	4.47	5,974	0.818
10	2,368	55,516	24,364	7.88	2.68	5.20	7,355	1.117

Notes: [i] Sample: Small urban and rural markets with less than 100,000 inhabitants, less than 8 SM incumbent banks, and less than 8 MM incumbent banks. [ii] Single-market banks are banks that hold more than 80 percent of its deposits in a single local market. Multimarket banks are banks not classified as single-market banks. [iii] The statistics for population, income per capita, number of banks, SM banks, MM banks, and population per bank are means over market-year observations, and the statistics for profits per banks are means over bank-market-year observations.

Table 10: Sell-off Value and Entry Cost Parameters (in million of 2007 $)

	Potential Entrant Definition 1	Potential Entrant Definition 2
Mean Entry Cost		
Single-market bank	10.374***	10.434***
	(1.037)	(0.972)
Multimarket bank	7.058***	7.070***
	(0.632)	(0.623)
Single-market bank × market size	1.189***	1.197***
	(0.261)	(0.265)
Multimarket bank × market size	1.387***	1.396***
	(0.315)	(0.325)
Mean Sell-off value		
Single-market bank	0.000	0.000
	(0.180)	(0.181)
Multimarket bank	0.008	0.008
	(0.014)	(0.013)
Number of Observations	22,425	
Number of Markets	1,725	

Notes: [i] Sample: Small urban and rural markets with less than 100,000 inhabitants, less than 8 SM incumbent banks, and less than 8 MM incumbent banks.
[ii] Estimation: Minimum distance estimator with weighting matrix that replicates GMM in POB. Optimization using Compass Search. [iii] Bootstrap standard errors with 500 simulations. [iv] Significance level: *** 1%, ** 5%, and * 10%.