# Estimation of the Impact of Mergers in the Banking Industry*

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**Abstract**

It is well-documented that merging banks make adjustments in post-merger bank branch density. Mergers are usually accompanied by substantial entry and exit. These phenomena contradict a widely-used assumption of merger prediction: product quality and entry are exogenous and are constant pre- and post-merger. This paper aims to develop a methodology of merger analysis that incorporates the impact of mergers on product quality and entry. To avoid multiple equilibria, I estimate the post-merger patterns of product quality and entry by exploiting the historical data on bank mergers. Combining them with the estimates of demand and supply, I simulate the post-merger equilibria of thirteen cases of bank mergers. Most of the predicted post-merger branch densities and market shares of merging institutions are closer to the actual outcomes than the widely used sum of pre-merger branch densities and market shares of merging banks respectively, which tend to overestimate post-merger branch densities and market shares for large banks. There are two main findings on post-merger patterns. First, a reduction in the branch density of merging banks is strongly associated with the presence of highly overlapped pre-merger bank branch networks or large pre-merger market shares of merging banks. Second, new entrants tend to arise in counties where the total county income is high or the deposits of the acquirers are large.

Keywords: Merger, Product quality, Entry

JEL Classification: L11, L13, L44, G21, G34

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# 1 Introduction

In the past two decades, the banking industry has experienced considerable growth and consolidation. Many banks have expanded their branch networks geographically through mergers. It is well-documented that merging banks make adjustments in post-merger bank branch density. Mergers are usually accompanied by substantial entry and exit. These phenomena contradict a widely-used assumption of merger prediction: product quality and entry are exogenous and are constant pre- and post-merger. Merger analysis could be improved by incorporating the full effects of mergers on subsequent market structure. For example, bank branch density potentially determines equilibrium prices and is an important factor that consumers consider when choosing banks. Entry and exit are known to influence prices. Merger prediction has typically focused solely on post-merger prices. The main goal of this paper is to develop a methodology to predict post-merger equilibrium, which includes the impact of mergers on product quality and entry.

This methodology includes three steps. The first step is to estimate consumer and bank behavior. Since banks make adjustments in their post-merger branch density and are allowed to enter and exit, this calls for a model that explicitly allows for the endogeneity of product quality and entry. The biases caused by the observed endogenous product quality and the endogenous number of entrants are corrected by instrumental variable techniques. Most papers assume that unobserved product qualities are exogenous. However, many important endogenous product qualities are not always available, such as the network size of ATMs, or are hard to quantify, such as bank services. To correct the potential bias caused by the unobserved endogenous product quality, I exploit the first order conditions for unobserved endogenous product quality to construct new moment conditions to estimate the model. With the estimates of demand and supply, I could simulate post-merger product quality and entry theoretically. However, the presence of multiple equilibria limits the predictive power. In the second step, I circumvent this problem by taking advantage of the rich historical data on bank mergers and let the data reveal the post-merger equilibrium. To account for the endogeneity of mergers, I select nationwide bank mergers whose merging institutions have presences in several markets. These mergers can be regarded as exogenous to a local market (county). I estimate the patterns of post-merger changes in product quality and entry in local counties from these mergers. The last step is to simulate equilibrium using the predicted product quality and entry jointly with demand and supply estimates.

To empirically analyze bank mergers, I compile a data set that covers commercial banks in the U.S. from 1994 to 2005. On the demand side, I find that high income consumers respond more favorably to an increase in the pure deposit interest rate (deposit interest rate minus service fees) and respond less to an increase in branch density than low income consumers. The main findings on the post-merger product quality and entry are as follows: First, a reduction in branch density of merging banks is strongly associated with the presence of highly overlapped pre-merger bank branch networks or large pre-merger market shares of merging banks. Second, new entrants tend to arise in counties where the total county income is high or the deposits of acquirers are large. Last, mergers between dominant banks (market shares >15%) result in a significant increase in their marginal deposit return rates (the ability of a bank to generate money from its deposits), while mergers between non-dominant banks have insignificant impact.

It is also worth mentioning that it is more reasonable to use the real pure deposit interest rate (the nominal pure deposit interest rate minus the opportunity cost [1]) than the nominal pure deposit interest rate to compute price elasticity in the banking industry. Otherwise, the estimated price elasticity varies a lot across years with the federal funds rate and would have no implications. I also find that failure to address the endogeneity of the observed product quality (branch density in this paper) results in underestimating the price elasticity.

After estimating the demand and supply as well as the post-merger patterns of product quality and entry, I apply the methodology to thirteen cases of within-market bank mergers. Compared with the widely-used prediction methodology that uses the sum of pre-merger branch densities and market shares of merging banks as their post-merger values, most predictions from the methodology in this paper are closer to the actual outcomes, especially when the pre-merger market shares of two merging banks are close.

This paper is based on the large literature on antitrust analysis. Berry and Pakes (1993) propose to simulate the post-merger equilibrium prices with the estimates of demand and supply, assuming that mergers cause changes in the ownership of products and no changes in post-merger product quality. Other researchers notice that this assumption may fail because mergers can cause changes in product quality as well as prices. Richard (2003) studies the impact of mergers on product quality and prices in the airline industry. He uses a duopoly model with only one observed product quality, and imposes an assumption: the post-merger demand and costs are the higher demand and lower costs of the two previous competitors respectively. However, it is hard to extend his model to industries with multiple firms. The model in this paper studies multiple firms with multiple product qualities.

This work also relates to other studies on consumer and bank behavior. The model is based on models presented separately by Dick (2002) and Ishii (2004). Dick is the first one to use a structural model to study the banking industry. Ishii adapts Dick's model to account

[1] I use the average loan rates of all large banks as the opportunity cost in each year in this paper.

for the fact that the quantity variable is a bank's amount of total deposits rather than its number of customers. My model further incorporates the fact that banks may increase the post-merger loan rates due to the reduction in the number of banks caused by mergers.

There are still some limitations of this methodology. Mergers in this work are restricted to those among commercial banks and savings banks (hereafter referred to as commercial banks).[2] Due to a lack of data, mergers between commercial banks and other depository institutions are not included in this analysis. I discuss both within-market and out-of-market mergers, but focus on the former.

The remainder of this paper is structured as follows. Section 2 gives an overview of the banking industry and bank mergers. Section 3 describes the data. Section 4 outlines the model and specifications used in this paper. Section 5 discusses the estimation methodology and explains how to implement merger simulations. Section 6 presents the results. Section 7 concludes.

## 2 Industry Background

The banking industry (commercial banks) constitutes a major part of the U.S. economy, employing about 2 million people, holding total assets of over $10 trillion, having total domestic deposits of $5.5 trillion and loaning a total of $6.2 trillion in 2007. Throughout the past two decades, and particularly in the nineties, the industry has undergone several changes in both its structure and regulation. One important change is the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994, which permits nationwide branching as of June 1997.

There was a significant response of banks to these regulatory changes. The number of mergers has averaged around 500 per year throughout the nineties. The number of commercial banks has decreased by thousands, reaching 7,527 in 2005 from 10,452 in 1994. Moreover, this sector has increased its concentration. The distribution of bank size has changed. The market shares of banks with assets greater than $10 billion (base year = 2002) has increased to 74% in 2003 from 43% in 1984. The market shares of small banks with assets less than $100 million (base year = 2002) has decreased to 2% in 2003 from 8% in 1984.[3] As the bank merger wave continues, it is important to understand and predict the impact of bank mergers.

[2] The number of commercial banks is much larger than that of savings banks.

[3] Data source: FDIC.

# 3 Data

Before introducing the model, I first discuss the data, as they indicate the modeling approach used in this paper. The data cover commercial banks in the US from 1994 to 2005 and come from several sources. Deposits of commercial banks and savings banks come from the Summary of Deposits from the Federal Deposit Insurance Corporation (FDIC). This provides branch-level deposits, and bank characteristics including branch addresses, headquarters, whether a bank belongs to a bank holding company, and whether a bank was a former savings association. As discussed below, I use both savings associations and credit unions as the outside goods. The data on deposits of savings associations are also obtained from the Summary of Deposits, and the data on deposits of credit unions are from the Freedom of Information Act (FOIA) Reports from the National Credit Union Administration (NCUA). All deposits and other values are in 2000 dollars. (I use the Consumer Price Index to deflate.) I count branches as offices with full service and positive office-level deposits. Offices with deposits above 1 billion dollars are excluded, because these offices are likely to be internet banks, such as the ING Direct, or are likely to be bank headquarters whose majority deposits come from nonfinancial businesses rather than individuals (households) in local markets. Offices with the same address and belonging to the same bank are counted as one branch. Data on bank mergers are also obtained from the FDIC.

I derive additional bank-level data from the Call Reports in June from the Federal Reserve Bank of Chicago. I estimate the bank-level deposit interest rate as the ratio of interest expense on deposits to deposits. Similarly, I calculate the bank-level service fees as the ratio of service charge on deposit accounts to deposits. The interest rates and service fees are all calculated as one year rates. Appendices A and B give the detailed definitions of the variables in this paper.

Finally, county-level demographic data are taken from both the U.S. Census and the Bureau of Economic Analysis. Information on the distribution of demographics was obtained by sampling individuals in the 2000 Census survey from the Integrated Public Use Microdata Series (IPUMS). I combine the micro data in 2000 with the annual county-level income and population growth rates from the Bureau of Economic Analysis to estimate micro data for other years in the study. Individual income was obtained by dividing household income by the size of the household.

I focus on counties with population above 200,000 from 1994 to 2005. There are 293 such counties in the sample.[4] Most within-county mergers, the focus of this paper, happen in these

[4]For some counties with population above 200,000 in some years and below 200,000 in other years, only samples in years with county population above 200,000 are included.

large counties.[5]

# 4 Empirical Framework

In order to investigate the effects of bank mergers, I estimate demand and supply first. I set out a model of consumer and bank behavior consisting of a three-stage game with complete information. In the first stage, fringe banks, as defined below, make entry decisions. In the second stage, all banks choose product quality, including both observed and unobserved. In the third stage, all banks choose prices and consumers choose products. Banks make entry, product quality and price decisions to maximize their profits given their costs and consumer preferences. Consumers maximize their utility given their individual preferences and products available on the markets. Most papers focus on the last stage and take firm decisions in the first two stages as exogenous.

Demand and supply are derived and estimated following a discrete choice approach adapted from a method proposed by Berry, Levinsohn, and Pakes (1995) (hereafter referred to as BLP). Three modifications are made for an application to the retail banking. First, as Ishii (2004) notes, the quantity variable is a bank's amount of total deposits rather than its number of customers. Second, bank mergers can influence loan prices in addition to deposit interest rates. Third, branch density, unobserved product quality, and entry are endogenous.

## 4.1 Market Definition and Data Summary

To implement the discrete choice approach, I define markets, as well as inside and outside goods. I define a market's geographic size as a county. The product market is defined as deposits at all insured depository institutions, including commercial banks, savings banks, savings associations and credit unions in a market (county). Depository institutions are divided into inside goods and outside goods. The inside goods consist of all FDIC-insured commercial banks and savings banks. The outside goods are composed of other depository institutions, including FDIC-insured savings associations and NCUA-insured credit unions. Each FDIC-insured commercial bank files a call report each quarter, from which I obtain service charge and interest expense on deposits, etc. Unfortunately, similar data for savings associations and credit unions are not available to the public, so they are labeled the outside goods.

[5] According to the statistics on counties with and without within-county bank mergers in California from 1990 to 2004 (in a separate paper of mine), the average number of branches in counties with within-county mergers is 185 while the average number of branches in counties without within-county mergers is 26. Counties with within-county mergers are much bigger those without within-county mergers.

I divide the inside goods into two categories: large banks and fringe banks. Large banks are defined as banks with market shares among all FDIC-insured depository institutions (hereafter referred to as FDIC market shares)[6] above 1% or total deposits in a county over 1 billion US dollars.[7] The rest are defined as fringe banks. Among large banks, I further define dominant banks as those commercial banks with FDIC market shares above 15%.

Table 1 displays summary statistics on market characteristics. The average number of dominant banks, large banks and fringe banks in a market are 1.636, 11.48 and 20.17, respectively.

Insert Table 1 about here.

The difference between large banks and fringe banks is evident. Table 2 shows the summary statistics of large banks and fringe banks. On average, large banks offer smaller interest rates and smaller service fees than do fringe banks. In 1994, the average deposit interest rate offered by fringe banks was 0.94% higher than that offered by large banks. In 2005, the difference was reduced to 0.10%. Large banks and fringe banks both slightly increased their service fees by 0.090% and 0.071%, respectively, from 1994 to 2005. The average number of branches of a large bank in a county was 9.27 in 1994 and 9.83 in 2005, respectively. The average number of branches of fringe banks in a county was 1.76 in 1994 and 1.91 in 2005, respectively. Compared with banks in 1994, banks in 2005 became geographically diversified. The average number of states in which banks maintain operations has increased from 1.08 in 1994 to 6.19 in 2005 for large banks, and from 1.03 in 1994 to 2.23 in 2005 for fringe banks. Banks in 2005 were also more likely to belong to a bank holding company, more likely to be international banks, and more likely to be transferred from a former savings association than banks in 1994. In 2005, many banks had headquarters outside of the markets. Large banks are also more likely to belong to a bank holding company, be international, and have headquarters in the same county and state; they are also less likely to be a former savings association than fringe banks.

Insert Table 2 about here.

To simplify the model, each branch of a fringe bank will be treated as a fringe bank, so that each fringe bank has only one branch. All fringe banks in the same market are assumed to be independent and identical except in their entry costs.

[6] In the definition, market shares among all FDIC-insured depository institutions is used instead of market shares among all insured depository institutions, because there are many similarities between commercial banks and savings associations. In several studies on banks, researchers examine commercial banks and savings associations together.

[7] As a robustness check, I redefine large banks as banks with FDIC market shares above 2% or total deposits in a county over 1 billion US dollars and estimate the model of demand and supply.

The definition of entry in this paper is different from the common definition. The number of entrants is defined as the change in the total number of branches of fringe banks. For example, if a fringe bank builds a new branch, this new branch is considered as an entrant. If a new fringe bank with two branches enters a market, this is counted as two entrants. This definition greatly simplifies entry analysis. The number of new entrants who differ only in entry costs can be studied instead of new entrants with different product quality in the counterfactual analysis.

For variables of the representative fringe bank in each market, the weighted average value computed by different weights is used, for example, deposits of banks as weights for average deposit interest rates and service rates. The detailed weight for each variable is listed in Appendix A.

In the model, large banks and fringe banks are different in the following ways. First, the branch network of a large bank is endogenous, while the branch network of each fringe bank is equal to one and is exogenous. Second, entry decisions of fringe banks are endogenous, while entry decisions of large banks are assumed to be exogenous because large banks usually enter or exit through mergers and acquisitions.

After defining and summarizing markets, the model and its specifications will be discussed.

## 4.2 Consumer Demand

In this section, the utility function and the corresponding formula for market shares in general are presented, followed by a discussion of a special demand model.

### 4.2.1 Utility Function

Based on the Survey of Consumer Finances, consumers appear to cluster their purchases for deposit services within their primary depository institution.[8] Therefore, it is assumed that a consumer chooses a single commercial bank for depository services. I treat each bank as a single product firm offering a basket of services. I assume that $m = 1, ..., MT$ markets[9] are observed, each with $i = 1, ..., I_m$ consumers and $j = 1, ..., J_m$ banks.[10] The conditional indirect utility function of consumer $i$ for choosing bank $j$'s services in market $m$ takes the following form:

[8] See Amel and Starr-McCluer(2001). See Elliehausen and Wolken (1990) and Kwast et al. (1997).

[9] Each market is a given county in a given year.

[10] $J_m$ stands for the representative fringe bank in market $m$ if there is at least one fringe bank. There are no fringe banks in some markets.

$$u_{ijm} = \alpha_{im} p_{jm} + x_{jm} \beta_{im} + \xi_{jm} + \epsilon_{ijm}, \tag{1}$$

where $p_{jm}$ is bank $j$'s real pure deposit interest rate as defined below, $x_{jm}$ is a $K$-dimensional (row) vector of observed variables for bank $j$ in market $m$ and a set of year and county dummy variable, $\xi_{jm}$ is a bank unobservable, $\epsilon_{ijm}$ is an individual- and bank-specific unobservable, $\alpha_{im}$ is consumer $i$'s marginal utility from income, and $\beta_{im}$ is a $K$-dimensional (column) vector of individual-specific preference coefficients. The utility of the outside alternative, savings associations and credit unions, is given the form

$$U_{i0m} = \xi_{0m} + \epsilon_{i0m},$$

where I normalize $\xi_{0m}$ to zero.

Below are some specifications used in the estimation. Suppose market $m$ is in year $t$. Bank $j$'s real pure deposit interest rate is defined by

$$p_{jm} = int_{jm} - ser_{jm} - disc_t,$$

where $int_{jm}$ is the deposit interest rate that bank $j$ pays to consumers, $ser_{jm}$ is the average service charge on deposit accounts (including maintenance charges, charges for their failure to maintain specified minimum deposit balances, etc.), and $disc_t$ is the opportunity cost in year $t$. The first two terms constitute the nominal pure deposit interest rate, $p^n_{jm}$. The real pure deposit interest rate is defined as the nominal pure deposit interest rate minus the opportunity cost. I use the average loan rate as the opportunity cost and calculate this rate as the average of loan rates of all large banks and representative fringe banks[11] from January to June (the same period that I use to compute deposit interest rate and service fees) in each year. If someone prefers to use price rather than interest rate, the corresponding price is the negative value of the interest rate. Similarly, the real price is defined as the nominal price plus the opportunity cost. That is, the nominal price for bank $j$'s services in market $m$ is $P^n_{jm} = ser_{jm} - int_{jm}$ and the real price is $P_{jm} = ser_{jm} - int_{jm} + disc_t$.

I divide observed bank characteristics, $x_{jm}$, into two categories: observed endogenous bank characteristics, $x^{en}_{jm}$, and observed exogenous bank characteristics, $x^{ex}_{jm}$. Observed endogenous characteristics are those observed characteristics that the manager of bank $j$ in local market $m$ can make decisions about. For instance, a bank can choose its branch density in a county or

[11] The average loan rate of fringe banks is higher than that of large banks. Including every fringe bank in the calculation of the yearly average loan rate would raise its value by about 0.4%. I include only the representative fringe bank in each market in the calculation since fringe banks are a minority of the total loan market.

the size of its fleet of ATMs or service quality. Unfortunately, among these characteristics, only branch density in a market is available for every bank in every market. Branch density, defined as the total number of branches divided by the size of a county (branches per square mile), is used as a measure of how convenient a bank is to potential consumers. The convenience of a bank is one of the most important factors for a customer in choosing a bank. I measure the branch density variable in logs to captures the declining marginal value of closeness. There are two other benefits: First, as shown in the next section, it helps to derive an analytic form of the optimal choices of the endogenous product quality. Second, the coefficient on the log value of branch density implies the trade-off between positive network effects and negative substitution effects among branches of a bank in the same market.[12] It is expected that the coefficient on the log value of branch density will be positive. For a fringe bank, which is assumed to have only one branch, the log value of its branch density is equal to the negative log value of the county size. Although I include only one endogenous characteristic in the application to banks, adding extra endogenous characteristics into the model does not increase the computation burden very much.

Observed exogenous bank characteristics, $x^{ex}_{jm}$, are those observed characteristics that a local manager cannot influence easily, due to bank history or decisions made by the bank's headquarters. Among the included observed exogenous characteristics are the log value of the number of states in which a bank has a presence, an indicator for whether its headquarter is in the same county, an indicator for whether its headquarter is in the same state, an indicator for being international, an indicator for being a former savings association, an indicator for whether the bank belongs to a bank holding company, a fringe bank dummy variable,[13] and the categories of asset size that the bank falls into (medium, big and mega).[14] Year and county dummy variables are included in observed exogenous characteristics to capture the macro economic environment of a specific year and a specific county.[15] Since I normalize $\xi_{0m}$ to 0, the county dummy captures the negative value of utility from outside goods.

The utility from unobserved product qualities, $\xi_{jm}$, stands for the utility from both unobserved exogenous and endogenous product characteristics, such as reputation, fleet of ATMs, and service quality. Let $\xi_{jm} = \log(q_{jm})$. Hence, $q_{jm}$ measures the quantity of the unobserved

[12] The detailed discussion is given in section 8.2.

[13] The dominant bank dummy variable is not included.

[14] The asset size categories, $D_{medium}$, $D_{big}$, $D_{mega}$, are defined as follows: Medium-sized banks have assets between 100 million and 300 million; big banks have assets between 300 million and 3 billion; mega banks have assets above 3 billion. The definition is based on the FFIEC form that banks are supposed to report to the regulatory authority. The only difference is that the FFIEC's large banks include both big banks and mega banks in my definition.

[15] It would be ideal to include a year-county-specific dummy, $d_{year,county}$, but it is difficult to implement due to the unusually large number of parameters.

product qualities. There are several benefits that result from measuring unobserved product qualities in logs. First, it is consistent with how observed endogenous product qualities enter the utility function. Second, $q_{jm}$ is guaranteed to be positive.

Whether to separate endogenous product qualities from exogenous product qualities may not matter much for the utility function, but it matters for the demand estimation procedure and the specification of supply side, and, therefore, it changes the estimates.

#### 4.2.2 Market Shares

With consumer utility functions, market shares can be computed. Assuming that each consumer chooses one bank that gives the highest utility, the set of individual- and bank-specific unobservables $\epsilon = (\epsilon_{i1m}, ..., \epsilon_{iJ_m m})$ that lead consumer $i$ to choose bank $j$ in market $m$ is implicitly defined by

$$A_{ijm} = \{\epsilon | u_{ijm}(x_{jm}, \xi_{jm}, p_{jm}, D_{im}, v_{im}; \theta^d) \geq u_{ilm}(x_{lm}, \xi_{lm}, p_{lm}, D_{im}, v_{im}; \theta^d), \forall l = 0, 1, ..., J_m\},$$

where $D_{im}$ is a $d \times 1$ vector of observed consumer demographic characteristics, $v_{im}$ captures the additional unobserved characteristics, and $\theta^d$ is a vector of all demand parameters. If $\epsilon$ has distribution $P^*_\epsilon(\cdot)$, then the probability that consumer $i$ chooses bank $j$ in market $m$ is

$$f_{ijm} = f_{jm}(D_{im}, v_{im}; \theta^d) = \int_{A_{ijm}} dP^*_\epsilon(\epsilon).$$

Note that the primary quantity variable of interest is not the market share of consumers, but rather the share of deposits in the banking industry. Unfortunately, the distribution of individual deposits, $Dep_{im}$, is not observed in the data. As suggested by Ishii (2004), I relate individual deposits to an observable variable, income $Y_{im}$, with the following simple assumption: $Dep_{im} = \tau_m Y_{im}$, where $\tau_m$ is the savings rate and is common for all consumers in market $m$. It turns out that $\tau_m$ is cancelled out from the nominator and denominator in the following equations. Assuming that $v_i$, $D_{im}$ and $\epsilon_{ijm}$ are independent, bank $j$'s market share is given by

$$
\begin{aligned}
s_{jm} &= \frac{\int_{(D,v)} Dep \cdot f_{jm}(D,v) dP_v^*(v) dP_D^*(D)}{\sum_{l=0}^{J_m} \int_{(D,v)} Dep \cdot f_{lm}(D,v) dP_v^*(v) dP_D^*(D)} \qquad (2) \\
&= \frac{\int_{(D,v)} Y \cdot f_{jm}(D,v) dP_v^*(v) dP_D^*(D)}{\sum_{l=0}^{J_m} \int_{(D,v)} Y \cdot f_{lm}(D,v) dP_v^*(v) dP_D^*(D)} \\
&= \frac{\int_{(D,v)} Y \cdot f_{jm}(D,v) dP_v^*(v) dP_D^*(D)}{\int_{(D,v)} Y \cdot dP_v^*(v) dP_D^*(D)} \\
&= \int_{(D,v)} f_{jm}(D,v) \frac{Y dP_D^*(D)}{\int_D Y \cdot dP_D^*(D)} dP_v^*(v) \\
&= \int_{(D,v)} f_{jm}(D,v) dP_D^{**}(D) dP_v^*(v),
\end{aligned}
$$

where $P^*(\cdot)$ denotes population distribution functions. The third equality comes from the fact that $\sum_{l=0}^{J_m} f_{lm}(D,v) = 1, \forall (D,v)$. The fourth is from $\int_{(D,v)} Y \cdot dP_D^*(D) dP_v^*(v) = \int_D Y \cdot dP_D^*(D)$. In the last equality, I define $dP_D^{**}(D) \equiv \frac{Y}{\int_D Y \cdot dP_D^*(D)} dP_D^*(D)$. Noticing that $\int dP_D^{**}(D) = 1$, I can regard $P_D^{**}(D)$ as a pseudo cumulative probability density function of $D$. The implication of the last equality is clear: When I simulate market shares, I draw individual demographics from the population distributions adjusted by income rather than the population distributions directly. Equation (2) gives us a general formula to compute market shares. If consumer preferences over product quality are homogenous, equation (2) can be greatly simplified.

*A Simplification: Logit Demand*

It is useful to consider a situation in which consumers have homogenous deposit levels and homogenous preferences for product quality, and consumer heterogeneity in preferences is restricted to enter the utility function only through $\epsilon_{ijm}$, which are distributed i.i.d. type-I extreme value over individuals and products. These assumptions lead to the logit demand model of McFadden (1974). Such a simplified utility function can be specified as:

$$u_{ijm} = \alpha p_{jm} + x_{jm}\beta + \xi_{jm} + \epsilon_{ijm}.$$

This utility function, along with homogenous deposits, implies that deposit shares are equal to shares of consumers and simplify to the following:

$$s_{jm} = \frac{\exp(\alpha p_{jm} + x_{jm}\beta + \xi_{jm})}{1 + \sum_{l=1}^{J_m} \exp(\alpha p_{lm} + x_{lm}\beta + \xi_{lm})}. \qquad (3)$$

The logit model has the well-known shortcoming of generating potentially unrealistic substitution patterns, but it has the advantage of processing large data sets and can be easily implemented. It provides a basis for comparison to the random coefficients logit model that studies the heterogeneity of consumer preferences.

## 4.3 Bank Supply

I now move from the demand side to the supply side to discuss how banks make decisions, starting with the profit function, talking about the marginal deposit return rate (as defined below), and then derive the first order conditions.

### 4.3.1 Profit Function

Each large bank is assumed to set its observed product quality and unobserved product quality, as well as its pure deposit interest rate to maximize profits. The only observed product quality here is branch density, $n_{jm}$. Since the network sizes of large banks are big, branch density can be treated as a continuous variable for simplicity. A fringe bank, after deciding to enter, sets its unobserved product quality and deposit interest rate to maximize profits. It does not choose any observed product quality, since the only observed product quality is branch density, which is assumed to be the negative log value of the size of a county for a fringe bank.

Both large banks and fringe banks take in deposits, which are primarily used to generate revenue through the funding of various credit instruments. Bank $j$ $(= 1, ..., J_m)$'s profit in local market $m$ is the following:

$$\pi_{jm} = (r_{jm} - mc_{jm} - p_{jm})M_m s_{jm} - n_{jm}c_{jm} - C_{jm},$$

where $r_{jm}$ is the marginal deposit return rate, $mc_{jm}$ is the marginal cost for endogenous product qualities related to marginal costs, $M_m$ is the total deposits of all depository institutions in market $m$, $c_{jm}$ is bank $j$'s cost for branch density, and $C_{jm}$ is bank $j$'s entry cost minus other noninterest income that is not related to deposits, such as income from underwriting securities. The marginal cost for endogenous product quality, $mc_{jm}$, is specified as

$$mc_{jm} = k_{jm}q_{jm},$$

where $k_{jm}$ is bank $j$'s cost for producing unobserved endogenous product quality. If $H$-dimensional endogenous product qualities are related to marginal costs, then $k_{jm}$ is an $H$-dimensional vector of individual product quality costs, each of which is the marginal cost for producing the corresponding individual product quality in $q_{jm}$.[16] It does not make any difference whether to use the nominal pure deposit interest rate or the real pure deposit interest rate in the profit function, since the yearly opportunity cost will enter the year dummy variable in the estimation of the marginal deposit return rate as discussed below.

### 4.3.2 Marginal Deposit Return Rate

The marginal deposit return rate, $r_{jm}$, measures the ability of a bank to make money from its deposits. It includes income from loans, loan losses, interest income from securities, service fees other than service charges on deposit accounts, other commission fees purchased by consumers, and marginal cost of processing deposits. It corresponds to the loan rates (if ignoring loan losses and other noninterest income) in the model presented by Dick (2002) and Ishii (2004), in which loan rates are assumed to be exogenous. The assumption of exogenous loan rates is fine if the number of banks in a market does not change. However, the impact of mergers on the marginal deposit return rate has to be considered in merger analysis because one important incentive for banks to merge is to raise loan rates and other service fees.

Theoretically, a bank can choose any level of loan rates. However, the higher the loan rates, the fewer loans are sold and the higher the default rates will be. That is, extremely high loan rates lead to low marginal deposit return rates. The maximum of the deposit return rate that a bank can achieve in a market is not random. It depends on the market structure as well as other exogenous bank and market characteristics. Suppose a bank's marginal deposit return rate is equal to the highest achievable deposit return rate. Since detailed branch-level or county-level data on loans and noninterest income are not available, the following reduced form of the marginal deposit return rate is used:

$$r_{jm} = \rho_N^r \ln(N_m + 1) + \rho_Y^r Y_{jm} + \varpi_{jm}, \tag{4}$$

$$\theta^s = (\rho_N^r, \rho_Y^r),$$

where $\rho_N^r \ln(N_m + 1)$ is the competition effect, $Y_{jm}$ is a vector of observed exogenous bank and market characteristics, $\varpi_{jm}$ is a bank- and market-specific unobservable, and $\theta^s$ is a vector of all supply parameters. The addition of 1 in $\ln(N_m + 1)$ is used to avoid $\ln 0$. $\ln(N_m + 1)$ is not simply the log of the total number of banks plus one. Now I outline some facts on the lending market that the specification of the competition effect is based on. Calomiris and Pornrojnangkool (2005) point out that different sized banks compete on different lending

[16] For example, if branch density is also related to marginal costs instead of fixed costs, then $mc_{jm} = c_{jm}n_{jm} + k_{jm}q_{jm}$.

markets and have different market power on those markets. Local loan market concentration has little or no effect on small borrowers and the largest borrowers.[17] Middle-market borrowers are most likely to suffer from allowing monopoly power to be created (or a merger between two dominant banks) in their local lending market, since they cannot borrow from small banks or banks outside of local markets. Based on the above facts, the competition effects are modeled in the following way:

$$\rho_N^r \ln(N_m + 1) = \rho_{domi}^r \cdot D_{domi} \cdot \ln(N_{domi,m} + 1) + \rho_{l\arg e}^r \ln(N_{l\arg e,m} + 1) + \rho_f^r \ln(N_{fm} + 1),$$

where $N_{domi,m}$, $N_{l\arg e,m}$, $N_{fm}$ represent the number of dominant banks, large banks, and fringe banks respectively. The interpretation of the above equation is clear: $D_{domi} \cdot \ln(N_{domi,m} + 1)$ is the impact of the number of dominant banks on the marginal deposit rates of dominant banks or loan rates of middle-market borrowers. $\rho_{l\arg e}^r \ln(N_{l\arg e,m} + 1) + \rho_f^r \ln(N_{fm} + 1)$ means that all banks compete for the rest of borrowers. The reason for separating large banks from fringe banks is that they have different market powers and different impacts on prices.

The number of dominant banks and large banks is assumed to be exogenous in the model. However, the number of fringe banks is endogenous and is correlated with the unobserved bank- and market-specific unobservable $\varpi_{jm}$ (hereafter referred to as bank- and market-specific deposit return rate), which suggest the need for instrumental variables. This will be discussed in section 5.4. I include in $Y_{jm}$ the dominant bank dummy variable, bank exogenous characteristics[18], market characteristics, and year and county dummy variables.

Based on the above specifications of the supply side, I then use the first order conditions to recover the underlying costs and unobserved marginal deposit return rates.

### 4.3.3 First Order Conditions

Given the demand function and the entry decisions made by banks in the first stage, bank $j$ chooses its product quality in the second stage and chooses its price in the third stage to maximize its profit, given its and the competitors' costs and consumer preferences. Although product quality and prices are chosen in sequence, the first order conditions (FOCs) are exactly the same as that the FOCs when they are chosen simultaneously.

$$\max_{\{p_{jm}, n_{jm}, q_{jm}\}} \pi_{jm} = (r_{jm} - k_{jm} q_{jm} - p_{jm}) M_m s_{jm} - n_{jm} c_{jm} - C_{jm}.$$

[17] Small borrowers can borrow from all banks. The largest borrowers have established credit and have access to many national or international banks and capital markets.

[18] The endogenous bank characteristic, branch density, is not included. There is some evidence showing that branches may help banks monitor borrowers to increase the marginal deposit return rates. Since a market is defined in this paper as a county, which is relatively small, these monitoring effects are not evident.

The optimal prices, $p_{jm}$, and the optimal product qualities, $n_{jm}, q_{jm}$, must satisfy the first order conditions

$$\begin{aligned}
-s_{jm} + (r_{jm} - k_{jm}q_{jm} - p_{jm})\frac{\partial s_{jm}}{\partial p_{jm}} &= 0, \\
-\frac{c_{jm}}{M_m} + (r_{jm} - k_{jm}q_{jm} - p_{jm})\frac{\partial s_{jm}}{\partial \ln n_{jm}}\frac{1}{n_{jm}} &= 0, \\
-k_{jm}s_{jm} + (r_{jm} - k_{jm}q_{jm} - p_{jm})\frac{\partial s_{jm}}{\partial \ln q_{jm}}\frac{1}{q_{jm}} &= 0,
\end{aligned}$$

where the first, second and third equations are the FOCs for $p_{jm}$, $n_{jm}$ and $q_{jm}$ respectively. Dividing the second and third equations by the first equation, I solve for $c_{jm}$ and $k_{jm}$,

$$\begin{aligned}
c_{jm} &= M_m s_{jm}\frac{\partial s_{jm}/\partial \ln n_{jm}}{\partial s_{jm}/\partial p_{jm}}\frac{1}{n_{jm}}, \\
k_{jm} &= \frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}}\frac{1}{q_{jm}}.
\end{aligned}$$

Then I substitute the two equations above into the FOCs and solve for $r_{jm}$, thereby obtaining equations that I take to the data:

$$r_{jm} = p_{jm} + \frac{s_{jm}}{\partial s_{jm}/\partial p_{jm}} + \frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}}, \tag{5}$$

$$\ln \frac{c_{jm}}{M_m s_{jm}} = \ln \frac{\partial s_{jm}/\partial \ln n_{jm}}{\partial s_{jm}/\partial p_{jm}} - \ln n_{jm}, \tag{6}$$

$$\ln k_{jm} = \ln \frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}} - \ln q_{jm}, \tag{7}$$

where

$$r_{jm} = \rho_N^r \ln(N_m + 1) + \rho_Y^r Y_{jm} + \varpi_{jm}.$$

One advantage of using the log value of endogenous product characteristics in the utility function and linear marginal cost functions is that an analytic relationship between the underlying cost for a particular product characteristic and that product characteristic can be obtained. This can make it easy for us to implement counterfactual experiments when the problem of multiple equilibria is not severe.

#### 4.3.4 Profit Rate

The first order conditions (5-7) are enough to estimate the demand and supply. Since detailed bank income statements are available, I can obtain extra moment conditions. The first order condition for the real pure deposit interest rate can be transformed to

$$r_{jm} - k_{jm}q_{jm} - p_{jm} = \frac{s_{jm}}{\partial s_{jm}/\partial p_{jm}}. \tag{8}$$

On the left hand side of the equation, $r_{jm} - k_{jm}q_{jm} - p_{jm}$, is the marginal profit rate of deposits of bank $j$ in market $m$. I define variable profit as marginal profit rate multiplied by total deposits. The difference between variable profit and total profit is fixed cost. Since deposit is one of the liabilities (fund sources), it is impossible to distinguish the revenue of deposits from the revenue of other liabilities in income statements, such as equity. I use the estimated marginal profit rate of total assets, which can be obtained from the income statement of banks, to approximate marginal profit rate of deposits. I assume that if profit rates from different fund sources are different, banks will reallocate fund sources. In equilibrium, the marginal profit rates of different fund sources should be equal. Then the marginal profit rate from deposits should be equal to the marginal profit rate of total assets (total assets are equal to total liabilities).

Equations (5)-(8)can be simplified in the case of homogenous consumer preferences.

*A Simplification: Logit Model*

When consumer preferences are homogenous, the first order conditions are reduced to

$$r_{jm} = p_{jm} + \frac{1}{\alpha(1-s_{jm})} + \frac{1}{\alpha} = \rho_N^r \ln(N_m+1) + \rho_Y^r Y_{jm} + \varpi_{jm},$$

$$\ln\frac{c_{jm}}{M_m s_{jm}} = \ln\frac{\beta_n}{\alpha} - \ln n_{jm},$$

$$\ln k_{jm} = \ln\frac{1}{\alpha} - \ln q_{jm}. \tag{9}$$

The corresponding marginal profit rate is

$$r_{jm} - k_{jm}q_{jm} - p_{jm} = \frac{1}{\alpha(1-s_{jm})}. \tag{10}$$

The mapping between the corresponding product characteristic and its cost is one-to-one. The logit model gives a straight-forward relationship among product quality, consumer preferences and bank costs. The higher the consumer preferences for branch density in a market, or the lower marginal cost for branch density of a bank in that market, the higher branch density of the bank in that market will be observed.

## 4.4 Discussion

Several aspects of the model are worth mentioning. In the following, information structure, prices, product quality and costs will be discussed.

### 4.4.1 Information Structure

I adopt the mainstream approach of a complete information structure. Another approach is to use an incomplete information structure, assuming that the unobserved product quality is exogenous and is revealed after banks choose the observed product quality. However, there are several problems with this approach: it leads to ex post regret; it is likely that some important unobserved endogenous product quality is ignored; and the expectation of banks' profit function makes the estimation procedure complicated.

### 4.4.2 Prices

There are two prices related to deposits: deposit interest rate and service fees. Unfortunately, they cannot be modeled separately in price decisions. In Dick's (2002) model, interest rate and service rate enter the demand function separately. However, the coefficients on interest rate and service fees should have the same absolute value according to the first order conditions, which contradicts her estimates. Since both service fees and interest rates are important to consumers' choices of banks and no additional data are available, I pool interest rate and service fees together as the nominal pure interest rate.

More importantly, it is the real pure deposit interest rate rather than the nominal pure deposit interest rate that matters to consumers. Here I use the average loan rate as the opportunity cost to compute the real pure interest rate. Many families in the US have savings accounts and all kinds of loans at the same time. The real pure interest rate is defined as the nominal pure interest rate minus the opportunity cost, which is the difference between putting money in a bank account and paying back debts. Radecki (1999) suggests using the federal funds rate as an approximation of forgone income for deposit balances, but the federal funds rate is not directly connected to consumers. Since in the logit demand model the yearly opportunity cost enters the year dummy variable, whether to use real or nominal pure deposit interest rates makes no difference in demand and supply estimates. However, it does make a difference in the calculation of price elasticity, as discussed in section 6.1.2. In the random coefficients logit model, it also makes a difference in demand and supply estimates when difference opportunity costs are used.

Since only the bank-level deposit interest rate and service fees are available, the price for a bank is assumed to be the same across all markets within a year. Obviously, the price variable is subject to measurement error. To correct for measurement error, Knittel and Stango (2004) implement the procedure in Lewbel (1997). This involves using higher moments of the observable data (the $x_{jm}$'s) as instruments for the variables with measurement error.

### 4.4.3 Product Quality

The exogeneity of some bank product qualities might be controversial. I use the dichotomous variables for size, whether the bank is medium, big or mega in terms of assets, and fringe bank dummy variable in terms of market shares, under the assumption that the market share of a bank has little feedback effect on the size category that a bank belongs to and there is no variation in the categories. Dick (2002) finds that there is almost no variation in terms of which size category a bank belongs to. For the fringe bank dummy, some banks do change from fringe banks to large banks or vice versa. However, the market shares of these banks are small and their changes between fringe and large banks do not have a significant impact on other large banks. The dominant bank dummy variable is not included in the utility function, since its potential feedback effect would be significant.

Many researchers include the average number of employees per branch as one bank characteristic but I exclude it in this paper. There are two reasons. First, there are employees on both deposit and loan sides and I cannot tell them apart in the call reports. Only the employees on the deposit side matter to consumers. Second, the number of employees per branch seems to be closely related to the amount of deposits in a branch rather than bank service quality. According to the National Establishment Time-Series (NETS) Database, the number of employees per branch varies a lot across branches within a bank in a market and almost does not change after mergers.

### 4.4.4 Costs

The final item is the cost function, which lies in the fundamental difference between models with exogenous and endogenous product quality. The specific costs for each product quality are the same across firms in the first model, but are different in the second model. It is the variation in costs and consumer preferences that jointly determine the variety of product quality across firms and markets in the second model.

In the model, I assume that the observed product quality, branch density in this paper, is determined by fixed costs, while the unobserved product quality is determined by marginal costs. Berry and Waldfogel (2006) find that some product qualities are determined by marginal costs while others are influenced by fixed costs. As a robustness check, I allow branch density to be determined by marginal costs. In the logit model, the recovered value of the marginal deposit return rate of each bank is changed by a constant. In the random coefficients logit model, it does not make much change in demand estimate either.

# 5 Estimation

Now I outline the estimation procedure. Section 5.1 gives the specification of consumer preferences. Section 5.2 illustrates the identification procedure. Section 5.3-5.4 discuss demand and supply instruments. Section 5.5 explains how to simulate within-market and out-of-market mergers separately.

## 5.1 Consumer Preferences

Consumer preferences vary with their demographic characteristics, including observed demographic characteristics, such as income, and unobserved demographic characteristics. Since the marginal cost for endogenous product quality cannot be negative, I have to guarantee that each individual's preferences for pure deposit interest rates and endogenous product qualities are positive and do not change signs across consumers. I assume that their log values follow normal distribution. The individual preferences for exogenous product qualities are assumed to follow normal distribution. Suppose $x_{jm}^{ex,\mu}$ is a $K^{\mu}$-dimensional (row) vector of exogenous variables that have random coefficients, $\beta_{im}^{en}$ is consumer $i$'s preference coefficient for $x_{jm}^{en}$ (branch density, $n$, in this paper), and $\beta_{im}^{ex,\mu}$ is a $K^{\mu}$-dimensional (column) vector of consumer $i$'s preference coefficients for $x_{jm}^{ex,\mu}$. The random coefficients for prices, endogenous variables and exogenous variables $x_{jm}^{ex,\mu}$ will be modeled as

$$\begin{pmatrix} \alpha_{im} \\ \beta_{im}^{en} \\ \beta_{im}^{ex,\mu} \end{pmatrix} = \begin{pmatrix} \alpha \exp(\sigma^{\alpha} v_{im}^{\alpha} + \pi^{\alpha} D_{im}) \\ \beta^{en} \exp(\sigma^{en} v_{im}^{en} + \pi^{en} D_{im}) \\ \beta^{ex,\mu} + \sigma^{ex,\mu} v_{im}^{ex,\mu} + \Pi^{ex,\mu} D_{im} \end{pmatrix}, \tag{11}$$

$$D_{im} \sim P_D^*(D),\ v_{im} \sim P_v^*(v),\ \sum = \begin{pmatrix} \sigma^{\alpha} & 0 & 0 \\ 0 & \sigma^{en} & 0 \\ 0 & 0 & \sigma^{ex,\mu} \end{pmatrix},\ \Pi = \begin{pmatrix} \pi^{\alpha} \\ \pi^{en} \\ \Pi^{ex,\mu} \end{pmatrix},$$

where $D_{im}$ is a $d \times 1$ vector of demographic variables, $\sum$ is a $(K^\mu + 2) \times (K^\mu + 2)$ matrix of parameters, $\Pi$ is a $(K^\mu + 2) \times d$ matrix of coefficients that measure how consumer preferences vary with demographics, $P_D^*(\cdot)$ is an empirical demographic distribution obtained from IPUMS, $v_i$ captures the additional unobserved demographic characteristics, and $P_v^*(\cdot)$ is assumed to has a standard multivariate normal distribution. For simplicity, I assume that $\sum$ is a diagonal matrix. I subtract $D_{im}$ by its mean so that $\ln \alpha$, $\ln \beta^{en}$ and $\beta^{ex,\mu}$ become the mean of $\ln \alpha_{im}$, $\ln \beta_{im}^{en}$ and $\beta_{im}^{ex,\mu}$, respectively.

Let $\theta^d = (\beta^{ex}, \theta^{nl})$ stand for a vector of all demand parameters. The vector $\beta^{ex}$ contains the linear parameters, and the vector $\theta^{nl} = (\alpha, \beta^{en}, \pi^\alpha, \pi^{en}, \Pi^{ex,\mu}, \sigma^\alpha, \sigma^\beta, \sigma^{ex,\mu})$ the nonlinear parameters. Combining equations (11) and (1), I have

$$u_{ijm} \equiv (x_{jm}^{ex}\beta^{ex} + \xi_{jm}) + (\alpha_{im}p_{jm} + x_{jm}^{en}\beta_{im}^{en}) + x_{jm}^{ex,\mu}(\sigma^{ex,\mu}v_{im}^{ex,\mu} + \Pi^{ex,\mu}D_{im}) + \epsilon_{ijm}.$$

The above indirect utility function is now expressed as a sum of four terms. The first term, $\delta_{jm} = x_{jm}^{ex}\beta^{ex} + \xi_{jm}$, is the mean utility from exogenous variables. The second term, $\alpha_{im}p_{jm} + x_{jm}^{en}\beta_{im}^{en}$, is the individual utility from endogenous variables, including income and endogenous bank variables. The third term, $x_{jm}^{ex,\mu}(\sigma^{ex,\mu}v_{im}^{ex,\mu} + \Pi^{ex,\mu}D_{im})$, is a mean-zero heteroskedastic deviation from the mean utility from exogenous variables. The fourth term, $\epsilon_{ijm}$, is an individual- and bank-specific unobservable. Only the first term is common to all consumers.

## 5.2 Identification

With all the specifications of the utility and profit functions, I illustrate how to estimate the model. The demand and supply parameters, $\theta = (\beta^{ex}, \theta^{nl}, \theta^s)$, will be estimated using generalized method of moments (GMM) with a non-linear optimization routine. It is based on the estimation procedure proposed by BLP (1995) with some modification to account for the endogeneity of the unobserved product quality.

Recall the first order condition for unobserved product quality (7)

$$\xi_{jm} = \ln(\frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}}) - \ln k_{jm}.$$

The above equation implies that the unobserved product quality is potentially correlated with other observed exogenous or endogenous product quality in the case of heterogeneous consumer preferences (or heterogeneous consumer preference for interest rate precisely). The assumption of exogenous product quality in the traditional demand estimation does not hold any more. Instead, I assume that the log value of the costs for producing the unobserved product quality is exogenous. Assuming that $-\ln k$ and $\varpi$ can be calculated, the following moment conditions can be formed:

$$G(\theta_0) = E[m_{jm}(\theta_0)] = E\begin{bmatrix} -\ln k_{jm}(\theta_0) \cdot z^D_{jm} \\ \varpi_{jm}(\theta_0) \cdot z^S_{jm} \end{bmatrix} = 0,$$

where $z^D_{jm}$ and $z^S_{jm}$ are vectors of demand and supply instruments, and $\theta_0$ is the true value of the parameter vector. If there are a total of $N$ bank observations in the sample, the sample moment condition can be formed as follows:

$$G_N(\theta) = \frac{1}{N}\sum_{jm}^{N} m_{jm}(\theta) = \frac{1}{N}\sum_{jm}^{N}\begin{bmatrix} -\ln k_{jm}(\theta) \cdot z^D_{jm} \\ \varpi_{jm}(\theta) \cdot z^S_{jm} \end{bmatrix}. \tag{12}$$

I can also add one more moment of (8) to use marginal profit rates of deposits estimated from bank income statements. Under some technical conditions, the estimator defined by minimizing $\|G_N(\theta)\|_A$ ($A$ is a weight matrix) is $\sqrt{N}$-consistent and asymptotically normal with variance-covariance matrix

$$(\Gamma' A \Gamma)^{-1}\Gamma' A V A \Gamma (\Gamma' A \Gamma)^{-1},$$

where $\Gamma = \partial G(\theta_0)/\partial\theta$ and $V = E[m(\theta_0)m(\theta_0)']$.

The above estimation procedure has thus far assumed that $-\ln k(\theta)$ and $\varpi(\theta)$ can be calculated. It is easy to compute $\varpi(\theta)$ from the reduced form of the marginal deposit return rate (4) by the following equation,

$$\varpi_{jm} = r_{jm} - \rho^r_N \ln(N_m + 1) - \rho^r_Y Y_{jm}.$$

The calculation of $-\ln k(\theta)$ is not direct. Notice that $-\ln k(\theta)$ is a linear function of $\xi$ and $\ln(\frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}})$, both of which are functions of $\delta$ and $\theta$ (or $\theta^d$ precisely):

$$\begin{aligned} -\ln k_{jm} &= \xi_{jm} - \ln(\frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}}), \\ \xi_{jm} &= \delta_{jm} - x^{ex}_{jm}\beta^{ex}. \end{aligned}$$

If $\delta$ is known, I can compute $-\ln k(\theta)$ easily.

The calculation of $\delta$ is a typical BLP (1995) computation procedure. It follows two steps. First, I compute market shares. Since no analytic expression exists for the integrals in market shares, I use the simulation methods as in Pakes and Pollard (1989) and BLP (1995), which allow $\theta$ to be estimated consistently and with only minor changes in its limiting properties. The market shares are simulated by taking $ns$ draws of individual consumers for each market. Then the simulated market share of bank $j$ in market $m$ is

$$\begin{aligned}
s_{jm}^{ns}(x,r,\xi,\theta) &= \frac{1}{ns}\sum_{i=1}^{ns} f_{jm}(D_{im},v_{im}) \\
&= \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp[\delta_{jm}+\alpha_{im}p_{jm}+x_{jm}^{en}\beta_{im}^{en}+x_{jm}^{ex,\mu}(\sigma^{ex,\mu}v_{im}^{ex,\mu}+\Pi^{ex,\mu}D_{im})]}{1+\sum_l \exp[\delta_{lm}+\alpha_{im}p_{lm}+x_{lm}^{en}\beta_{im}^{en}+x_{[m}^{ex,\mu}(\sigma^{ex,\mu}v_{im}^{ex,\mu}+\Pi^{ex,\mu}D_{im})]},
\end{aligned}$$

$$\alpha_{im}=\alpha\exp(\sigma^{\alpha}v_{im}^{\alpha}+\pi^{\alpha}D_{im}), \quad \beta_{im}^{en}=\beta^{en}\exp(\sigma^{en}v_{im}^{en}+\pi^{en}D_{im}),$$

where $v_{im}^{\alpha}$, $v_{im}^{en}$, $v_{im}^{ex,\mu}$ and $D_{im}$, $i=1,...,ns$, are draws from $P_v^*(v)$ and $P_D^{**}(D)$, respectively.[19]

Second, with the simulated market shares, I invert the system of equations to solve for $\delta$. For the random coefficients logit model, the system of equations is nonlinear. It can be solved numerically by using the contraction mapping suggested by BLP, which amounts to computing the series

$$\begin{aligned}
\delta_{.m}^{h+1} &= \delta_{.m}^{h}+\ln S_{.m}-\ln s\left(p_{.m},x_{.m},\delta_{.m}^{h},P_{ns};\theta^{nl}\right), \\
h &= 1,...,H, \quad m=1,...,MT,
\end{aligned}$$

where $P_{ns}$ is the empirical distribution of $ns$ simulation draws $\{v_{im}^{\alpha},\ v_{im}^{en},\ v_{im}^{ex,\mu},\ D_{im}\}_{i=1,...,ns}$, $s\left(p_{.m},x_{.m},\delta_{.m}^{h},P_{ns};\theta^{nl}\right)$ are the simulated market shares, $S_{.m}$ are the observed market shares, $H$ is the smallest integer such that $\left\|\delta_{.m}^{H}-\delta_{.m}^{H-1}\right\|$ is smaller than some tolerance level, and $\delta_{.m}^{H}$ is the approximation to $\delta_{.m}$.

Now that I have calculated $\delta(\theta)$, I can compute both $\xi$ and $\ln(\frac{\partial s_{jm}/\partial \ln q_{jm}}{\partial s_{jm}/\partial p_{jm}})$, calculate $-\ln k(\theta)$, get $G_N(\theta)$, and finally compute $\|G_N(\theta)\|_A$. The minimization routine can be simplified by noting that the first order conditions for a minimum to $\|G_N(\theta)\|_A$ for my specifications are linear in $\beta^{ex}$ and $\theta^s$ for any given $\theta^{nl}$. As a result $\beta^{ex}$ and $\theta^s$ can be "concentrated out" of those conditions, allowing me to confine the nonlinear search to a search over $\theta^{nl}$. This search is performed using the Nelder-Mead (1965) non-derivative "simplex" search routine.

It is worth mentioning that the vector of demand parameters cannot be estimated using the demand moments alone in the case of heterogeneous consumer preferences, since I use the first order condition for unobserved product quality to correct its endogeneity. Otherwise, the estimates are biased. This is different from the traditional demand estimation procedure.

[19] I use 200 Sobol sequences to draw from $P_v^*(v)$ and $P_D^{**}(D)$ in each market.

*A Simplification: Logit Model*

Estimation of the logit demand is substantially less complicated than that of the random coefficients logit model. The market share function (3) gives the following expression:

$$\ln(s_{jm}) - \ln(s_{0m}) = \alpha p_{jm} + x_{jm}\beta + \xi_{jm}. \tag{13}$$

From (9), the exogeneity of $\ln k_{jm}$ in the logit model actually implies the exogeneity of $\xi_{jm}$ $(= \ln q_{jm})$, which implies that the traditional demand estimation is still valid. Hence, the demand parameters, $\theta^d = (\alpha, \beta)$, can be estimated using standard linear instrumental variable techniques.

After I obtain the demand estimate, I can use (5) to recover the marginal deposit return rates. Then the supply parameters, $\theta^s$, can be estimated using standard linear instrumental variable techniques.

On the other hand, I could estimate the coefficient on pure interest rate directly by using bank income statements. First, I can estimate bank-level marginal profit rate of total assets from income statements, which is approximately equal to the marginal profit rate of total deposits according to the arbitrary condition. Second, noticing that equation (10) can be transformed to

$$\alpha = \frac{1}{(r_{jm} - k_{jm}q_{jm} - p_{jm})(1 - s_{jm})}, \tag{14}$$

I estimate bank- and market-specific coefficient on pure interest rate by substituting observed market shares and estimated profit rates into equation (14). Finally I take the deposit-weighed average value of the estimated bank- and market-specific coefficient on pure interest rate as the estimated coefficient on pure interest rate. I use deposits as weight because the estimated profit rate of a bank with large total deposits is more accurate than that of a bank with small market shares. With the estimated coefficient on pure interest rate, I can obtain the rest demand parameters by the following equation

$$\ln(s_{jm}) - \ln(s_{0m}) - \widehat{\alpha} \cdot p_{jm} = +x_{jm}\beta + \xi_{jm}, \tag{15}$$

and then follow the procedure as in the logit model to estimate supply.

## 5.3 Demand Instruments

The estimation procedure described above requires suitable instruments. I start with demand instruments, and then talk about supply instruments in section 5.4. Demand instruments, $z^D$, are uncorrelated with $-\ln k$. Different from the tradition, the vector of firm endogenous characteristics, $x^{en}$, are not included. Similar to the tradition, the vector of bank exogenous characteristics, $x^{ex}$, are included in the demand instruments, and prices are not included. Following Berry (1994) and BLP (1995), I use bank exogenous characteristics and the sums of the values of the same characteristics of products offered by other firms as instruments.

Cost shifters provide another source of demand instruments. I include these variables in $z^D$: expenses on premises and equipment, other expenses, a credit risk cost variable, loan charge-offs, wages, number of employees per branch, indicators showing whether most bank loans are sold to small businesses and small farms, cash, federal funds and securities, real estate and loans to individuals. The first three and the last four variables are normalized by assets. Expenses on premises and equipment and other expenses are both operating cost variables. Premises and equipment expenses include expenses on utilities, janitorial services, repairs, furniture, etc. Other expenses include legal fees, postage, deposit insurance assessments, directors' fees, etc. The credit risk cost variable employed is provisions for loan and lease losses. Loan charge-offs are bad debts and negatively affect earnings. Wages are calculated based on the bank's labor expenses and the number of employees. The last four variables show the portfolios that a bank holds and may have different effects on costs. The detailed definitions of instrumental variables are given in Appendix B.

To correct for the measurement error in pure deposit interest rate, I use the fifth order moments of exogenous bank characteristics as instrument variables. I present the results without and with EIV-IV (Error-in-Variables Instrumental Variable).

## 5.4 Supply Instruments

Now I move to supply instruments. The number of incumbent fringe banks is endogenous, suggesting the need for additional exogenous variables that are correlated with the number of entrants but are uncorrelated with the unobserved bank- and market-specific deposit return rate. The instrument variable that I use is the potential number of entrants. The number of potential entrants is positively associated with the number of entrants and is exogenous to the unobserved market characteristics in a local market, and therefore constitutes a valid instrument. Since most entrants are from the same state, I use the number of banks in the same state to approximate the number of potential entrants. Specifically, I include in the log value of the number of state dominant, large and fringe banks, which are defined as banks with state market shares above 10%, between 1% and 10% and below 1% respectively.[20] The

[20] The definition of potential entrants is similar to Berry (1992)'s model of entry in the airline industry, in which he defines the number of potential entrants as the first period number of firms operating in both endpoint cities and in only one endpoint city of an airline route.

reason to divide them into three groups is that banks with different state market shares may differ in their entry costs. This uncorrelation may fail if the economy of counties within a state is strongly correlated. Usually demographic characteristics vary a lot even within a small state.

I also include in $z^S$ the dominant bank dummy, other bank exogenous characteristics, market characteristics, year and county dummy variables.

## 5.5 Post-Merger Evolution

Finally, I explain how to implement merger simulations (including both within-market and out-of-market mergers), and show the specifications that I use to estimate the post-merger changes in product quality and entry. To minimize the endogeneity of mergers, I also use an alternative way to simulate mergers by imposing some reasonable assumptions on post-merger bank variables.

As mentioned earlier, to circumvent the problem of multiple equilibria, I use the historical data on mergers to estimate the post-merger patterns of product quality, bank- and market-specific deposit return rate of merging banks as well as entry of fringe banks. To account for the endogeneity of mergers, I select nationwide bank mergers that merging banks operate on several markets. I assume that a local market plays a small role in the decisions of mergers between those large banks covering several markets. Then these mergers can be regarded as exogenous to a local market. Many researchers propose a variety of methods to control for the endogeneity of mergers. For example, Park (2007) uses a matching model in a study of the M&As in the Mutual Fund Industry. However, these solutions have very limited applications.

I assume that a post-merger market reaches a new equilibrium in one or two years. Each observation used in this study has been checked to make sure that the post-merger merging institutions had stopped making adjustments in bank branch density. Some researchers believe that the effects of mergers sometimes cannot be revealed in two years. However, many banks were involved in a sequence of mergers. Analyzing a longer period between pre- and post-merger would make it difficult to separate the impact of one merger from another merger that affected the same bank. It is also hard to separate the impact of mergers from other changes in economic environments.

To avoid the possible intervention from antitrust regulation, I delete the data on mergers between two dominant banks in the same markets, which are mostly like to be forced to divest some branches after mergers. To control for the potential antitrust intervention in the remaining samples, I include pre-merger market shares of merging institutions in the following analysis. This is because banks with large market shares tend toward intervention.

In the following, I discuss two types of bank mergers in sequence: within-market mergers and out-of-market mergers. Usually the impact of within-market mergers on branch density and market shares is much bigger than that of out-of-market mergers.

### 5.5.1 Within-Market Mergers

What happen after within-market mergers?

First, non-merging large banks are assumed to stay in the market since large banks usually exit through mergers.

Second, for non-merging banks, I assume that their observed and unobserved product quality, and bank- and market-specific deposit return rate remain at the pre-merger level. This is a reasonable assumption. In Table 15 that presents a merger simulation, non-merging large banks increased or decreased their branch networks by only one branch following mergers, which is normal adjustment even for markets without within-market mergers.

Third, for merging banks, the exogenous characteristics in the utility function are perfectly predictable after mergers. For example, the number of states of operation is the total number of the states that the two pre-merger banks operate. If some observed exogenous variables are not perfectly predictable following mergers, I use them in the demand and supply estimation, but put them into the utility from unobserved product quality during the estimation of how the utility from unobserved product quality evolves.

Fourth, for merging banks, I estimate how their product quality and unobserved bank- and market-specific deposit return rates evolve after mergers. This involves study on the post-merger patterns of new merging banks and I denote them as (i) to (iii) in the following.

(i) I estimate the evolution of the observed endogenous product quality of new merging banks by using the following forms:

$$\ln n_{j\_new,m} = \rho_0^n + \rho_1^n(\ln n_{j1m}, \ln n_{j2m}) + \rho_2^n X_{j1j2m} + \varepsilon_{j1j2m}^n, \tag{16}$$

where $n_{j\_new,m}$, $n_{j1m}$, $n_{j2m}$ are branch densities of the new merging bank, the acquirer and the target respectively, $\rho_1^n(\ln n_{j1m}, \ln n_{j2m})$ is a function of $\ln n_{j1m}$ and $\ln n_{j2m}$, $X_{j1j2m}$ is a vector of exogenous bank- and market- characteristics, $\varepsilon_{j1j2m}^n$ captures unobserved merger-specific effect, and $(\rho_0^n, \rho_1^n, \rho_2^n)$[21] are parameters to be estimated. I include in $X_{j1j2m}$ the ratio of overlapped ZIP codes and the pre-merger FDIC market share of each bank. The ratio of overlapped ZIP codes is defined as the ratio of the number of ZIP codes where two merging banks have overlapped pre-merger branch networks to the total number of ZIP codes that at least one pre-merger merging bank has a presence. For $\rho_1^n(\ln n_{j1m}, \ln n_{j2m})$, I use two

[21] Let $\rho_1^n$ stand for the parameters in $\rho_1^n(\ln n_{j1m}, \ln n_{j2m})$.

specifications: a linear function of $\ln(n_{j1m} + n_{j2m})$ as well as a linear function of $\ln n_{j1m}$ and $\ln n_{j2m}$.

For mergers between two dominant banks, the post-merger branch density of the new merging bank is probably set by the antitrust regulators and is known beforehand. In the merger simulation, I can just use this predetermined branch density instead of the predicted branch density from (16).

(ii) I estimate the evolution of the utility from unobserved product quality of new merging banks by using the following forms:

$$\ln q_{j\_new,m} = \rho_0^q + \rho_1^q(\ln q_{j1m}, \ln q_{j2m}) + \rho_2^q X_{j1j2m} + \varepsilon_{j1j2m}^q, \tag{17}$$

where $q_{j\_new,m}$, $q_{j1m}$, $q_{j2m}$ are the utility from the unobserved product quality of the new merging bank, the acquirer and the target respectively, $\rho_1^q(\ln q_{j1m}, \ln q_{j2m})$ is a function of $\ln q_{j1m}$ and $\ln q_{j2m}$, $X_{j1j2m}$ is a vector of exogenous bank and market characteristics, $\varepsilon_{j1j2m}^q$ captures unobserved merger-specific effect, and $(\rho_0^q, \rho_1^q, \rho_2^q)$[22] are parameters to be estimated. I include in $X_{j1j2m}$ the pre-merger FDIC market share of each bank. For $\rho_1^q(\ln q_{j1m}, \ln q_{j2m})$, I use two specifications: a linear function of the pre-merger market share weighted average of $\ln q_{j1m}$ and $\ln q_{j2m}$ as well as a linear function of $\ln q_{j1m}$ and $\ln q_{j2m}$.

(iii) I estimate the evolution of the unobserved bank- and market-specific deposit return rates of new merging banks by using the following form:

$$\varpi_{j\_new,m} = \rho_0^\varpi + \rho_1^\varpi(\varpi_{j1m}, \varpi_{j2m}) + \rho_2^\varpi X_{j1j2m} + \varepsilon_{j1j2m}^\varpi, \tag{18}$$

where $\varpi_{j\_new,m}$, $\varpi_{j1m}$, $\varpi_{j2m}$ are the unobserved bank- and market-specific deposit return rates of the new merging bank, the acquirer and the target respectively, $X_{j1j2m}$ is a vector of exogenous bank and market characteristics, $\varepsilon_{j1j2m}^\varpi$ captures unobserved merger-specific effect, and $(\rho_0^\varpi, \rho_1^\varpi, \rho_2^\varpi)$[23] are parameters to be estimated. I include in $X_{j1j2m}$ the pre-merger FDIC market share of each bank. For $\rho_1^\varpi(\varpi_{j1m}, \varpi_{j2m})$, I use two specifications: a linear function of the pre-merger market share weighted average of $\varpi_{j1m}$ and $\varpi_{j2m}$ as well as a linear function of $\varpi_{j1m}$ and $\varpi_{j2m}$.

Finally, the post-merger competition effect in the marginal deposit return rate of every bank changes. The change is caused by either the reduced number of large banks or possible changes in the number of fringe banks. The reduced number of large banks is equal to the number of within-market mergers. Fringe banks in the market decide whether to stay in the market and other potential fringe banks might enter as well. Because fringe banks in the same

[22] Let $\rho_1^q$ stand for the parameters in $\rho_1^q(\ln q_{j1m}, \ln q_{j2m})$.
[23] Let $\rho_1^\varpi$ stand for the parameters in $\rho_1^\varpi(\varpi_{j1m}, \varpi_{j2m})$.

market differ in their entry costs, it is hard use a structural model to estimate the distribution of fringe banks' entry costs in a specific market. Therefore, I use a reduced form to estimate the post-merger number of fringe banks from the historical data on mergers:

$$N_{fm,new} = \rho_0^N + \rho_1^N N_{fm,old} + \rho_2^N X_{j1j2m} + \varepsilon_{j1j2m}^N, \tag{19}$$

where $N_{fm,new}$ and $N_{fm,old}$ are the post-merger and pre-merger numbers of fringe banks in market $m$, $X_{j1j2m}$ is a vector of bank and market characteristics, $\varepsilon_{j1j2m}^N$ captures unobserved merger heterogeneity, and $(\rho_0^N, \rho_1^N, \rho_2^N)$ are parameters to be estimated. I include in $X_{j1j2m}$ the total income of market $m$, the pre-merger deposits of targets and acquirers involved in within-market mergers in market $m$ respectively.

There are two situations that need extra attention. First, if the estimated post-merger number of fringe banks is negative, I assume there are no post-merger fringe banks. Second, if some fringe banks change from fringe banks to large banks or if some banks change from savings associations to commercial banks, then the recorded number of fringe banks is increased but they are not new entrants. Therefore, I compute the post-merger number of fringe banks based on pre-merger bank categories (fringe banks or not) in the above estimation of the post-merger number of fringe banks.

### 5.5.2 Out-of-Market Mergers

Usually out-of-market mergers happen when banks seek geographic diversification. For merging banks involved in out-of-market mergers, I assume that there are no changes in product quality and no changes in bank- and market-specific deposit return rates. There are only three possible changes: the perfectly predictable exogenous bank characteristics, the possible changes in large banks caused by other within-market mergers and the number of fringe banks. The last two can be predicted and estimated following the same procedure discussed in the within-market mergers.

### 5.5.3 Alternative Merger Simulations

Since the above estimation procedure may still suffer from the endogeneity of mergers, I simulate mergers by using reasonable assumptions on the post-merger patterns rather than patterns estimated from the historical data on mergers. Merger simulations using these assumptions have less or no problems of the endogeneity of mergers and can provide us with some useful benchmarks. Since both branch densities and entry of fringe banks are observed and probably suffer less from the endogeneity of mergers, I still use their estimates in the merger simulation. Especially when mergers incurred intervention from regulators, the post-merger branch density of the merging bank is known beforehand. Therefore I impose assumptions only on post-merger unobserved variables of merging banks as follows: the post-merger unobserved product quality and unobserved bank- and market-specific deposit return rate take their pre-merger market share weighted values of two merging banks.

I report and compare merger simulations using historical data and using the above assumptions.

# 6 Results

In this section, I report estimation results and merger simulations. Section 6.1 gives estimates of demand and supply. Section 6.2 shows the post-merger patterns of product quality and entry. Section 6.3 presents merger simulations.

## 6.1 Demand and Supply

Two primary demand specifications are estimated. I first estimate the logit demand model because this specification can be easily implemented on large data sets. I then estimate the random coefficients logit demand model, but I only apply it to the demand estimation in counties with populations of more than 500,000 in the year 2000 because of the unusually large data size.

### 6.1.1 Logit Demand

Table 3 reports the results from the logit demand model with four specifications by estimating equation (13). Column (i) shows results for the OLS estimation. Columns (ii), (iii) and (iv) give the IV results with different endogenous variables and instruments. The instruments used for column (ii), (iii) and (iv) are price instruments (or instruments for nominal pure deposit interest rate), price and branch density instruments, price and branch density and measurement error instruments respectively. Since the yearly opportunity cost enters the year dummy, the estimates using nominal pure deposit interest rate (deposit interest rate - service fees) are the same as those using real pure deposit interest rate (deposit interest rate - service fees - opportunity cost). The effect of the endogeneity of the price is evident. The coefficient on nominal pure deposit interest rate becomes larger by a factor of 3.2 when price instruments are used.

Insert Table 3 about here.

The effect of the endogeneity of branch density is also evident. When both price and branch density instruments are used, the coefficient on nominal pure deposit interest rate (hereafter referred to as the coefficient on interest rate) becomes larger by a factor of 1.36, compared to the coefficient on interest rate when only price instruments are used. The willingness to pay for the extra log value of branch density, measured by $\beta^n/\alpha$, does not change much. The increase in the coefficient on interest rate implies that the higher the unobserved product quality, the smaller the nominal pure deposit interest rate. Comparing columns (iii) and (iv), the instruments for measurement errors do not change the results much.

All coefficients on observed exogenous bank characteristics are significant and are of the expected sign. Consumers appear to value branch density, the geographic diversification of the bank as measured by the number of states in which the bank operates, an international bank, the origin of a bank, and large bank size. Consumers appear to dislike a bank that used to be a savings association, a bank that belongs to a bank holding company and a bank with a very small market share (a fringe bank).

The coefficient on the log value of branch density implies the trade-off between positive network effects and negative substitution effects among branches of a bank in the same markets.[24] The estimated coefficient on the log value of branch density in both columns (iii) and (iv) in Table 3 are close to 1, which implies that branches of a bank in the same market behave independently.

The logit demand estimates of counties with population above 500,000 are very similar to those in Table 3 (data not shown).

However, the estimated coefficient on interest rate varies across years. This could be caused by either changes in consumer preferences on price change over time or failure to control for the measurement error. This implies the estimated coefficient on interest rate may still be biased. As mentioned in section 5.2, I could estimate the coefficient on interest rate directly by using income statements in the logit mode and Table 4 shows the results. The estimated price coefficient using deposits as weights is 45.17, which is smaller than that without using any weights. The estimated average marginal profit rate does not vary much when different weights are used.

Insert Table 4 about here.

With the estimated coefficient on interest rate, I could estimate the rest demand parameters by equation (15). Columns (i) and (ii) in Table 5 give the results without and with instruments for branch density. The estimated coefficient on the log value of branch density is raised from below 1 to above 1 when branch density instruments are used. This tells that the network

[24] The detailed reason is given in the appendix.

effect is positive. The rest demand estimates are of expected signs and similar to Table 3 qualitatively. In the following analysis, I use demand estimates in Tables 4 and 5.

#### 6.1.2 Price Elasticity

The coefficient on interest rate discussed above represents the marginal utility of income and allows us to calculate price elasticity of demand. Researchers usually compute price elasticity using nominal interest rate.[25] There are several problems with this calculation in the banking industry. The computed price elasticity varies a lot across years with the federal funds rate. Intuitively, banks with the same nominal pure interest rates and the same market shares should have different own price elasticities in years with different federal funds rates. However, the two own price elasticities are exactly the same if they are computed from the nominal prices in the logit model.

One solution is to use real interest rate instead of nominal interest rate when calculating and interpreting price elasticity. As mentioned before, consumers care about real interest rate more than nominal interest rate. The real interest rate is defined as the nominal interest rate minus the yearly opportunity cost. I use the average loan rate of all banks and the representative fringe banks in each year, $\overline{loan_t}$, as the opportunity cost. The real interest rate for bank $j$'s services becomes $int_{jm} - ser_{jm} - \overline{loan_t}$ (suppose market $m$ is in year $t$), which is the difference between putting money in a bank account and paying back debts. It is easy to obtain the relationship between the real price elasticity and the nominal price elasticity:

$$\eta_{jkt} \equiv \frac{\partial s_{jm}}{\partial p_{km}} \frac{p_{km}}{s_{jm}} = \frac{\partial \ln s_{jm}}{\partial p_{km}} p_{km} = \frac{\partial \ln s_{jm}}{\partial p^n_{km}} p_{km} = (\frac{\partial \ln s_{jm}}{\partial p^n_{km}} p^n_{km}) \frac{p_{km}}{p^n_{km}} = \eta^n_{jkm} \frac{p_{km}}{p^n_{km}}$$

where the third equation comes from the two facts: (i) $\frac{\partial \ln s_{jm}}{\partial p^n_{km}}$ contains only price coefficient and market shares; (ii) in the logit model the yearly opportunity cost enters the year dummy variable in the estimation and does not affect demand estimates.

To illustrate how price elasticities computed from different opportunity costs vary across years, I compute the average own price elasticity of all banks in each year using three different

[25] In the logit model, where market shares are as defined in equation (3), the elasticity of the bank $j$'s share with respect to the price of bank $k$ in market $m$ can be computed as follows:

$$\eta_{jkm} \equiv \frac{\partial s_{jm}}{\partial p_{km}} \frac{p_{km}}{s_{jm}} = \frac{\partial \ln s_{jm}}{\partial p_{km}} p_{km},$$

where

$$\frac{\partial \ln s_{jm}}{\partial P_{km}} = \begin{cases} -\alpha(1 - s_{jm}) & if\ j = k, \\ \alpha s_{km} & \text{otherwise.} \end{cases}$$

opportunity costs: average loan rate, federal funds rate (as suggested by Radecki (1999)) and no opportunity cost. To illustrate the variation of price elasticity over years, I present the maximum and minimum of the average price elasticities in the 12 sample years in Table 6. The price elasticity computed from the average loan rate is most stable across years among the three price elasticities, with the minimum and maximum values equal to-2.651 and -2.023 respectively. The average own real price elasticity using the average loan rate is -2.347 (Table 7). It is bigger than the price elasticities computed from the other two opportunity costs in terms of the absolute values.

Insert Table 6 about here.

Insert Table 7 about here.

To get the implication of price elasticity in a particular year, I can transfer the real price elasticity to the nominal price elasticity in year $t$ by the following equation:

$$\eta_{jkm}^{n} = \eta_{jkm} \frac{p_{km}^{n}}{p_{km}} = \eta_{jkm} \frac{int_{jm} - ser_{jm}}{int_{jm} - ser_{jm} - \overline{loan}_t}.$$

The implication of the above equation is clear. Even if real price and real price elasticity are constant across years, nominal price elasticity varies with opportunity costs across years. The above results also imply that the real pure deposit interest rate should be used in the random coefficients logit model, in which the yearly opportunity cost cannot be controlled by the year dummy variable.

#### 6.1.3 Marginal Deposit Return Rate

Now I move from the demand side to the supply side. Table 8 presents results from a model of "supply." I recover marginal deposit return rates from the first order conditions (5), using demand estimates in the logit model. I then regress the estimated marginal deposit return rates on the number of competitors, bank exogenous characteristics, market characteristics, and year and county dummy variables by estimating equation (4). Columns (i) and (ii) in Table 8 give the results for OLS estimation and IV estimation with instruments for the number of fringe banks.

Insert Table 8 about here.

The estimated competition effects from IV estimation are similar to that without instruments. For competition effects, the impact of the number of dominant banks on the marginal deposit return rate of dominant banks is slightly significantly negative. If the number of dominant banks decreases from 2 to 1 by a merger, the marginal deposit return rate of the new merging bank is expected to increase by about \$0.0004 per dollar.[26] The increase in deposit return rate is qualitatively consistent with what Calomiris and Pornrojnangkool (2005) find: the merger of Fleet and BankBoston results in an increase in the average interest rate credit spreads to medium-sized borrows of roughly one percent. The impact of the total number of large banks and fringe banks on marginal deposit return rate is insignificant. This is not surprising because as the number of banks increases, the loan rate drops rapidly. A significant price drop is only observed when the original number of banks is as small as 2 or 3. The number of large banks in a market is usually much larger than that in my samples of big counties.[27] Most of coefficients on other variables are of the right sign. For bank characteristics, the coefficient on dominant dummy variable is significantly positive. It shows that dominant banks enjoy some market power, or that small banks cannot invest on a large profitable project but large banks can. Fringe banks are not significantly inferior to large banks. The coefficient on the indicator for headquarters in the county is significantly positive, which shows that local banks get private information on their local market and enjoy high return rates. The coefficient on the indicator of big banks is bigger than that on medium banks and mega banks. For market characteristics, the population, average personal income and savings rate all have a positive impact on marginal deposit return rate.

### 6.1.4 Random Coefficients Logit Demand

Finishing the discussion of homogenous consumer preference, I study heterogeneity of consumer preferences and how demographic characteristics affect consumer preferences by estimating the random coefficients logit model. The demand system is derived from the utility function in (12). The coefficients on two endogenous variables, real pure deposit interest rate (hereafter referred to as real interest rate) and log of branch density, are random. The real interest rate is the nominal interest rate minus the average loan rate. As a robustness check, I also use the federal funds rate as the opportunity cost to compute the real interest rate. I use the log of income per capita to measure observed consumer heterogeneity. The mean of the log of individual coefficients on price and log of branch density are $\ln\alpha$ and $\ln\beta$ respectively. Both instruments for price and branch density are used. The results are displayed in Table 9 the results. The first panel shows the results with exogenous unobserved product quality, which can be estimated by estimating demand only. The second panel presents the results with endogenous product quality using its first order condition to correct its endogeneity, jointly estimating the demand and supply equations. The results of the supply side are given

[26] $0.00098\times[\log(2+1)-\log(1+1)]\approx 0.0004$

[27] An extreme case is the Bertrand model in which the equilibrium price drops from monopoly price directly to competitive price (marginal cost) as the number of firms increase from 1 to 2.

in Table 10.

Insert Table 9 about here.

The effect of the endogeneity of unobserved product quality is evident. The exponential value of the mean of the log of individual interest rate coefficients becomes larger by a factor of 12 when the endogeneity of unobserved product quality is corrected. The interactions between bank characteristics and demographics are significant. Results in both panels show that affluent consumers appear to care less about branch density, which is consistent with the results of a study by Dick (2002). Wealthier consumers also appear to respond more favorably to an increase in interest rate. This is what one would expect given that wealthier consumers have more deposits, and thus rising interest rates will benefit wealthier consumers more significantly than less affluent consumers. Estimates of standard deviations of taste parameters are not significant, suggesting that most of the heterogeneity is explained by the demographics.[28]

Insert Table 10 about here.

The competition effects in Table 10 are not significant. The results also show that both mega banks and dominant banks have high deposit return rate. The signs of some bank and market exogenous characteristics are not very consistent with that from the logit model (Table 8), such as the sign of the log value of average personal income. The inconsistent estimates from the two models are due to the correlation among these exogenous bank and market characteristics, or more fundamentally, the marginal deposit return rate is recovered from the first order conditions rather than is observed directly.

## 6.2 Post-Merger Evolution

In the following analysis, I use the estimates from the logit demand model because it includes more markets than the random coefficients logit model. Tables 11-14 present how post-merger bank product quality of merging banks in within-market mergers and entry of fringe banks evolve. The results come from analyzing historical data on bank mergers. I use FDIC market shares instead of market shares, because savings associations are more similar to commercial banks than credit unions. Column (i) in each table gives estimates of the specification that I use in merger simulations in the next section.

[28]I try to include random coefficients on constant, the fringe bank dummy and the log value of number of states in which the bank operates, but neither is significant. All other coefficients on observed bank characteristics are consistent with that in Table 3 in terms of signs and magnitude.

### 6.2.1 Branch Density

Table 11 presents the post-merger changes in branch density of merging banks. The results are obtained by estimating (16) with three different specifications. The specification in column (i) gives the highest $R^2$ value. Columns (i) and (ii) differ in a constant term and the coefficient on constant is insignificant. The coefficient on the log of the sum of pre-merger branch densities is positive. In column (iii), the coefficients on the log of both the pre-merger branch density of the acquirer and the target are both positive. The higher the pre-merger branch density of either the acquirer or the target, the higher the branch density of the new merging bank is. The coefficients on the ratio of overlapped ZIP codes are significantly negative for all specifications. This is what one would expect because if two branches from two merging banks are too close to each other, the new bank tends to divest one branch. The coefficient on either bank's pre-merger market share is significantly negative for all specifications because banks may reduce product quality due to their growing post-merger market power. This may also reflect the unobserved government intervention, forcing big merging banks to divest branches. The coefficient on log value of the sum of branch densities is 0.9960 in column (i). This implies that the sum of the pre-merger branch densities is a good approximation for the post-merger branch density if two merging banks have no overlapped branch networks and both banks have small pre-merger market shares. In column (i), the coefficient on pre-merger market share of either merging bank is negative. Mergers between banks with larger market shares may divest more branches because the new bank enjoys bigger market power. Big merging banks reduce branch densities even if there are no overlapped pre-merger branch networks. The reduction in branches of merging banks is not symmetric. A one percent increase in the pre-merger market share of the target causes more reduction in post-merger branch density than a one percent increase in the pre-merger market share of the acquirer.

Insert Table 11 about here.

### 6.2.2 Unobserved Product Quality

Table 12 shows the post-merger change in unobserved product quality of merging banks. The results are obtained by estimating (17). High pre-merger unobserved product quality or high market share of either bank can lead to high unobserved product quality of the new bank. In column (i), the coefficient on the pre-merger market share weighted unobserved product quality is 0.5987, which is far below 1. This tells us that merging banks reduce average unobserved product quality as well as observed product quality (branch density).

Insert Table 12 about here.

#### 6.2.3 Unobserved Bank- and Market-Specific Deposit Return Rate

Table 13 gives the post-merger evolution of the unobserved bank- and market-specific deposit return rate. The results are obtained by estimating (18). High pre-merger bank- and market-specific deposit return rate of either merging bank can lead to high post-merger bank- and market-specific deposit return rate. The coefficient on bank- and market-specific term of the acquirer is 0.7984, which is much higher than that on the target, 0.2392. This implies that the bank- and market-specific deposit return rate is mostly determined by that of the acquirer. The high market share of either merging bank generally leads to a high post-merger market share, and to big market power, which then leads to a higher marginal deposit return rate.

Insert Table 13 about here.

#### 6.2.4 Entry of Fringe Banks

Table 14 presents how the post-merger number of fringe banks changes. The results are obtained by estimating (19). Columns (i) and (ii) give the results from the OLS estimation, regressing the post-merger number of fringe banks on the pre-merger number of fringe banks, market characteristics, and deposits of acquirers and targets. The $R^2$ is very high and the coefficient on the pre-merger number of fringe banks is almost 1. The coefficient on total income is positive. If the total income of a county is about \$8 billion, one fringe bank is expected to enter following mergers. The bigger the deposits of acquirers, the more entrants there are. If the deposits of pre-merger acquirers are about \$3 billion, one fringe bank is expected to enter. The closest non-negative integer to the prediction is used as the estimated number of fringe banks in merger simulations in the next section.

Insert Table 14 about here.

### 6.3 Merger Simulations

With the demand and supply estimates as well as the post-merger patterns of product quality and entry, I apply the methodology of merger analysis in this paper to analyze thirteen cases of within-market bank mergers. A widely used prediction methodology uses the sum of pre-merger branch densities and market shares of merging banks as their post-merger values. I use the results from this method as the benchmark to compare them with the prediction from the model presented in this paper. Table 15 shows the merger prediction of all banks in one market. Table 16 reports merging banks only in the thirteen mergers. In the panel "Prediction" of Tables 15 and 16, H stands for prediction using historical data on mergers and W stands for prediction using the market share weighted pre-merger level of unobserved variables, including the unobserved product quality and unobserved bank- and market-specific deposit return rate.

Insert Table 15 about here.

Insert Table 16 about here.

In Table 15, there is one within-market and two out-of-market mergers. For two banks in the within-market merger, the pre-merger numbers of branches in the county were 11 and 12, and the pre-merger market shares were 0.0275 and 0.0241 respectively. The post-merger number of branches and market share of the new merging bank were 20 and 0.412 respectively. For the post-merger number of branches, the benchmark prediction is 23 and the model prediction is 19.43. For the post-merger market share, the benchmark gives 0.0516, the model prediction is 0.0504 using historical data on mergers, and is 0.0428 using the market share weighted unobserved variables. The two predictions from the model are closer to the actual outcome than the benchmark, which overestimates both the post-merger number of branches and market share. For banks in out-of-market mergers, the impact of mergers on their numbers of branches and market shares is small. Some banks in the "Pre-Merger" panel disappeared in the "Post-Merger" panel, because they became fringe banks; I take this into consideration when calculating the post-merger number of fringe banks. The numbers in parentheses in the "Branches" column in the "Post-merger" panel are the post-merger numbers of branches of those banks that became fringe banks and "-" stands for the bank that was involved in a voluntary liquidation and closing. Then, the adjusted post-merger number of fringe banks becomes $41(= 50 - 6 - 3)$ and the prediction is 45.

To give a general idea of how the methodology works, Table 16 presents the pre-merger number of branches and market shares of merging banks and the post-merger predictions from the model and the benchmark. The first column assigns a number to each merger. Among the thirteen mergers, numbers 4 and 10 are out of the merger samples that I use to estimate the post-merger patterns of product quality and entry, and the rest are in the merger samples. Let us start with number of branches. The model outperforms the benchmark twelve times out of thirteen (numbers 1-13). I then move to market shares. For the first five mergers (numbers 1-5), the ratio of pre-merger market shares of two merging banks is close to 1 (between 50% and 200%). The model predictions (H) outperform the benchmark for four out of five mergers (numbers 1-4). For the other eight mergers (numbers 6-13), the market shares of two banks are disproportional. The model prediction (H) and the benchmark have close predictive power. When the market shares of two banks are disproportional, the post-merger bank is largely determined by the bank with the larger market share and few branches are divested. The benchmark can provide a good approximation in this situation. The prediction of market shares using pre-merger market share weighted unobserved variables are similar to that from the prediction using historical data. The model predictions (H) and (W) have similar prediction patterns.

# 7 Conclusions and Future Work

This paper presents a model that allows firms to enter and exit a market and compete with product quality. It furthers our understanding of the impact of mergers on product quality and entry. The methodology of merger analysis presented in this paper has important implications: it extends merger prediction to the nonprice dimension in the banking industry such as branch density, and it provides a model that can help regulate mergers. For example, when two dominant banks in a market merge, it is natural to ask how many branches the new bank should divest without significantly reducing consumer welfare. The model presented in this study can provide the answer.

The model presented in this study also indicates that it is useful to use the real price instead of the nominal price in the banking industry. For example, unlike the nominal price elasticity that varies across years, the real price elasticity is stable and can be transformed easily to nominal price elasticity with the opportunity cost given. Both the real and nominal price elasticities can help us understand how consumers react to prices under different macro economic conditions, which determine the opportunity cost.

The methodology of merger analysis presented here can be applied to other industries where the historical data on mergers are rich and firms operate on multiple markets. One possible application is the airline industry. I can extend the study by Richard (2003) from duopoly markets to markets with multiple firms, asking how mergers change flight frequency and how to predict the change. Another possible application is the telecommunication industry; it would be interesting to analyze how mergers affect innovations and the variety of services (treating the adoption of innovations and the number of services as two endogenous variables) in local markets.

One limitation of the model presented in this paper is that the estimation procedure may suffer from the endogeneity of mergers. I use nationwide mergers and reasonable assumption on unobserved post-merger variables to minimize the impact of the endogeneity of mergers. If I develop an estimation method that solves this problem, I could incorporate more data on mergers than the limited information that I use in this paper. Another limitation to my model is its incorporation of a static model. Mergers, especially merger waves, are essentially dynamic processes and my model has not yet been extended to a dynamic model.

# 8 Appendix

## 8.1 Robustness

This appendix considers several alternative specifications to explore the robustness of both the demand- and the supply-side results of section 6. I use a different definition of fringe banks in the logit model, different opportunity cost in the random coefficients logit model, fixed cost for branch density, and branch density instead of the log of branch density in the utility function.

First, I try to incorporate a different definition of fringe banks. I define fringe banks as banks with market shares among all FDIC-insured depository institutions below 2% and total deposits in a county less than 1 billion US dollars. Using the new definition of fringe banks, I estimate demand and supply. Results in Tables 17-21 are very similar to that in Tables 3-8.

Second, I use the federal funds rate as the opportunity cost instead of the average loan rate to estimate the random coefficients logit model again. The estimates using federal funds rate as the opportunity cost (data not shown) are very similar to the estimates using average loan rate as the opportunity cost. The price coefficient from using the federal funds rate as the opportunity cost is a little smaller than that from using the average loan rate.

In the following robustness checks, I use different specifications of the demand and supply functions. Third, I modify the model so that branches are correlated to fixed costs but still use the log value of branch density in the utility function. Theoretically, it will not change anything in the case of the logit model on the estimates of either the demand and supply sides expect a constant term in the estimate of the marginal deposit return rate. According to the results from the random coefficients logit model, the demand estimates are almost the same and the change in supply estimates change very little (data not shown).

Fourth, it does not make a large difference if I use the log value of the number of branches or the log value of branches per capita. This is because the log value of county size enters the county dummy variable. Although the population of a county varies across years, the variance is very small and is mostly absorbed by the year dummy variable and county dummy variable. The above robustness check applies to both fixed costs and to the marginal costs of branches.

Finally, I use the number of branches or branch density instead of using the log value of branch density in the utility function and assume that branches are correlated with fixed costs in the logit model. Unfortunately, the results contradict intuition: the higher the market share of a bank, the higher its fixed cost related to building up a branch.

## 8.2 Branch Network Effects

The log value of branch density is equal to the log value of the number of branches minus the log value of county size, which enters the county dummy variable. Therefore, the estimated coefficients on the log value of the branch density and the log value of the number of branches are the same in both specifications. Let $N_{jm}$ stand for the total number of branches of bank $j$ in market $m$. In the logit model, the market share of bank $j$ is $N_{jm}^{\beta^n}$ times the market share of each individual branch of bank $j$ in market $m$, $s_{jm}^b$.

$$\begin{aligned} s_{jm} &= \frac{\exp(\alpha p_{jm} + \beta^n \ln N_{jm} + x_{jm}^{ex}\beta^{ex} + \xi_{jm})}{1 + \sum_{l=1}^{J_m} \exp(\alpha p_{lm} + \beta^n \ln N_{lm} + x_{lm}^{ex}\beta^{ex} + \xi_{lm})} \\ &= N_{jm}^{\beta^n} \frac{\exp(\alpha p_{jm} + x_{jm}^{ex}\beta^{ex} + \xi_{jm})}{1 + \sum_{l=1}^{J_m} N_{jm}^{\beta^n} \exp(\alpha p_{lm} + x_{lm}^{ex}\beta^{ex} + \xi_{lm})} \\ &= N_{jm}^{\beta^n} s_{jm}^b. \end{aligned}$$

If $\beta^n$ is equal to 1, the market share of bank $j$ is the sum of $N_{jm}$ independent branches, or each branch of the same bank behaves independently. If $\beta^n$ is greater than 1, the positive network effect dominates. If $\beta^n$ is less than 1, then the substitution effect dominates and branches tend to steal business from each other.

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Table 1: Market Characteristics Description (County Population > 200,000)

| Variable | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| Average personal income ($1, base year = 2000) | 30,336 | 7,609 | 11,318 | 85,826 |
| County population | 640,096 | 788,420 | 2,000,027 | 9,941,197 |
| Total deposits ($1, base year = 2000) | $1.18\times10^7$ | $2.13\times10^7$ | 783,225 | $3.43\times10^8$ |
| Savings rate | 0.5274 | 0.3094 | 0.1572 | 5.4289 |
| Number of dominant banks | 1.636 | 0.8485 | 0 | 4 |
| Number of large banks | 11.48 | 3.695 | 3 | 26 |
| Number of fringe banks | 20.17 | 41.97 | 0 | 482 |

Notes: There are 12 years, 293 counties and 3290 markets (year-county).

FDIC market shares refer to market shares among all FDIC-insured depository institutions in a market.

A dominant bank is a bank with its FDIC market share above 15%.

A large bank is a bank with its FDIC market share above 1% or its total deposits in a county over US$1B.

A fringe bank is a bank with its FDIC-market share below 1% and its total deposits in a county less than US$1B.

Table 2: Market Average for Large and Fringe Bank Prices and Characteristics: 1994 vs 2005
A fringe bank is a bank with its FDIC market shares below 1% and its total deposits in a county less than US$1B.

| | Large Banks | | Fringe Banks | |
|---|---|---|---|---|
| Variable | 1994 | 2005 | 1994 | 2005 |
| Deposit interest rate | 2.44% | 1.47% | 3.58% | 1.57% |
| Service fees | 0.592% | 0.605% | 0.691% | 0.636% |
| Market share | 6.09% | 5.82% | 0.33% | 0.31% |
| FDIC market share | 6.80% | 6.67% | 0.36% | 0.35% |
| Number of branches in a county | 9.27 | 9.83 | 1.76 | 1.91 |
| Branch density | 0.0279 | 0.0267 | 0.0057 | 0.0048 |
| Number of states | 1.08 | 6.19 | 1.03 | 2.23 |
| Age | 70.1 | 76.7 | 42.5 | 53.2 |
| Medium (assets of US$100M-300M) | 20.0% | 14.6% | 26.1% | 26.3% |
| Big (assets of US$300M-3B) | 29.4% | 31.3% | 18.7% | 35.1% |
| Mega (assets over US$3B) | 34.0% | 50.6% | 4.25% | 17.0% |
| Bank holding company | 80.4% | 89.5% | 56.7% | 75.6% |
| International | 13.7% | 21.2% | 5.45% | 6.06% |
| A former savings association | 2.96% | 4.96% | 4.44% | 5.41% |
| Headquarters in the county | 56.8% | 37.6% | 59.8% | 34.8% |
| Headquarters in the state | 99.4% | 68.3% | 99.5% | 83.1% |
| Number of observations | 2975 | 3587 | 2589 | 3122 |

Notes: The deposit interest rates and service fees are both calculated as one-year rates.

Table 3: Logit Demand Model (County Population > 200,000)
Dependent Variable: $\ln(s_{jm}) - \ln(s_{0m})$

| | OLS | IV | | |
|---|---|---|---|---|
| | | Price | Price and branch | EIV |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
| Interest rate − service fees | 5.935*** | 18.82*** | 25.67*** | 24.87*** |
| | (0.2801) | (0.7408) | (0.8385) | (0.8237) |
| $\ln($branch density$)$ | 0.6955*** | 0.7332*** | 1.090*** | 1.069*** |
| | (0.0041) | (0.0046) | (0.0102) | (0.0100) |
| $\ln($number of states$)$ | 0.0669*** | 0.0869*** | 0.0295*** | 0.0321*** |
| | (0.0060) | (0.0062) | (0.0070) | (0.0069) |
| Headquarters in the county | 0.5615*** | 0.5532*** | 0.4017*** | 0.4106*** |
| | (0.0087) | (0.0089) | (0.0106) | (0.0104) |
| Headquarters in the state | 0.1686*** | 0.1820*** | 0.1114*** | 0.1150*** |
| | (0.0125) | (0.0128) | (0.0143) | (0.0141) |
| International | 0.2010*** | 0.2361*** | 0.2078*** | 0.2083*** |
| | (0.0096) | (0.0099) | (0.0110) | (0.0109) |
| A former savings association | -0.0885*** | -0.1454*** | -0.1685*** | -0.1655*** |
| | (0.0142) | (0.0148) | (0.0164) | (0.0162) |
| Bank holding company | -0.0618*** | -0.0048 | -0.0764*** | -0.0742*** |
| | (0.0093) | (0.0100) | (0.0112) | (0.0110) |
| Fringe | -0.7299*** | -0.6921*** | -0.5136*** | -0.5245*** |
| | (0.0159) | (0.0162) | (0.0185) | (0.0183) |
| Medium | 0.3933*** | 0.3870*** | 0.2501*** | 0.2581*** |
| | (0.0125) | (0.0127) | (0.0145) | (0.0143) |
| Big | 0.7425*** | 0.6921*** | 0.3281*** | 0.3504*** |
| | (0.0133) | (0.0139) | (0.0178) | (0.0175) |
| Mega | 1.124*** | 1.106*** | 0.5382*** | 0.5710*** |
| | (0.0160) | (0.0164) | (0.0230) | (0.0226) |
| $R^2$ | 0.8411 | 0.8343 | 0.7965 | 0.8009 |
| First-stage $R^2$ (interest rate − service fees) | - | 0.6072 | 0.6072 | 0.6083 |
| First-stage $R^2$ ($\ln($branch density$)$) | - | - | 0.8276 | 0.8293 |
| Markets | 293 | 293 | 293 | 293 |
| Years | 12 | 12 | 12 | 12 |
| Observations | 42450 | 42427 | 42427 | 42427 |

Notes: County and year effects are included.

Standard errors are in parentheses.

***significant at 1%; **significant at 5%; *significant at 10%

Table 4: Average Marginal Profit Rate and Estmated Coefficient on (interest rate − service fees) $\alpha$ using bank income statements

| Weight | Equal Weight | Deposits |
|---|---|---|
| Average Marginal Profit Rate | 0.0289 | 0.0293 |
| | (0.000153) | (0.000093) |
| $\alpha$ | 119.7 | 45.17 |
| | (19.00) | (3.415) |

Notes: Standard errors are in parentheses.

Table 5: Logit Demand Model (County Population > 200,000)
using bank income statements
Dependent Variable: $\ln(s_{jm}) - \ln(s_{0m}) - \widehat{\alpha} \cdot (\text{interest rate} - \text{service fees})$

| | OLS | IV |
|---|---|---|
| Explanatory Variable | (i) | (ii) |
| $\ln(\text{branch density})$ | 0.8073*** | 1.183*** |
| | (0.0048) | (0.0107) |
| $\ln(\text{number of states})$ | 0.1306*** | 0.0535*** |
| | (0.0072) | (0.0079) |
| Headquarters in the county | 0.5342*** | 0.3715*** |
| | (0.0106) | (0.0120) |
| Headquarters in the state | 0.2112*** | 0.1238*** |
| | (0.0152) | (0.0163) |
| International | 0.3074*** | 0.2555*** |
| | (0.0115) | (0.0123) |
| A former savings association | -0.2565*** | -0.2514*** |
| | (0.0171) | (0.0183) |
| Bank holding company | -0.1082*** | -0.0029 |
| | (0.0112) | (0.0122) |
| Fringe | -0.6464*** | -0.4526*** |
| | (0.0192) | (0.0209) |
| Medium | 0.3698*** | 0.2241*** |
| | (0.0151) | (0.0165) |
| Big | 0.5855*** | 0.2132*** |
| | (0.0161) | (0.0195) |
| Mega | 1.066*** | 0.4476*** |
| | (0.0194) | (0.0258) |
| $R^2$ | 0.8118 | 0.7862 |
| First-stage $R^2$ ($\ln(\text{branch density})$) | - | 0.8276 |
| Markets | 293 | 293 |
| Years | 12 | 12 |
| Observations | 42450 | 42427 |

Notes: County and year effects are included.
Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 6: Yearly Average Estimated Own Price Elasticity
Logit Demand Model (County Population > 200,000)

| Opportunity Cost | Maximum | Minimum |
|---|---|---|
| Average loan rate | -2.651 | -2.023 |
| Federal funds rate | -1.588 | -0.157 |
| No opportunity cost | 0.208 | 1.272 |

Table 7: Estimated Own Price Elasticity
Logit Demand Model (County Population > 200,000)

| Opportunity Cost | Mean | Median | 25th Percentile | 75th Percentile |
|---|---|---|---|---|
| Average loan rate | -2.347 | -2.336 | -2.628 | -2.028 |
| Federal funds rate | -0.916 | -0.944 | -1.379 | -0.440 |
| No opportunity cost | 0.866 | 0.879 | 0.431 | 1.282 |

Table 8: Marginal Deposit Return Rate, $r^0_{jm}$
Logit Demand Model (County Population > 200,000)

| | Logit | | Income Statement | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
| *COMPETITION* | | | | |
| Dominant$\cdot \ln$ (number of dominant banks + 1) | -0.00183*** | -0.00184*** | -0.00098* | -0.00098* |
| | (0.00059) | (0.00059) | (0.00059) | (0.00059) |
| $\ln$ (number of large banks + 1) | -0.00001 | -0.00041 | 0.00044 | 0.00059 |
| | (0.00047) | (0.00064) | (0.00046) | (0.00062) |
| $\ln$ (number of fringe banks + 1) | 0.00021 | -0.00036 | 0.00022 | -0.00032 |
| | (0.00015) | (0.00068) | (0.00014) | (0.00061) |
| *BANK CHARACTERISTICS* | | | | |
| $\ln$(number of states) | -0.00192*** | -0.00191*** | -0.00201*** | -0.00200*** |
| | (0.00011) | (0.00010) | (0.00011) | (0.00011) |
| Headquarters in the county | 0.00088*** | 0.00088*** | 0.00030** | 0.00031*** |
| | (0.00016) | (0.00016) | (0.00015) | (0.00016) |
| Headquarters in the state | -0.00111*** | -0.00111*** | -0.00131*** | -0.00131** |
| | (0.00022) | (0.00022) | (0.00022) | (0.00022) |
| International | -0.00277*** | -0.00277*** | -0.00288*** | -0.00288*** |
| | (0.00017) | (0.00017) | (0.00017) | (0.00017) |
| A former savings association | 0.00420*** | 0.00422*** | 0.00425*** | 0.00426*** |
| | (0.00025) | (0.00025) | (0.00025) | (0.00025) |
| Bank holding company | -0.00496*** | -0.00497*** | -0.00506*** | -0.00507*** |
| | (0.00016) | (0.00016) | (0.00016) | (0.00016) |
| Fringe | -0.00021 | -0.00018 | -0.00045 | -0.00042 |
| | (0.00028) | (0.00028) | (0.00028) | (0.00028) |
| Dominant | 0.00767*** | 0.00767*** | 0.00369*** | 0.00369*** |
| | (0.00066) | (0.00066) | (0.00065) | (0.00065) |
| Medium | 0.00024 | 0.00026 | -0.00014 | -0.00012 |
| | (0.00022) | (0.00022) | (0.00022) | (0.00022) |
| Big | 0.00316*** | 0.00317*** | 0.00229*** | 0.00230*** |
| | (0.00023) | (0.00023) | (0.00023) | (0.00023) |
| Mega | 0.00023 | 0.00025 | -0.00119*** | -0.00118*** |
| | (0.00027) | (0.00027) | (0.00027) | (0.00027) |

Table 8 (Continued): Marginal Deposit Return Rate $r^0_{jm}$
Logit Demand Model (County Population > 200,000)

| | Logit | | Income Statement | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
| *MARKET CHARACTERISTICS* | | | | |
| ln(population) | 0.0065*** | 0.0075*** | 0.0067*** | 0.0077*** |
| | (0.0012) | (0.0016) | (0.0012) | (0.0016) |
| ln(personal income) (income in $1000) | 0.0055*** | 0.0053*** | 0.0056*** | 0.0054*** |
| | (0.0015) | (0.0016) | (0.00154) | (0.0016) |
| ln(savings rate) | 0.0018*** | 0.0020*** | 0.0022*** | 0.0024*** |
| | (0.0005) | (0.0007) | (0.0007) | (0.0007) |
| $R^2$ | 0.5185 | 0.5183 | 0.3432 | 0.3430 |
| First-stage $R^2$ | - | 0.9141 | - | 0.9141 |
| Markets | 293 | 293 | 293 | 293 |
| Years | 12 | 12 | 12 | 12 |
| Observations | 42450 | 42450 | 42450 | 42450 |

Notes: County and year effects are included.
Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 9: Random Coefficients Logit Demand Model (County Population > 500,000) using the average loan rate as the opportunity cost

| | Exogenous $\xi$ | | | Endogenous $\xi$ | | |
|---|---|---|---|---|---|---|
| | Mean ($\beta$'s) | Std. ($\sigma$'s) | ln(income) | Mean ($\beta$'s) | Std. ($\sigma$'s) | ln(income) |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
| Interest rate − service fees | 15.4868*** | 0.0506 | 0.8194*** | 21.5848*** | 0.0167 | 0.7188** |
| − average loan rate | (2.8788) | (0.7291) | (0.2282) | (2.0898) | (0.8859) | (0.3150) |
| ln(branch density) | 1.0688*** | 0.0038 | -0.4542*** | 0.9335*** | 0.0054 | -0.5576*** |
| | (0.0595) | (0.1449) | (0.0398) | (0.0887) | (0.1656) | (0.0538) |
| ln (number of states) | 0.0156 | - | - | 0.0072 | - | - |
| | (0.0136) | - | - | (0.0154) | - | - |
| Headquarters in the county | 0.3044*** | - | - | 0.2883*** | - | - |
| | (0.0197) | - | - | (0.0203) | - | - |
| Headquarters in the state | 0.0821*** | - | - | 0.0790*** | - | - |
| | (0.0242) | - | - | (0.0268) | - | - |
| International | 0.1603*** | - | - | 0.1621*** | - | - |
| | (0.0198) | - | - | (0.0229) | - | - |
| A former savings association | -0.2039*** | - | - | -0.1841*** | - | - |
| | (0.0264) | - | - | (0.0267) | - | - |
| Bank holding company | -0.0622*** | - | - | -0.0794*** | - | - |
| | (0.0251) | - | - | (0.0267) | - | - |
| Fringe | -0.6719*** | - | - | -0.7056*** | - | - |
| | (0.0592) | - | - | (0.0603) | - | - |
| Medium | 0.1942*** | - | - | 0.1852*** | - | - |
| | (0.0464) | - | - | (0.0509) | - | - |
| Big | 0.3072*** | - | - | 0.2865*** | - | - |
| | (0.0520) | - | - | (0.0563) | - | - |
| Mega | 0.4907*** | - | - | 0.4512*** | - | - |
| | (0.0613) | - | - | (0.0646) | - | - |
| Markets | 84 | | | 84 | | |
| Years | 12 | | | 12 | | |
| Observations | 13318 | | | 13318 | | |

Notes: County and year effects are included. Income is measured in $1.
Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 10: Marginal Deposit Return Rate $r^0_{jm}$
Random Coefficients Logit Model (County Population > 500,000)
using the average loan rate as the opportunity cost

| Explanatory Variable | Exogenous $\xi$ (i) | Endogenous $\xi$ (ii) |
|---|---|---|
| *COMPETITION* | | |
| Dominant$\cdot \ln$(number of dominant banks + 1) | -0.0603 | -0.0674 |
| | (0.0524) | (0.0575) |
| $\ln$(number of large banks + 1) | -0.0024 | -0.0026 |
| | (0.0076) | (0.0062) |
| $\ln$(number of fringe banks + 1) | -0.0026 | -0.0028 |
| | (0.0028) | (0.0033) |
| *BANK CHARACTERISTICS* | | |
| $\ln$(number of states) | 0.0002 | 0.0014 |
| | (0.0011) | (0.0012) |
| Headquarters in the county | 0.0044*** | 0.0048*** |
| | (0.0018) | (0.0011) |
| Headquarters in the state | 0.0012 | 0.0017 |
| | (0.0011) | (0.0015) |
| International | -0.0007 | -0.0004 |
| | (0.0018) | (0.0017) |
| A former savings association | 0.0025 | 0.0020 |
| | (0.0024) | (0.0019) |
| Bank holding company | -0.0022 | -0.0003 |
| | (0.0038) | (0.0044) |
| Fringe | 0.0004 | -0.0007 |
| | (0.0014) | (0.0015) |
| Dominant | 0.0807 | 0.0887 |
| | (0.0528) | (0.0636) |
| Medium | 0.0043 | 0.0049*** |
| | (0.0029) | (0.0012) |
| Big | 0.0124 | 0.0137*** |
| | (0.0073) | (0.0023) |
| Mega | 0.0176** | 0.0210*** |
| | (0.0086) | (0.0050) |

Table 10 (Continued): Marginal Deposit Return Rate $r^0_{jm}$
Random Coefficients Logit Model (County Population > 500,000)
using the average loan rate as the opportunity cost

| Explanatory Variable | Exogenous $\xi$ (i) | Endogenous $\xi$ (ii) |
|---|---|---|
| *MARKET CHARACTERISTICS* | | |
| ln(population) | 0.0149 | 0.0158 |
| | (0.0160) | (0.0148) |
| ln(personal income) (income in \$1000) | -0.0296 | -0.0395 |
| | (0.0510) | (0.0225) |
| ln(savings rate) | -0.0001 | -0.0000 |
| | (0.0112) | (0.0070) |
| Markets | 84 | 84 |
| Years | 12 | 12 |
| Observations | 13318 | 13318 |

Notes: County and year effects are included.
Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 11: Evolution of ln(Post-Merger Branch Density) (County Population > 200,000)

| Explanatory Variable | (i) | (ii) | (iii) |
|---|---|---|---|
| ln(sum of pre-merger branch densities) | 0.9960*** | 0.9920*** | - |
| | (0.0069) | (0.0102) | - |
| ln(pre-merger branch density of the acquirer) | - | - | 0.5280*** |
| | - | - | (0.0271) |
| ln(pre-merger branch density of the target) | - | - | 0.4500*** |
| | - | - | (0.0276) |
| # overlapped zip codes / # all zip codes | -0.3407*** | -0.3253*** | -0.7558*** |
| | (0.0796) | (0.0850) | (0.1138) |
| Pre-merger FDIC market share of the acquirer | -0.5909*** | -0.5361*** | -0.3456 |
| | (0.1539) | (0.1865) | (0.2919) |
| Pre-merger FDIC market share of the target | -0.7180*** | -0.6835*** | -0.3198 |
| | (0.1940) | (0.2053) | (0.2781) |
| Constant | - | -0.0254 | 0.7807*** |
| | - | (0.0487) | (0.0747) |
| $R^2$ | 0.9973 | 0.9811 | 0.9666 |
| Observations | 205 | 205 | 205 |

Notes: Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 12: Evolution of ln(Post-Merger Unobserved Product Quality)
Logit Demand Model (County Population > 200,000)

| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| Pre-merger market share weighted average of | 0.5987*** | 0.5990*** | 0.6020*** | - |
| ln(pre-merger unobserved product quality) | (0.0598) | (0.0600) | (0.0607) | - |
| ln(pre-merger unobserved product quality | - | - | - | 0.2971*** |
| of the target) | - | - | - | (0.0608) |
| ln(pre-merger unobserved product quality | - | - | - | 0.2755*** |
| of the target) | - | - | - | (0.0635) |
| Pre-merger FDIC market share of the acquirer | - | - | -0.5131 | -0.2608 |
| | - | - | (0.4393) | (0.4500) |
| Pre-merger FDIC market share of the target | - | - | 0.5322 | 0.5067 |
| | - | - | (0.5023) | (0.5344) |
| Constant | - | 0.0068 | 0.0169 | 0.0169 |
| | - | (0.0302) | (0.0715) | (0.0742) |
| $R^2$ | 0.3292 | 0.3020 | 0.3389 | 0.3111 |
| Observations | 205 | 205 | 205 | 205 |

Notes: Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 13: Evolution of Post-Merger Unobserved Bank- and Market-Specific Deposit Return Rate $\varpi$ Logit Demand Model (County Population > 200,000)

| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| Pre-merger market share weighted average of $\varpi$ | - | - | 0.8229*** | 0.8145*** |
| | - | - | (0.0718) | (0.0712) |
| Pre-merger $\varpi$ of the acquirer | 0.7984*** | 0.7975*** | - | - |
| | (0.0480) | (0.0483) | - | - |
| Pre-merger $\varpi$ of the target | 0.2392*** | 0.2410*** | - | - |
| | (0.0478) | (0.0487) | - | - |
| Pre-merger FDIC market share of the acquirer | -0.0008 | 0.0115 | 0.0061 | - |
| | (0.0029) | (0.0047) | (0.0050) | - |
| Pre-merger FDIC market share of the target | 0.0102*** | 0.0143** | -0.0002 | - |
| | (0.0034) | (0.0047) | (0.0057) | - |
| Constant | - | -0.0014 | -0.0005 | - |
| | - | (0.0007) | (0.0008) | - |
| $R^2$ | 0.5990 | 0.5989 | 0.3955 | 0.3908 |
| Observations | 205 | 205 | 205 | 205 |

Notes: $\varpi$ stands for the unobserved bank- and market-specific deposit return rate.
Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 14: Evolution of the Post-Merger Number of Fringe Banks (County Population > 200,000)

| Explanatory Variable | (i) | (ii) |
|---|---|---|
| Pre-merger number of fringe banks | 0.9878*** | 0.9921*** |
| | (0.0231) | (0.0238) |
| Total county income | 0.1404*** | 0.1274*** |
| (in $1,000,000,000) | (0.0305) | (0.0349) |
| Deposits of targets | -1.4041*** | -1.479*** |
| (in $1,000,000,000) | (0.3761) | (0.3887) |
| Deposits of acquirers | 0.3586*** | 0.3622*** |
| (in $1,000,000,000) | (0.1317) | (0.1320) |
| Constant | - | 0.6136 |
| | - | (0.7911) |
| $R^2$ | 0.9838 | 0.9781 |
| Observations | 176 | 176 |

Notes: Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 15: Merger Simulation (Alameda County, CA)

| | Pre-Merger (2001) | | Post-Merger (2003) | | Prediction | | |
|---|---|---|---|---|---|---|---|
| Banks | Branches | Shares | Branches | Shares | Branches (H) | Shares (H) | Shares (W) |
| | 46 | 0.2039 | 46 | 0.1968 | 46 | 0.2029 | 0.2037 |
| | 38 | 0.1572 | 38 | 0.1556 | 38 | 0.1563 | 0.1570 |
| | 14 | 0.0320 | 15 | 0.0442 | 14 | 0.0318 | 0.0320 |
| M | 11 | 0.0275 | | | | | |
| OM1 | 14 | 0.0262 | 15 | 0.0284 | 14 | 0.0255 | 0.0257 |
| M | 12 | 0.0241 | 20 | 0.0412 | 19.43 | 0.0504 | 0.0428 |
| | 4 | 0.0199 | 4 | 0.0199 | 4 | 0.0198 | 0.0199 |
| | 2 | 0.0138 | 4 | 0.0182 | 2 | 0.0138 | 0.0138 |
| | 5 | 0.0132 | (6) | | 5 | 0.0131 | 0.0131 |
| | 4 | 0.0126 | (-) | - | 4 | 0.0125 | 0.0126 |
| | 3 | 0.0099 | 3 | 0.0149 | 3 | 0.0099 | 0.0099 |
| OM2 | 4 | 0.0095 | (3) | | 4 | 0.0094 | 0.0095 |
| | 6 | 0.0094 | 7 | 0.0107 | 6 | 0.0093 | 0.0094 |
| Fringe | 39 | 0.0016 | 50 | 0.0015 | 45 | 0.0015 | 0.0016 |

Notes: H stands for merger simulations using historical data on mergers.

W stands for merger simulations using the market share weighted average of pre-merger variables.

M stands for a within-market merger.

OM stands for an out-of-market merger.

M: Bank of the West acquired United California bank on April 1, 2002.

OM1: U.S. Bank National Association acquired U.S. Bank National Association on August 9, 2001.

OM2: City National Bank acquired CivicBank of Commerce on February 28, 2002.

Table 16: Summary of Within-Market Mergers

| | Pre-Merger | | | | Post-Merger | | Prediction | | | Sum of Pre-Merger | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Acquirer | | Target | | | | | | | | |
| Number | Branches | Shares | Branches | Shares | Branches | Shares | Branches (H) | Shares (H) | Shares (W) | Branches (S) | Shares (S) |
| 1 | 12 | 0.0241 | 11 | 0.0275 | 20 | 0.0412 | 19.4 | 0.0504 | 0.0428 | 23 | 0.0516 |
| 2 | 20 | 0.0708 | 42 | 0.1139 | 49 | 0.1345 | 50.0 | 0.1380 | 0.1538 | 62 | 0.1847 |
| 3 | 5 | 0.0257 | 5 | 0.0339 | 8 | 0.0420 | 9.0 | 0.0589 | 0.0534 | 10 | 0.0596 |
| 4 | 19 | 0.0529 | 9 | 0.0428 | 25 | 0.0976 | 25.8 | 0.0970 | 0.1043 | 28 | 0.0957 |
| 5 | 20 | 0.0782 | 22 | 0.0753 | 27 | 0.1422 | 32.4 | 0.1600 | 0.1359 | 42 | 0.1535 |
| 6 | 6 | 0.0261 | 21 | 0.1405 | 23 | 0.1234 | 24.2 | 0.1060 | 0.1244 | 27 | 0.1666 |
| 7 | 21 | 0.0911 | 5 | 0.0222 | 21 | 0.1582 | 22.5 | 0.1121 | 0.1159 | 26 | 0.1133 |
| 8 | 21 | 0.1583 | 4 | 0.0223 | 22 | 0.1703 | 21.2 | 0.1394 | 0.1562 | 25 | 0.1806 |
| 9 | 34 | 0.2200 | 17 | 0.0861 | 43 | 0.2888 | 37.3 | 0.2135 | 0.2368 | 51 | 0.3061 |
| 10 | 11 | 0.0376 | 3 | 0.0124 | 13 | 0.0418 | 13.5 | 0.0517 | 0.0473 | 14 | 0.0500 |
| 11 | 12 | 0.1373 | 3 | 0.0368 | 13 | 0.1599 | 13.2 | 0.1681 | 0.1766 | 15 | 0.1741 |
| 12 | 21 | 0.0974 | 4 | 0.0225 | 23 | 0.0857 | 22.9 | 0.0973 | 0.1172 | 25 | 0.1199 |
| 13 | 31 | 0.1045 | 4 | 0.0231 | 38 | 0.1256 | 30.6 | 0.1210 | 0.1163 | 35 | 0.1276 |

Notes: H stands for merger simulations using historical data on mergers.
W stands for the merger simulations using weighted pre-merger variables.
S stands for merger prediction of branches and market shares by using the sum of pre-merger values of two merging banks.

Table 17: Robustness Checks, Logit Demand Model (County Population > 200,000)
A fringe bank is a bank with its FDIC market share below 2% and its total deposits in a county less than US$1B.

| | OLS | IV | | |
|---|---|---|---|---|
| | | Price | Price and branch | EIV |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
| Interest rate − service fees | 5.497*** | 19.09*** | 27.99*** | 27.34*** |
| | (0.3215) | (0.8160) | (0.9569) | (0.9370) |
| ln(branch density) | 0.6438*** | 0.6881*** | 1.1143*** | 1.0923*** |
| | (0.0047) | (0.0055) | (0.0119) | (0.0115) |
| ln (number of states) | 0.0511*** | 0.0709*** | 0.0211*** | 0.0233*** |
| | (0.0061) | (0.0063) | (0.0073) | (0.0072) |
| Headquarters in the county | 0.4604*** | 0.4496*** | 0.3103*** | 0.3175*** |
| | (0.0098) | (0.0101) | (0.0120) | (0.0118) |
| Headquarters in the state | 0.1518*** | 0.1677*** | 0.1064*** | 0.1093*** |
| | (0.0130) | (0.0133) | (0.0153) | (0.0151) |
| International | 0.1948*** | 0.2349*** | 0.2065*** | 0.2073*** |
| | (0.0098) | (0.0103) | (0.0118) | (0.0116) |
| A former savings association | -0.0688*** | -0.1263*** | -0.1740*** | -0.1708*** |
| | (0.0165) | (0.0172) | (0.0197) | (0.0195) |
| Bank holding company | -0.0789*** | -0.0190 | -0.1145*** | -0.1147*** |
| | (0.0113) | (0.0120) | (0.0139) | (0.0137) |
| Fringe | -0.7201*** | -0.6763*** | -0.3104*** | -0.3293*** |
| | (0.0209) | (0.0215) | (0.0261) | (0.0257) |
| Medium | 0.3400*** | 0.3380*** | 0.2078*** | 0.2143*** |
| | (0.0186) | (0.0191) | (0.0221) | (0.0218) |
| Big | 0.6705*** | 0.6218*** | 0.2484*** | 0.2678*** |
| | (0.0191) | (0.0197) | (0.0242) | (0.0239) |
| Mega | 1.009*** | 0.9939*** | 0.4133*** | 0.4426*** |
| | (0.0214) | (0.0219) | (0.0286) | (0.0281) |
| $R^2$ | 0.8568 | 0.8494 | 0.8030 | 0.8074 |
| First Stage $R^2$ (price) | - | 0.6459 | 0.6459 | 0.6459 |
| First Stage $R^2$ (ln(branch density)) | - | - | 0.8637 | 0.8637 |
| Markets | 293 | 293 | 293 | 293 |
| Years | 12 | 12 | 12 | 12 |
| Observations | 32100 | 32088 | 32088 | 32088 |

Notes: County and year effects are included.
Standard errors are in parentheses.
***significant at 1%; **significant at 5%; *significant at 10%

Table 18: Robustness Checks, Average Marginal Profit Rate and Estimated Coefficient on (interest rate − service fees) $\alpha$ using bank income statements
A fringe bank is a bank with its FDIC market share below 2% and its total deposits in a county less than US$1B.

| Weight | Equal Weight | Deposits |
|---|---|---|
| Average Marginal Profit Rate | 0.0293 | 0.0295 |
| | (0.000125) | (0.000098) |
| $\alpha$ | 140.9 | 46.48 |
| | (21.83) | (0.654) |

Notes: Standard errors are in parentheses.

Table 19: Robustness Checks, Logit Demand Model (County Population > 200,000) using bank income statements

Dependent Variable: $\ln(s_{jm}) - \ln(s_{0m}) - \widehat{\alpha} \cdot (\text{interest rate} - \text{service fees})$

A fringe bank is a bank with its FDIC market share below 2% and its total deposits in a county less than US$1B.

| Explanatory Variable | OLS (i) | IV (ii) |
|---|---|---|
| ln(branch density) | 0.7744*** | 1.214*** |
| | (0.0057) | (0.0122) |
| ln (number of states) | 0.1122*** | 0.0421*** |
| | (0.0074) | (0.0082) |
| Headquarters in the county | 0.4280*** | 0.2823*** |
| | (0.0120) | (0.0135) |
| Headquarters in the state | 0.2006*** | 0.1210*** |
| | (0.0159) | (0.0174) |
| International | 0.3159*** | 0.2555*** |
| | (0.0120) | (0.0131) |
| A former savings association | -0.2381*** | -0.2519*** |
| | (0.0202) | (0.0219) |
| Bank holding company | -0.0993*** | -0.0523*** |
| | (0.0137) | (0.0153) |
| Fringe | -0.6046*** | -0.2228*** |
| | (0.0256) | (0.0292) |
| Medium | 0.3316*** | 0.1909*** |
| | (0.0229) | (0.0250) |
| Big | 0.5202*** | 0.1462*** |
| | (0.0234) | (0.0269) |
| Mega | 0.9621*** | 0.3342*** |
| | (0.0263) | (0.0322) |
| $R^2$ | 0.8262 | 0.7955 |
| First-stage $R^2$ (ln(branch density)) | - | 0.8637 |
| Markets | 293 | 293 |
| Years | 12 | 12 |
| Observations | 32100 | 32088 |

Notes: County and year effects are included.

Standard errors are in parentheses.

***significant at 1%; **significant at 5%; *significant at 10%

Table 20: Robustness Checks, Estimated Own Real Price Elasticity

Logit Demand Model (County Population > 200,000)

A fringe bank is a bank with its FDIC market share below 2% and its total deposits in a county less than US$1B.

| Opportunity costs | Mean | Median | 25th Percentile | 75th Percentile |
|---|---|---|---|---|
| Average loan rate | -2.431 | -2.434 | -2.721 | -2.119 |
| Federal funds rate | -0.978 | -1.003 | -1.452 | -0.495 |
| No opportunity cost | 0.861 | 0.872 | 0.413 | 1.279 |

Table 21: Robustness Checks, Marginal Deposit Return Rate $r^0_{jm}$
Logit Demand Model (County Population > 200,000)
A fringe bank is a bank with its FDIC market share below 2% and its total deposits in a county less than US$1B.

| | Logit | | Income Statement | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
| *COMPETITION* | | | | |
| Dominant$\cdot \ln$ (number of dominant banks + 1) | -0.00204*** | -0.00205*** | -0.00129** | -0.00130** |
| | (0.00057) | (0.00057) | (0.00056) | (0.00056) |
| $\ln$ (number of large banks + 1) | -0.00047 | -0.00108 | -0.00003 | -0.00060 |
| | (0.00049) | (0.00069) | (0.00048) | (0.00069) |
| $\ln$ (number of fringe banks + 1) | -0.00005 | -0.00083 | -0.00002 | -0.00082 |
| | (0.00019) | (0.00067) | (0.00019) | (0.00066) |
| *BANK CHARACTERISTICS* | | | | |
| $\ln$(number of states) | -0.00178*** | -0.00178*** | -0.00184*** | -0.00183*** |
| | (0.00011) | (0.00011) | (0.00011) | (0.00011) |
| Headquarters in the county | 0.00105*** | 0.00106*** | 0.00058*** | 0.00059*** |
| | (0.00018) | (0.00018) | (0.00018) | (0.00018) |
| Headquarters in the state | -0.00124*** | -0.00123*** | -0.00139*** | -0.00138*** |
| | (0.00023) | (0.00023) | (0.00023) | (0.00023) |
| International | -0.00306*** | -0.00306*** | -0.00315*** | -0.00315*** |
| | (0.00018) | (0.00018) | (0.00017) | (0.00017) |
| A former savings association | 0.00400*** | 0.00402*** | 0.00401*** | 0.00403*** |
| | (0.00030) | (0.00030) | (0.00029) | (0.00029) |
| Bank holding company | -0.00522*** | -0.00523*** | -0.00531*** | -0.00532*** |
| | (0.00020) | (0.00020) | (0.00020) | (0.00020) |
| Fringe | -0.00011 | 0.00014 | -0.00021 | -0.00007 |
| | (0.00037) | (0.00037) | (0.00037) | (0.00037) |
| Dominant | 0.00705*** | 0.00705*** | 0.00382*** | 0.00382*** |
| | (0.00063) | (0.00062) | (0.00062) | (0.00062) |
| Medium | -0.00018 | -0.00015 | -0.00048 | 0.00044 |
| | (0.00034) | (0.00036) | (0.00033) | (0.00033) |
| Big | 0.00282*** | 0.00285*** | 0.00208*** | 0.00211*** |
| | (0.00034) | (0.00034) | (0.00034) | (0.00034) |
| Mega | -0.00015 | -0.00012 | -0.00136*** | -0.00132*** |
| | (0.00037) | (0.00038) | (0.00037) | (0.00037) |

Table 21 (Continued): Robustness Checks, Marginal Deposit Return Rate $r^0_{jm}$

Logit Demand Model (County Population > 200,000)

A fringe bank is a bank with its FDIC market share below 2% and its total deposits in a county less than US$1B.

| | Logit | | Income Statement | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| Explanatory Variable | (i) | (ii) | (iii) | (iv) |
| *MARKET CHARACTERISTICS* | | | | |
| ln(population) | 0.0052*** | 0.0064*** | 0.0054*** | 0.0066*** |
| | (0.0013) | (0.0017) | (0.0013) | (0.0016) |
| ln(personal income) (income in $1000) | 0.0051*** | 0.0051*** | 0.0052*** | 0.0051*** |
| | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| ln(savings rate) | 0.0013** | 0.0015** | 0.0017** | 0.0019*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| $R^2$ | 0.5563 | 0.5561 | 0.3800 | 0.3796 |
| First-stage $R^2$ | - | 0.9271 | - | 0.9271 |
| Markets | 293 | 293 | 293 | 293 |
| Years | 12 | 12 | 12 | 12 |
| Observations | 32100 | 32100 | 32100 | 32100 |

Notes: County and year effects are included.

Standard errors are in parentheses.

***significant at 1%; **significant at 5%; *significant at 10%

Appendix A: Description of Variables

| Variable | Description |
|---|---|
| Market share | Deposits of a commercial bank in a county / Total Deposits of all FDIC-insured depository institutions and credit unions in a county |
| FDIC market share | Deposits of a commercial bank in a county / Total Deposits of all FDIC-insured depository institutions |
| Deposit interest rate | Interest expense on domestic deposits / Domestic deposits |
| Service fees | Service charge on deposit accounts / Deposits |
| Loan interest rate | Interest income on loans / Loans |
| Branch density | Number of branches in a county / Land area of a county in square miles |
| Number of states | Number of states that a bank has a presence |
| Headquarters in the county (1=yes) | Whether a bank's Headquarters is in the county |
| Headquarters in the state (1=yes) | Whether a bank's Headquarters is in the same state as the local county |
| International (1=yes) | Whether a bank has an international banking facility (IBF) |
| A former savings association (1=yes) | Whether a bank was a former savings association that has converted to a bank charter and is still a SAIF insured institution |
| Bank holding company (1=yes) | Whether an institution is a member of a bank holding company |
| Fringe (1=yes) | Whether a bank's market share within all FDIC-insured depository institutions is less than 1% and its total deposits in a county are less than US$1B |
| Dominant (1=yes) | Whether a bank's market share within all FDIC-insured depository institutions is above 15% |
| Medium (1=yes) | Bank with assets of US$100M to 300M |
| Big (1=yes) | Bank with assets of US$300M-3B |
| Mega (1=yes) | Bank with assets over US$3B |

Appendix B: Description of Demand Instruments

| Instruments | Description |
|---|---|
| Labor costs | Salaries and Employee Benefits / Number of employees |
| Employees per branch | Number of bank employees / Number of branches |
| Expenses of premises and fixed assets / Assets | Premises and fixed assets including capitalized lease / Total assets. (Expenses including: utilities, repairs, taxes, insurance, equipment, etc.) |
| Other non-interest expenses / Total assets | Other expenses including: legal fees, amortization, advertising, etc. |
| Credit risk / Assets | Provision for loan and lease losses / Total assets |
| Loan charge-offs / Assets | Total loan charge-offs / Total assets |
| Loans to small business indicator | Whether all or substantially all of the dollar volume of loans secured by nonfarm nonresidential properties and commercial and industrial loans have amounts of US$100,00 or less |
| Agriculture loans to small farms indicator | Whether all or substantially all of the bank's "loans secured by farmland and "loans to finance agricultural production and other loans to farmers have original amounts of $100, 000 or less. |
| Cash / Assets | |
| Federal funds + securities / Assets | |
| Real estate loans / Assets | |
| Loans to individuals / Assets | |

Appendix C: Weights for Fringe Banks in a local market

| Variable |
|---|
| Weights: Deposits of a fringe bank / Total deposits of all fringe banks |
| Deposit interest rate |
| Service fees |
| |
| Weights: Number of branches of a fringe bank / Total number of branches of all fringe banks |
| $\ln$(number of states) |
| Headquarters in the county |
| Headquarters in the state |
| International |
| A former savings association |
| Bank holding company |
| Medium |
| Big |
| Mega |