Bank Merger Incentives and Market Competition: A Two-sided Matching Model with Externalities

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Abstract

The Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 enabled banks to expand their geographic markets across states in United States. The nationwide branching from deregulation and the resulting bank consolidation have brought a more competitive market environment. In particular, branch networks play an important role in bank merger analysis. Using commercial banks' branch-level location data in Texas from 1994 to 2005, I estimate a two-sided matching model of merging and target banks with transferable utility. This paper analyzes the incentives to decide mergers and the effects of market competition. To study post-match values, I apply the maximum score estimator developed by Fox (2010). In my model, observable bank-specific and match-specific attributes determine match value. I find the positive assortative matching of bank sizes and quality-related cost measures. Moreover, banks prefer to match with target banks that have geographically overlapped markets and this is a key factor for match values. I extend a standard matching model to incorporate externalities of market competition and merger activities of rivals. Competitive rivals lessen the effects of mergers but mergers that increase market power have positive externalities on unmatched banks.

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1 Introduction

Throughout the past decade, the banking industry has undergone several changes in both its structure and regulations. US banking regulation constrained bank growth through restrictions on bank expansions both within states (intrastate banking and branching) and between states (interstate banking and branching). One important change is the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 (IBBEA), which permits nationwide branching as of June 1997. This federal law allows banks to expand branch networks through merger and acquisition or de-novo branching, but some states did not permit interstate banking through de-novo branching[1]. It means that a bank must acquire another bank and merge the two structures in order to operate branches across state lines. After these regulations lifted, there has been a considerable consolidation of the banking industry. The total number of banking institutions declined in half from 10453 in 1994 to 5876 as of June 30, 2013 in U.S. In contrast, the number of branches are growing steadily.

Although the Rielge-Neal act enables interstate and intrastate de-novo branching, most of entries are made by mergers and most exits are absorbed by existing banks through M&As. This massive consolidation has raised concerns over possible anti-competitive effects of mergers. Given the importance of bank mergers in the economy, it is crucial for researchers to understand the impacts of mergers.

On the basis of a sample for the period between 1994 and 2005, this paper examines the effects of bank mergers. I focus on two issues. What are the consequences of mergers on aspects of prices and banking markets. And second, I analyzes the incentives of bank mergers and the competitiveness of local banking markets.

To investigate the behaviors of banks, I consider a two-sided matching model with transferable utility and endogenous transfers (Roth and Sotomayor, 1990). Banks are partitioned into two sides, potential merging banks and target banks. In a merger, a bank pays the transfer price in the exchange of obtaining new branches and assets. A target bank is paid the transfer price and exits the market. A bank faces a trade-off between the match synergy value and the transfer. Banks on both sides care about whether they

[1]While twenty-five states adopt interstate branching by merger and acquisition as of 1997, only thirteen states allowed interstate de-novo branching. By the end of 2005, twenty two states plus the District of Columbia permitted de-novo branching

match with the right partners in a matching model. Specifically, an one-to-one matching model is considered for the analysis. For an extension to enhance the explanation of a matching model, potential merging banks can choose whether to match with target banks or stay unmatched. Two-sided matching models are pervasive in empirical analyses, for example, the marriage market (Becker, 1973), the venture capital market (Sorensen, 2007), loan market between bank and firm (Chen and Song, 2013), and mutual funds (Park, 2012) and bank mergers (Akkus *et al.*, 2013).

Manski (1975) introduces a semi-parametric maximum score estimation for discrete choice models. The estimator of Manski (1975) is consistent when choice probabilities are rank ordered by choice payoffs but suffers from a dimensionality problem. Fox (2010b) introduces the maximum score estimator to estimate a matching model and provides solutions for the dimensionality problem. Fox's (2010b) maximum score estimators use pairwise stable inequalities regarding the match values implied by matching equilibrium. The equilibrium is a consequence of single-agent best responses. The match values in matching equilibrium are greater than any other values from switching partners. The post-merger value functions from a match transform observable bank-specific attributes and match-specific covariates into outputs.

The main contributions of this paper are two-fold. First, I analyze the critical incentives to determine the match value by using branch-level data of commercial banks in Texas from 1994 to 2005. In a sense, the most relevant paper is Akkus *et al.* (2013), which use revealed preferences of buyer and target banks in a two-sided matching market with incorporating transfer data and indicates that mergers have greater match value if markets overlap more. Without transfer data, the value of the score is invariant to scaling of the parameters. Parameters show the relative importance of each attribute that contributes for match synergy values. My paper finds the evidence that bank size and operating cost measures have positive assortative matching. This finding suggests that large banks tend to match with larger target banks and small banks tend to match with small banks. Also, banks with high operating cost efficiency prefer to merge with target banks with better cost efficiency. And banks merging with target banks that have geographically overlapped markets, have higher match values.

Second, I incorporate market competition as externalities. It is because externalities rely on the entire assignment of all firms and all matches. Since deregulation lifted entry barriers, banks can expand geographical markets into new counties, new MSA, new states, which encourages the level of competition in banking industry. Even though banks can diversify branch networks and risks across many geographical markets, banks are relatively more exposed to competitive rivals. The existence of competing rivals influences behaviors of other banks. Standard matching models focus only on merger-target match values and do not fully take into account the rivalry nature of competitive banks. With only pre-merger characteristics, I can obtain the restrictive results. Banks care not only about whether they can merge or not, but also whether other rival banks merge. To allow for externalities, the match product function is a function of the characteristics of banks in a match and entire assignment. There have been challenges to apply externalities on matching models. Baccara *et al.*(2012) study matching faculty members to offices in a new building with network externalities. Uetake and Watanabe (2012) incorporate post-merger negative competition externalities on profit.

My paper considers rivals' merger activities as well as market competition into the matching model. From the previous literature (Kim and Singal, 1993; Hannan and Praeger, 1998; Sapienza, 2002), non-merging banks change the price according to merger activities of rivals sharing same markets. Prior literature shows that unmatched rival banks follow the strategy of merging banks. My paper finds the evidence that competitive rivals lessen the post-merge values. Also, merger activities of rivals have different impacts on merging banks and unmatched banks. Active merger activities in the same market weaken the merger effects of the merging bank. But merger activities that increase market power in local markets have positive externalities on unmatched banks.

The structure of this paper is as follows. In section 2, I explain the banking industry in brief. In section 3, the description for the data are provided and bank specific measures are introduced. In section 4, structural matching model and maximum score estimator are presented. In section 5, several hypotheses are tested prior to estimating the matching model. Section 6 presents the estimation results. Section 7 provides brief concluding remarks.

1.1 Related Literature

My paper adds to several strands of literature. The first strand of the related literature is the literature on bank mergers in terms of price change. Most papers focus on the ex-post price and performance change of the consolidated banks and rivals. Focarelli and Panetta (2003) investigate the pricing effects of M&As in Italian banks and find that short-run effects generate negative price changes to consumers but efficiency gains through mergers lead to favorable price change in the long run. Sapienza (2002) and Erel (2011) analyze the effects of mergers on loan spread, but reach different results. Sapienza (2002) finds that horizontal mergers with small targets resulted in lower loan rate in Italy. Banks, however, reduce lending to small borrowers after mergers. On the other hand, Erel (2011) notes that the reduction in loan spreads is significant only for small loans, and finds that larger acquirer does not drop small business lending of smaller targets. In addition, he points out that in-market and out-of-market mergers have different effects on market structure and efficiency.

Another strand of the literature about merger is about analyzing the welfare effects. Traditional economic theory compares in-market mergers with market expansion mergers (out-of-market merger). The prior literature has identified ex-ante characteristics that affect the magnitude of the two off-setting effects, market power and cost efficiency. Williamson (1968) points that geographical overlap is a key component to determine which effect dominates. Hannan and Prager (1998) find the evidence that bank mergers can lead to an increase in market power and a reduction in deposit interest rates which would counterbalance this effect.

Also, there is literature to investigate rivals' reactions following mergers. Kim and Singal (1993), Hannan and Praeger (1998) show that merging banks do not pass efficiency gain to customers so merging banks lower deposit interest rate after merger. And non-merging banks sharing same overlapping markets lower deposit rates. Kahn *et al.* (2002) examine systematic tendency between acquirors, targets and un-exposed (unmatched) banks. Also, the literature considering the extent of competition between banks includes Cohen and Mazzeo (2007b). They endogenize the operating decisions of three types of depository institutions and analyzed how the competitive effect influences market structure across the bank types in the rural areas.

There are several papers estimating two-sided matching models. Most papers estimate matching models with transferable utility. Becker (1973) studies the one-to-one marriage markets between men and women. Sorensen (2007) investigates the matching between venture capitalists and entrepreneurs and Park (2012) analyzes mutual fund merger markets. Chen and Song (2013) find positive assortative matching of firm sizes and geographical proximity and banks prefer firms that had the prior loan relationship. Sasaki and Toda (1996), and Hafalir (2008) are the only papers that investigates a two-sided matching model with externalities. Both papers propose an "estimation function" to model how neighboring players (rivals) react to a player's deviation. Uetake and Watanabe

(2012) consider banking matching models between incumbents and potential entrants (merger by entry) in rural banking markets with non-transferability and incorporate post-merger negative competition externalities. Akkus *et al.* (2013) are close to mine in that they study bank mergers with transfer data. My paper adds to these papers by incorporating externalities considering the incentives of bank mergers.

2 Industry Background

The banking Industry has experienced a regulatory and structural change after the Riegle-Neal act in 1994. The RN Act include both interstate and intrastate de-regulations. Before 1990s, the banking industry in the U.S. were highly fragmented. Most of banks tend to concentrate their banking activities in specific geographic areas. After the passage of the Riegle-Neal Act enabled nationwide branching as of June 1997, there has been significant consolidation in the U.S. banking industry.

2.1 Massive consolidation Trends

One clear trend of the commercial banking industry after the 1990s is the continuous drop in the number of banking institutions. At the same time, the size of existing banks has been increased steadily. This decline in the number of banks is evidenced by the exit and entry rate. Figure 1 shows that after 1980s, the number of total banking institutions has continued declining in Texas and all around the U.S. But the number of branches has grown. Specifically, the number of branches in Texas has been increased tremendously after the late 1980s. The average number of branches in Texas has grown from 3.63 in 1995 to 7.86 in 2005. Figure 1 presents the time series of entry and exit rate in U.S and Texas. The exit and entry rate is calculated as a fraction of the banking population in the previous year.[2]. Dunne *et al.* (1989) report that the average entry rate is $14-19$ % annually and the exit rate is lower on average than entry rates in most industries. However, I find that the exit rate is much higher than the entry rate in banking industry. Figure 3 (a) shows that most of the bank exits have taken place through mergers and presents that the number of banks mergers is peaked around 1997 at the time that the

[2]The data of issuance of new bank charters, and other charter additions and deletions are came from FDIC Historical Statistics on Banking (www.fdic.gov/hsob)

RN Act became effective and decreases steadily since 1999. Figure 3 (b) shows that the percentage of within-state merger among total mergers in T.X stayed at 100 % but dropped 80−90 % after interstate branching was allowed in 1998. In 2011, the fraction of with-in state mergers dropped around 60 %.

2.2 Concentration and Geographical Market Expansion

Figure 4 provides further evidence of market concentration by contrasting the Lorenz curve[3] of deposits in 1995 with that in 2000 and 2005 for Harrison county, which is the one of the biggest counties in Texas, and for the Texas state. In figures, both markets become more concentrated. The portion of fringe banks in the deposit market share decreases steadily and larger dominant banks cover almost 80 % of total market shares by the end of the sample. Table 1 presents the number of commercial banks and market shares by asset size. I find that the number of large banks increases from 5% to almost 20%, but the number of small banks decreased significantly. I can infer that banks that exit tend to be small, and surviving banks tend to be the larger banks that were able to expand into other markets. Table 2 displays the summary statistics of commercial banks in Texas. The number of counties each bank engages has grown from 1.6 in 1995 to 2.6 in 2005.

3 Description of the Data and Variables

I focus on the period of massive consolidation that occurred following the Riegle-Neal Act of 1994. The dataset used is a panel of banking institutions between 1994 and 2005.

3.1 Data

The data cover commercial banks and their mergers in Texas state, U.S. from 1994 to 2005 and compiled from three different sources. First, information on bank ownership and deposits can be obtained from Summary of Deposits (SOD) as of June 30th of each year at Federal Deposit Insurance Cooperation (FDIC). This provides deposits by

[3]The closer the curves to the y-axis, the more asymmetric ,ant therefore the more concentrated, the market becomes

branch and the addresses of the branches for each bank and thrift. Also the location of headquarters, whether a bank belongs to a bank holding company, and whether a bank was a former savings associations are obtained. I exclude saving associations [4] and comprise only FDIC insured banks that had at least one branch in my analysis. Since boundaries of counties have been relatively static and the movement of each bank differs between urban and rural counties, I define a county as a geographic unit for my analysis. Texas state has 254 counties. Also, I take account of branches as brick and mortar offices with full service. I exclude branches with limited service such as drive-through facilities, consumer credit offices and branches for home banking.[5].

Data on mergers are obtained from the history of each commercial bank provided by the FDIC. The National Information Center (NIC) and FDIC record the history of all depository institutions that ever existed in the United States. This information includes mergers, acquisitions and bankruptcy, and allows me to identify all the merger cases and to define which banks are active or passive. Table 4 shows an example of bank history. Each bank is given a unique number from FDIC (Certificate #) or FED ID number (RSSD9001). When a merge between banks ocurrs, the certificate number of passive (target) bank disappears and becomes part of an existing (merging) bank.[6] Thus combined balance sheets and unified branch networks are recorded under the certificate number of active bank. Even though the name of the bank can be changed after the merger, the certificate number is consistent. To construct bank mergers, I exclude bank

[4] The strategies and products that saving associations deal with are different from commercial banks.

[5] Each branch in SOD data has unique number and the type of service each office provide is identified. After on-line banking is popular since early 2000s, on-line banking deposits increase significantly. The percentage of brick and mortar offices has decreased to 89 % in 2005 from 97 % in 1994. Offices with deposits above 1 billion dollars are excluded from analysis. Deposits from Internet banking are counted under specific home-banking branches, but these offices never deal with individual customers in local markets. These branches disrupt the analysis of banking markets.

[6] I distinguish between mergers and acquisitions because they have different motivations. Only mergers that involve the full integration of bidder and target banks are counted for this analysis. When previously independent bidder and target banks merge, target banks lose its charter after merger and become part of bidder banks and have the same balance sheet with a unified branch network. Thus, Fox (2010b) and my model assume a full transfer model. Park (2012) uses a fixed shared rule instead of a full transferable utility in mutual fund industry.

failures and mergers with assistance cases[7].

Even if a bank merger is a mutual contract between a merging bank and a target bank, all of the merger applications must be approved by one or more regulatory agencies[8] For example, FDIC[9] has determined that the transaction would not result in a monopoly or further any combination or conspiracy to monopolize or to attempt to monopolize the business of banking in any part of the United States ,and that the transaction would not have the effect in any section of the country to substantially lessen competition or tend to create a monopoly or in any other manner to restrict competition. (Federal Deposit Insurance Corporation Merger Decisions Annual Report To Congress)[10] Table 5 shows the examples of approved merger applications by FDIC.

Finally, I use additional bank-level data regarding balance sheets and income statements from the Report on Condition and Income (known as Call Reports) and Thrift Financial Reports in June from the Federal Reserve Board. Call Reports contain information on assets, interest expenses on deposits, interests income from loans, total employees and non-interest expenses including wages and premises. Some bank performance related indexes are also contained: ROA, net charge-off rates and loan loss provision. All financial data are on an individual bank basis. I estimate the bank-level deposit interest rate as the ratio of interest-expenses to total domestic deposits. Similarly, the interest rate on Loans can be calculated as the ratio of interest-revenue to net loans. Each bank must maintain an allowance (reserve) for loan and lease losses that is adequate to absorb estimated

[7]A failing institution is absorbed into an acquiring institution that receives FDIC assistance. Assisted mergers were the Federal Savings and Loan Insurance Corporation's preferred resolution method. Therefore, the acquiring institution is not responsible for unpaid assessments of the failed institution.

[8]Agarwal *et al* (2012) find that inconsistent regulators hamper the effectiveness of regulations. The fact that banks with national charters are subject to different regulatory procedures than banks with state charters increase the cost of mergers between banks of different charter types.

[9]When the result of a merger will be a national bank, the Comptroller of the Currency (OCC) must approve the merger. When the result will be a state chartered, Federal Reserve member bank, the Fed must approve the merger. And when the result will be a state, non member bank, the FDIC and state authorities must both approve the merger. The Federal Reserve must approve all bank holding company acquisitions.

[10]Additional report can be downloaded from the FDIC's Public Information Center's website at www.fdic.gov/news/publications/public/index

credit losses associated with its loan and lease portfolio. Thus, net loans are defined as total loans minus unearned income and loan loss allowances (provisions). Service fees are calculated as the ratio of service charges on deposit accounts to total deposits. The interest rates and service fees are all calculated as one year rates. I also use the bank's total number of branches and employees to calculate the number of employees per branch.

Demographic data at the county level are taken from US Census 2000 and Bureau of Economics Analysis. This provides median household income and total population for each county in Texas.

3.1.1 Sample Selection

The unit of observation for this analysis is the match between a merging bank and a target bank. To make the geographic analysis more tractable, I restrict the sample to the state of Texas. This enables econometricians to look closely on tracking the movement of rival banks after mergers. Texas is one of the largest state, consisting of 254 counties. Even if Texas passed the deregulation law of 1994 on Aug, 28, 1995 for intrastate branching, the Riegle-Neal Act allowed states to "opt-out" of interstate branching by passing a law to prohibit it before June 1, 1997. A state that "opted-out" of interstate branching prevented both state and national banks from branching into or out of its borders. Texas and Montana were the only states to "opt-out" of interstate branching. But they subsequently adopted inter-state branching in 1998 and 2002. Figure 3 (b) shows the evidence that % of within-state mergers dropped first from 100% in 1998.

I drop observations for U.S branches of foreign institutions, branches which have zero deposits or zero premises expenses. Also, I drop the very few branches for which the Summary of Deposits data does not match with Call Report data. My sample consists of 8598 banks from 1994 to 2005 in Texas. This process yields a total of 288 bank merger matches in Texas. To test the impact of merger activities on rival banks, I include unmatched banks in sample. In estimation of the matching model, the maximum score estimator maximizes the number of inequalities comparing observed sum of match values with counter-factual sum of match values. Thus, sample selection requires to check whether a merger meets the criteria. I exclude possible matches of bank mergers that involve market concentration severe enough to violate U.S Antitrust Guidelines

(HHI>1800 and ΔHHI>200) under counter-factual assignment[11]. The MSA-level deposit HHI (Herfindahl Hirschman Index) is the standard tool used in antitrust analysis.

I classify banks into merging banks, unmatched banks and target banks. Merging and target banks are observed in the data. Unmatched banks in sample are among potential merging banks that have operated in same and contiguous markets where target banks engaged before merger. I construct selected sample which consists of 937 unmatched cases and 1225 banks in total for matching models. Table 6 displays the summary statistics of 3 classified group of banks.

3.2 The Characteristics of Bank and Market Structure

It is believed that bank performance and risk measures are closely related with geographic networks. Before investigating the incentives of bank mergers, I describe some measures of the bank characteristics and market structure.

3.2.1 Cost Efficiency and Risk

Cost efficiency can be measured by non-interest expenses over assets. Non-interest expenses include salaries to their employees, expenses on premises and fixed assets and other non-interest expenses including advertising expenditures [12]. Premises and equipment expenses include expenses on utilities, janitorial services, repairs, furniture and maintenance. Other expenses include legal fees, postage, deposit insurance assessments and directors' fees. Although on-line banking has increased tremendously after late 1990s and ATM networks take the place of many roles of offices,branching is the most effective tool to collect deposits. Ho and Ishii (2011) estimate a spatial model of consumer demand for retail bank deposits that accounts for consumer's dis-utility from distance traveled. These operating costs stem from geographical networks of branches. Also, Dick (2006) finds that the number of employees per branch and a bank's geographic diversification affect significantly the consumer's utility. Average number of employees per branch or

[11] Akkus *et al*(2013) include $HHIviolate$, which equals the fraction of target MSAs for which a merger with a merging bank would lead to Antitrust scrutiny, as a covariate term

[12] Only banks with advertising expenditure-to operating income over 1% are required to report their advertising expenditures to the supervisory authorities.

wages are indicators for bank quality. Wages are calculated based on the bank's labor expenses and the number of employees.

$\ddot{O}rs$(2003) argues that advertising increases bank profitability, and emphasizes that non-price competition through advertisement plays an important role in the banking industry. According to surveys by the American Bankers Association, roughly 1% of bank operating costs, on average, was devoted to advertising in 1996, while total bank marketing expenditures were close to $4 billion in 2001. (Dick, 2007) Thus, the high ratio of non-interest expenses over asset indicates that the bank provides better service for consumers.

Another measure of bank performance is credit risk from loan portfolios. This is measured by loan loss provisions or charged-off losses over loans. Loan charge-offs are bad debts and negatively affect earnings. Also, a non-performing loan ratio measured by the sum of loans over ninety days late and loans not accruing over total loans can be used. Aguirregabiria *et al.* point out that diversification of geographic risks is another motivation for banks to determine branch networks. They introduce a new measure of risk to identify bank preferences towards geographic deposit risk separately from the costs of geographical expansion of branch networks.

3.2.2 Market Competition

When analyzing the impact of mergers among incumbent banks, it is crucial to incorporate market competition and market structure simultaneously into a model. How do I measure the degree of market competition and what is the relation with concentration? A standard measure of market concentration is the Herfindahl-Hirschman Index (HHI, herein)[13]. HHI index gives more weight to changes in market shares of the largest banks since large banks have greater shares. When taking account of market structure, it is traditionally believed that the relation between competition and concentration is inversely related. But, the impact of mergers cannot be fully captured by measuring the change in concentration only. Even though the merger causes an obvious increase in concentration in market shares, but pro-competitive mergers occasionally observed.

Banks compete in retail markets by setting interest rates and the number of branches. Then a tough rivalry reduces the interest rates and competition is enhanced. The

[13]HHI is the sum of squared market shares and captures the degree of concentration in branching at the local market level.

traditional entry literature models the profit function as a decreasing function of the number of active operating firms. The number of firms or dominant firms are used to measure market competition. Cohen and Mazzeo (2007a, 2007b) propose a model of monopolistic competition in branching to estimate the competitive response of banks. Dick (2006) points out that the basic market structure hasn't been affected throughout nationwide branching but the growth in the tail of small banks are noticeable. Figure 4 shows the Lorenz curve for deposits. The number of dominant banks is virtually unchanged between year 1995 and year 2000. Cerasi *et al.* (2011) propose a new measure of competition to address the impact of mergers on competition.

3.3 Market Overlap Between Mergers and Competition

Post-merger bank values and consumers' welfare depend on the motives underlying the banks' decision to consolidate. To study the effects of consolidation, it is important to check why banks want to merge. A bank can enter new markets for economies of scale and cost efficiency. The other motive is to acquire market power through obtaining new branches in the same market. The net effects of mergers depend on whether the market power or efficiency effect dominates. One important condition that determines the increase to the acquiring bank's market power is whether it operates in the same markets as the target bank.

3.3.1 In-Market vs Out-Of-Market Mergers

I define in-market merger in which branches of each bank serve in the same markets before merger. When target and merging banks do not have any geographical overlap and consolidated banks penetrate new markets through merger, it is called Out-of-Market Mergers or market-expansion mergers. Two types of mergers are likely to produce different effects on market structure, which in turn affect prices and products of merging banks and rivals. These effects are closely related the post-merger bank's value[14].

[14] Agarwal *et al* (2012) and Akkus *et al* (2013) suggest that inconsistent regulators impose significant implict costs on banks through regulations. To quantify the implicit costs of bank chartering through frictions in the bank merger market, Akkus *et al* (2013) allows the merger value function to depend on whether the acquirer and target have the same type of charter and regulated by the same regulator.

In-market mergers have much more potential than out-of-market mergers for exercising market power and creating efficiency gains. In-market mergers bring the loss of competition that stems from more concentrated markets after mergers ,and consolidated banks obtain market power. Thus price[15] will increase.

On the other hand, in-market mergers offer more opportunities for cost efficiency than out-of market mergers. That is, the least efficient branches can be eliminated through mergers. However, out-of-market mergers have different motives than do in-market mergers. Out-Of-Market mergers happen when banks seek geographic diversification or efficiency gains due to economies of scale.

If the cost efficiency gain dominates, merging banks will lower costs and lead to more favorable price to customers. But if market power effect dominates, adverse price change is observed. Separating in-market merger and out-of-market mergers(i.e. market-expansion) is a relatively tricky task merger after geographical barriers have been lifted. Thus, measuring market-overlap is necessary to capture merger's match value.

$$MktOverlap_{Mer,Tar} = \frac{\sum_h branch_h^{Mer} \times 1[branch_h^{Tar} > 0]}{\sum_h branch_h^{Mer}} \tag{3.1}$$

The market overlap index gives how many branches that the merging bank own in the previous period, overlap with the branches of target banks. This measure of market overlap has a maximum value of 1, when all branches exist in same markets (in-market mergers only) and a minimum value of 0, when the buyer bank enters new markets (out-of-market mergers only). Houston *et al.* (2001) use a similar equation with (3.1). Some papers use deposit shares to calculate market overlap[16]. Definition of market is different across papers[17]. I define markets' geographic size as a county and market overlap is calculated under county-level. Some studies analyze the importance of market overlap

[15] bank j's price in market m is defined as P_{jm}=loan interest rate$_{jm}$ + service fee rate$_{jm}$ - deposit interest rate$_{jm}$

[16] Hannan and Prager (1998) and Erel (2011) use deposit shares in each h markets and following statistic : $MktOverlap = \frac{\sum_h min(Deposit_h^{Mer}, Deposit_h^{Tar})}{\sum_h (Deposit_h^{Mer} + Deposit_h^{Tar})}$

[17] Most banking literature about consumer demand estimation conducts the analysis under MSA level (Dick, 2006; Focarelli and Panetta, 2003; Erel, 2011). Ho and Ishii (2011) define a market to be a MSA, or in rural areas to be a county. Cohen and Mazzeo (2007b) focus on rural markets and define market size as a county.

between the target and acquiror on price. Houston and Ryngaert (2001) find indirect evidence that in-market mergers are more profitable. Stock market returns are positively correlated with the degree of geographical overlap between the target and the acquiror.

3.3.2 The Impact of Merger Effects on Rival Banks

An ownership change can affect rival banks in the same market. Previous research suggests that rivals' reaction differs according to dominating effects of mergers. In general when market power effect prevails, the rivals adopt a "follower" strategy, changing prices unfavorably for customers. However if cost efficiency effects dominates, then rival banks might be able to reduce prices to maintain their market share. When in-market mergers happen, then merging banks can consolidate less efficient branches. Consumers move to the better managed banks. Thus unmatched rival banks also have an opportunity to remove less competitive branches and consolidate branches to provide better service to compete with consolidated banks. The effect of out-of-market mergers on rival banks is weaker than in-market mergers.

$$Rival^k_{Mer} = \frac{\sum_h 1[min(branch_{hk}, branch_h^{Tar}) > 0] \times 1[Rival^{in}_{hk} > 0]}{\sum_h 1[min(branch_{hk}, branch_h^{Tar}) > 0]} \tag{3.2}$$

Thus, merger activity index of rivals measures how many markets that each bank engages in, are expected to be exposed to in-market merger activities after merger. $Rival^{in}_{hk}$ is a dummy variable if the bank k's rival banks merge with target banks as in-market mergers in market h, and otherwise is zero.

4 Model

4.1 Two-sided, One-to-One Matching Model

I model bank mergers as one-to-one, two-sided matching with transferable utility. The two-sided matching model exclusively partitions banks into two groups such as merging firms (active) and target firms (passive). Firms on the one side of the group can match only with the firms from the other group. The definition of transferable utility is that payoffs to an opposite agent making a match are additively separable(quasi-linear) in the transfer paid to that agent by its partner.

For a number of M markets, I denote a two-sided merger market using two finite disjointed sets of firms : Merging(buying) group by $\mathcal{A}$=$\{a_1$,...,$a_m\}$ and target(merged) group by $\mathcal{T}$=$\{t_1$,...,$t_m\}$[18]. Both types of banks simultaneously maximize their expected post-match values by making their matching decisions. Each merging bank matches with a target bank.

In a two-sided matching game with an assignment E (can be called *observed*), consider two merging banks a_i, $a_j \in \mathcal{A}$, two target banks t_i ,$t_j \in \mathcal{T}$, and the match reference function is $\mu_m(a_i) = t_i$ and $\mu_m(a_j) = t_j$, all in a matching market m . The match reference function $\mu_m : \mathcal{A} \to \mathcal{T}$, an observed bijection assigning each merging bank to a particular target partner in a market m. An assignment E is a physically possible set of matches. Further, let $\tilde{E}$ (can be called $counterfactual$) be the assignment E except that $\{a_i, \mu_m(a_j)\}$ and $\{a_j, \mu_m(a_i)\}$ match and $\{a_i, \mu_m(a_i)\}$ and $\{a_j, \mu_m(a_j)\}$ do not match .

Let $f_m\Big(a_i, \mu_m(a_i)\Big)$ denotes the post-match production function which transforms the merging bank a_i's endowment captured by firm attributes and the target bank t_i's characteristics into some joint-output values shared between a_i and t_i. To allow externalities, I write that firm a_i's post-match product function depends on the assignment E when firm a_i matches with downstream firm t_i in an assignment E, and can be written as $f_m\Big(a_i, \mu_m(a_i)|E\Big)$.

When a match(or merger) occurs, the merging bank a_i earns match-product value $f_m\Big(a_i, t_i|E\Big)$ even if it pays match price p_{a_i,t_i} to the target firm t_i. And match price is transferred to the target bank and t_i exits the market. I assume that once target banks leave the market, it is not allowed to enter banking markets again. Thus if a_i and t_i agreed to match, the total match-value function (i.e. post-merger value) is the summation of the merging bank's payoff $v^u(a_i, t_i|E)$ and the target's payoff $v^d(a_i, t_i|E)$ after merger . Most of prior empirical assignment models assume that a fixed sharing rule predetermines how the match synergy is split between the matched pair. The setting in this paper allows values to be transferable so that the division of match-output is

[18]Since I assume an one-to-one matching model between merging and target banks, dim($\mathcal{A}$)=dim($\mathcal{T}$)

determined endogenously at the time the match occurs and is different across matches.

$$f_m\Big(a_i, t_i|E\Big) \equiv \upsilon^u(a_t, t_i|E) + \upsilon^d(a_i, t_i|E) \tag{4.1}$$

$$\upsilon^u(a_i, t_i|E) = f_m\Big(a_i, t_i|E)\Big) - p_{a_i,t_i} \tag{4.2}$$

$$\upsilon^d(a_i, t_i|E) = p_{a_i,t_i} \tag{4.3}$$

An assignment E is a $m \times m$ matrix with elements $e_{m,m} \in \{0,1\}$, defined for all possible pairs $\{a_i, t_j\} \in \mathcal{A} \times \mathcal{T}$, where $e_{i,i}$ =1 if a_i and t_i are matched and $e_{i,j}$ =0 if a_i and t_j are unmatched for $i, j = 1, ..., m$. In my model setting, an assignment E is a diagonal matrix so off-diagonal elements are all zero.

Definition 4.1. *(Pairwise Stability) : An match μ is pairwise stable if it is individually rational and is not blocked by any matching pair, i.e. for every pair (a_i, t_i), $t_i \in \mu_m(a_i)$*

$$f_m\Big(a_i, \mu_m(a_i)|E\Big) - p_{a_i,t_i} \geq f_m\Big(a_i, \mu_m(a_j)|\tilde{E}\Big) - p_{a_i,t_j}$$

for all $j \neq i$ and $t_j \in \mu_m(a_j)$

The intuition for this condition is that an assignment is stable if no pair of counter-factual bank can break off the current matching and be both strictly better off under a new assignment when they (counter-factual) are matched.

Since every firm is assumed to behave rationally, merging firm a_i's best response is that matching with t_i (which is, observed) have a higher value than any other matches (which is, counter-factual). And an assignment is stable. For target bank t_j to match with a_j , the match price $p(a_j, t_j)$ must be strictly greater than any other offer from a_i.When bank a_i merges with t_i, the transfer price p_{a_i,t_i} must be weakly greater than any other offers from a competing bank, i.e. p_{a_j,t_i}. Also, the merging bank a_i doesn't have to pay strictly more than the transfer p_{a_j,t_i} to the target bank t_i because higher transfer reduces the bank a_i's payoff. Thus $p_{a_j,t_i} = \upsilon^d(a_j, t_i|\tilde{E}) = \upsilon^d(a_i, t_i|E) = p_{a_i,t_i}$.

This revealed preference matching equilibrium gives the inequalities like

$$\upsilon^u(a_i, \mu_m(a_i)|E) \geq \upsilon^u(a_i, \mu_m(a_j)|\tilde{E}), \tag{4.4}$$

that is,

$$\upsilon^u(a_i, \mu_m(a_i)|E) - p_{a_i,t_i} \geq \upsilon^u(a_i, \mu_m(a_j)|\tilde{E}) - \{\upsilon^d(a_i, \mu_m(a_i)|E) + p_{a_i,t_i} - \upsilon^d(a_j, \mu_m(a_i)|\tilde{E})\}.$$

For a merging bank a_j, I use the same logic to obtain a similar inequality

$$\upsilon^u(a_j, \mu_m(a_j)|E) \geq \upsilon^u(a_j, \mu_m(a_i)|\tilde{E}),$$

that is,

$$\upsilon^u(a_j, \mu_m(a_j)|E) - p_{a_j,t_j} \geq \upsilon^u(a_j, \mu_m(a_i)|\tilde{E}) - \{\upsilon^d(a_j, \mu_m(a_j)|E) + p_{a_j,t_j} - \upsilon^d(a_i, \mu_m(a_j)|\tilde{E})\},$$

where I use $\upsilon^d(a_i, t_j|\tilde{E}) = \upsilon^d(a_j, t_j|E) = p_{a_j,t_j}$. Adding two inequalities (1.6) and (1.7) leaves, as the transfers p_{a_j,t_j} and p_{a_i,t_i} cancel out,

$$\begin{aligned}
\upsilon^u(a_i, \mu_m(a_i)|E) + \upsilon^u(a_j, \mu_m(a_j)|E) \geq\ & \upsilon^u(a_i, \mu_m(a_j)|\tilde{E} + \upsilon^u(a_j, \mu_m(a_i)|\tilde{E}) \\
& - \{\upsilon^d(a_i, \mu_m(a_i)|E) + \upsilon^d(a_j, \mu_m(a_j)|E)\} \\
& + \{\upsilon^d(a_j, \mu_m(a_i)|\tilde{E}) + \upsilon^d(a_i, \mu_m(a_j)|\tilde{E})\}
\end{aligned}$$

Rearranging two of the υ's and substituting in the Definition 1.4.1 and equation (1.3), $f_m\Big(a_i, \mu_m(a_i)|E\Big) \equiv \upsilon^u\Big(a_i, \mu_m(a_i)|E\Big) + \upsilon^d\Big(a_i, \mu_m(a_i)|E\Big)$, leaves

Definition 4.2. *The matches (a_i, t_i) and (a_j, t_j) satisfy local production maximization, that is,*

$$f_m\Big(a_i, \mu_m(a_i)|E\Big) + f_m\Big(a_j, \mu_m(a_j)|E\Big) \geq f_m\Big(a_i, \mu_m(a_j)|\tilde{E}\Big) + f_m\Big(a_j, \mu_m(a_i)|\tilde{E}\Big). \quad (4.5)$$

This Definition (1.9) says that if I take any two pairs that are matched in a pairwise stable outcome and switch the partners, the observed sum of match values is greater than or equal to the counter-factual sum of match values after the swap. This condition illustrates the fact that in a matching market, the decision of two firms to team up depends on their effective choice sets, which are constrained by the decisions of other firms in the market. This equilibrium is called local production maximization not derived from a complete equilibrium concept, but from single agent best responses and transferable utility. This characterization of the equilibrium matching is the basis for the estimation method described in the next section.

4.2 Objective Function for the Match Value Function

In order to form the empirical analog of definition (1.9), I first parameterize the match value function $F(a_i, t_i)$ as equation (1.8) below. In section 4.3, I will introduce the maximum score estimator that maximizes the match product function (objective function) computationally. One of the biggest advantages of the maximum score estimator is that an objective function can be set up easily. An objective function has following forms $F(a_i, t_i) = f_m(a_i, t_i) + \varepsilon_{a_i,t_i}$

$$F(a_i, t_i) = \beta_w W_{a_i} W_{t_i} + \beta_c Covariates(a_i, t_i) + \gamma_1 X_{a_i} + \gamma_2 X_{t_i} + \varepsilon_{a_i,t_i} \tag{4.6}$$

where $W_{a_i} = (W_{a_{1i}}, W_{a_{2i}}, W_{a_{3i}})$ is an attribute vector of the merging bank a_i and $W_{t_i} = (W_{t_{1i}}, W_{t_{2i}}, W_{t_{3i}})$ is the same attribute vector for the target t_i, X_{a_i} and X_{t_i} are buyer-specific and target-specific covariates, $Covariates(a_i, t_i)$ is a vector of match-specific covariates and ε_{at} is an unobserved match-specific error term that is assumed as independent across matches. These match-specific error terms are added to the specification of the match value function in order to allow the empirical model to give full support to the data. Bank fixed effects are observed by the each bank but unknown to the econometricians. These bank-specific fixed effects enter into both sides of inequality and cancel out, so they are unidentified. Theoretically bank fixed effect are valued equally by all potential mergers and differencing them out leaves the matching unaffected.

A match product function F describes how the characteristics of the target firm and endowment of the merging firm can be combined to generate a matching output. To capture the operating aspects of the size measure, I use the value of assets as the major measure for bank size. Asset size of banks and the number of branches are included in bank-specific attributes. Also, several bank performance measures : loan loss provision (risk) and cost efficiency are applicable to interaction terms W_{a_i}, W_{t_i}. I consider a market overlap measure between merging and target banks for match-specific covariates $Covariates(a_i, t_i)$.

However, for a pairwise maximization matching without transfer data, non-interaction terms such as γ_1 and γ_2 are unidentified. A matching between buyer and target firms exchange money transfers instead of acquiring target's branches , but it is common not to open transfer data to the public. It can be another advantage that maximum score estimator explains the match value function well without transfer data. This paper estimates the matching model without transfer data[19]

[19]The maximum score estimator proposed by Fox (2010a, 2010b) does not use transfer data. But, Akkus *et al.* (2013) demonstrate that estimator with transfer gives more precise results and can identify parameters that cannot be identified without transfer data.

The interaction terms and match-specific covariates capture the match-specificity for post-merger value studied in this paper. These can be identified by comparisons between observed and counter-factual matches in maximum score estimation.

The cross-partial derivatives on the interaction terms reflect the observed matching pattern on the target bank. One of the primitives that govern a two-sided matching game is the concept of complementarity vs substitution. Complementarity implies that the cross-derivatives are positive.

$$\frac{\partial^2 F(a_i, t_i)}{\partial W_{a_i n} \partial W_{t_i n}} = \beta_{w,n} > 0 \quad , (n = 1, 2, 3, 4) \tag{4.7}$$

Substitution, on the other hand, implies negative cross-partial derivatives and anti-assortative matching.

If I allow for externalities and use no transfer data, an objective function can be extended as

$$\begin{aligned} F(a_i, t_i|E) &= \beta_w W_{a_i} W_{t_i} + \beta_c Covariates(a_i, t_i) \\ &\quad + \omega_1 Mkt_{competition}(a_i, t_i|E) + \omega_2 Rival(a_i, t_i|E) + \varepsilon_{a_i, t_i} \end{aligned} \tag{4.8}$$

For unmatched case, I can input W_0=1 for W_{t_i} ,then

$$F(a_i, 0|E) = \beta W_{a_i} + \omega_1 Mkt_{competition}(a_i, 0|E) + \omega_2 Rival(a_i, 0|E) + \varepsilon_{a_i, 0}$$

4.3 Estimation of Matching Model

To estimate F, I apply a semi-parametric approach, i.e the maximum score estimation developed by Fox (2010b). When I deal with N upstream firms and N downstream firms in a matching market, then N^2 matches and N! assignments should be considered. For example, in one-to-one matching involving 100 firms on each side, then there are 100!=9.33$\times$ 10^{157} possible assignments. Computational issues in matching games restricts the use of matching methods, but computationally simple, maximum score estimator was investigated by Fox (2010a, 2010b). This pairwise maximum score objective function produces the same objective function value which compares pairs of two choice scores and generates $\frac{(N-1)\times N}{2}$ necessary inequalities. Estimation uses the empirical analog of the sum of match product inequalities definition (1.4.2). Specifically the maximum score estimator $\hat{\beta}$ maximizes the following maximum score objective function.

$$Q(\beta) = \sum_{m=1}^{M} \sum_{a_i=1}^{a_m-1} \sum_{a_j=a_i+1}^{a_m} 1[f(a_i, \mu_m(a_i)|E, \beta) + f(a_j, \mu_m(a_j)|E, \beta) \\ \geq f(a_i, \mu_m(a_j)|\tilde{E}, \beta) + f(a_j, \mu_m(a_i)|\tilde{E}, \beta)] \tag{4.9}$$

I first specify the product function up to the parameter vector β. β describes the observed matching pattern in the bank merger markets and thus reveals the relative degrees of complementaries or substitutability between merging and target bank attributes and match-specific covariates. β is structurally identified in the main analysis.

I define the parameter space to be $\Omega = R^{\chi}$, where χ is the number of parameters to be estimated. Thus maximum score estimation searches across Ω to find $\hat{\beta}$ that maximizes the number of pairwise stable inequalities. In other words the estimation algorithm picks $\hat{\beta}$ that makes the observed match best "fit" the equilibrium outcome in terms of the pairwise stable conditions.

The pairwise maximum score estimator $\hat{\beta}$ is a consistent estimator for β^0, the true parameters in the data generating process if the model satisfies Manski's rank order property. Statistical consistency of the maximum score estimators rely on the assumption that the error terms follow the rank-order property. The structure unobservable is not modeled up for matching model.[20] Fox (2010a) provides proofs of set identification and consistency for maximum score estimators in a two-sided matching model.

Since Akkus *et al.*(2013) and Fox (2010b) conduct Monte Carlo experiments for estimators without transfer data as well as with transfer data. And show that multinomial maximum score estimator is a tractable and useful procedure. Without transfer data, the value of the score is invariant to the scaling of the parameters. The scale is never identified and estimation requires a normalization for one of the coefficients that must have a nonzero contribution to preferences.

The objective function is a step function, and I solve the maximization problem using the differential evolution (DE) algorithm performed by NMaximize function in Mathematica. Specifically I modified toolkit developed by Fox and Santiago (2014).

[20]Bajari, Fox and Ryan(2006) show that estimation can allow for agent-specific fixed effects over nests of alternatives.

4.3.1 Subsampling Confidence Intervals

Aside from the original work of Manski (1975), Kim and Pollard (1990) show that the maximum score estimator converges slowly at the rate $n^{1/3}$ and has a very complex limiting distribution from which to draw inference. As Delgado, Rodriguez-Poo and Wolf (2001) show, subsampling method makes consistent inference available on the maximum score estimator. The detailed overview of subsampling is referred to Politis, Romano and Wolf (1999).

I use the subsampling method to construct the confidence intervals for the estimates in the match model. Since the data ranges from 1994 to 2004, 6 years out of those 11 years are chosen as elements in subsamples. The number of subsamples to use in constructing the approximation to the estimator's distribution is set to 200. The matching estimation toolkit of Fox and Santiago (2014) is applied to implementing subsampling inference for the point maximum score estimates. The results are presented in section 5.

4.4 Extensions of Standard Matching Model

4.4.1 Un-matching Outside-Option

In data, I observe which bank merges with which target bank and which bank stays unmatched. To extend the standard merger matching model, I add un-matching outside option for each bank. Each bank chooses the best option out of two options {merge, not merge}. Thus a bank in my sample should be included under either G_m(set of merging firm) or G_{um}(set of unmatched firm) upon its choice and even one firm was included in G_{um} set this period but it never affects next period's choices

Similar to the match-only cases in section 4.1, I denote the potential merging group by $\mathcal{A}$={a_1,...,a_m, a_{m+1}, ..., a_p} and the target (merged) banks by $\mathcal{T}$={t_1,...,t_m}. In this case, dim($\mathcal{A}$)>dim($\mathcal{T}$) since there are m merging firms that match with target banks and $p-m$ unmatched banks in $\mathcal{A}$. In a two sided matching game with assignment E, consider two potential merging banks $a_i \in G_m$ and $a_p \in G_{um}$. Econometricians can observe which banks can be categorized to G_m group and G_{um} group.

The match reference function $\mu_m : \mathcal{A} \to \mathcal{T} \cup \emptyset$, a bijection assigning each potential merging bank to a particular target partner(bank) in market m or empty set (i.e. unmatched). Further, let $\tilde{E}$ (counter-factual) be the assignment E except that $\{a_i, 0\}$

unmatched and $\{a_p, \mu_m(a_i)\}$ match.

For an unmatched firm $a_p \in G_{um}$, a_p's best response indicates that the unmatched value function $f_m\Big(a_p, 0|E\Big)$ gives higher values than matching with targets. So this revealed preference matching equilibrium gives the pairwise stable inequality :

$$f_m\Big(a_p, 0|E\Big) \geq f_m\Big(a_p, \mu_m(a_i)|\tilde{E}\Big) - p_{a_p,t_i} \tag{4.10}$$

For merging bank $a_i \in G_m$, matching with $t_i = \mu_m(a_i)$ has a higher post-match value than any other matches including un-matched. Then pairwise stable inequality gives

$$f_m\Big(a_i, \mu_m(a_i)|E\Big) - p_{a_i,t_i} \geq f_m\Big(a_i, 0|\tilde{E}\Big) \tag{4.11}$$

Arranging above two inequalities (1.12) and (1.13), then I can obtain pairwise stable inequality similar to Definition (1.4.2).

$$f_m\Big(a_i, \mu_m(a_i)|E\Big) + f_m\Big(a_p, 0|E\Big) \geq f_m\Big(a_i, 0|\tilde{E}\Big) + f_m\Big(a_p, \mu_m(a_i)|\tilde{E}\Big) \tag{4.12}$$

For the estimation with un-matched banks, the maximum score objective function can be extended to following forms.

$$\begin{aligned} Q(\beta) = \sum_{m=1}^{M} \sum_{a_i=1}^{a_m-1} \sum_{a_j=a_i+1}^{a_m} & 1[a_j \in G_{um}] \times [f_m\Big(a_i, \mu_m(a_i)|E\Big) + f_m\Big(a_j, 0|E\Big) \\ & \geq f_m\Big(a_i, 0|\tilde{E}\Big) + f_m\Big(a_j, \mu_m(a_i)|\tilde{E}\Big)] \\ & \quad + 1[(a_j \in G_m] \times [f(a_i, \mu_m(a_i)|E, \beta) + f(a_j, \mu_m(a_j)|E, \beta) \\ & \geq f(a_i, \mu_m(a_j)|\tilde{E}, \beta) + f(a_j, \mu_m(a_i)|\tilde{E}, \beta)]. \end{aligned} \tag{4.13}$$

4.4.2 Incorporating Externalities

If firms are under competitive condition, then the decision of other firms to match may raise post-merge utilities of other firms if the merger reduces competition. Or lower the profits of rivals if consolidation produces a lower cost competitor. Banks care not only about whether they can merge, but also about whether rival banks merge or not. The idea of such an effect is that the behavior (or characteristics) of a household/firm is influenced by the behavior of others in the same neighborhood.

Economists have long been concerned with the identification of endogenous social effects. These effects have been called "peer effects", "neighborhood effects" or "externalities" depending on the context. Manski (1993) termed this an "endogenous effect", i.e. that "the propensity of an individual to behave in some way varies with the prevalence of the behavior in the group". He analyzes the problem of identifying endogenous social effects from observations of the distribution of behavior in a population. These neighborhood effects are important with regard to amplify the effects of changes in households' or firm choices. Following Manski (1993), neighborhood effects are known as a "social multiplier".[21]

Because the post-match value of a bank depends on market competition from rival banks as well as firm's matching, I need to incorporate externalities into the matching model. Since competing rivals depend on the entire assignment that include all other firms' matches, market competition and rivals' merger activities are regarded as externalities in matching models.

When externalities are present, a deviating pair needs to consider how other agents will react to the deviation. Before allowing externalities into the matching model, it is necessary to define more assumptions for stable assignments. In order to reduce the computational burden of maximum score estimator, Fox (2010b) assumes that there are no remaining match changes once the assignment are determined. Then this assignment is called *stable* if there is no trade to improve both firms regardless of the transfers, keeping all other matches fixed.

Since externalities depend on assignment E and $\tilde{E}$, I need to assume firm beliefs about counter-factual externalities. One of the significant challenges in considering externalities in the matching models is that underlying effects of externalities are often unobservable or difficult to pin down. Sasaki and Toda (1996), and Hafalir (2008) are the only papers that investigates a two-sided matching model with externalities. Both papers propose an "estimation function" to model how neighboring players (rivals) react to a player's deviation. In the presence of externalities, a deviating player need to consider not only his own matching but also about how other players react to the deviation because they affect the blocking possibility of the match. Thus, a matching is *stable* if there exists no blocking pair in this sense. In Definition (1.4.2.), a merging bank a_i believes that t_i will match with a_j when a_i drops t_i and there is no time for target t_i bank to find any other

[21] Manski (1993) discussed three hypotheses to explain how groups may affect individuals: endogenous, contextual, and correlated effects. Exogenous effects and correlated effects do not generate this "social multiplier".

partner than available a_j bank after a merging bank a_i drops t_i. Thus, t_i must match with a_j.

However, preferences are defined over assignment rather than matching under externalities environment. If a merging bank a_i deviates to form a blocking pair with a target bank t_j, then a merging bank a_i has to consider not only that a target bank t_j has incentive to be matched with a bank a_i, but also what rival banks including t_i would react after the deviation. A merging bank a_i's expectations about the possible entire match changes after the deviation are crucial.

I assumes that players in matching models are myopic and ignore the implications of their choices on their peers' selections. Consistent with Bacarra *et al* (2012), It implies that network effects play no role in choice, but in payoffs.

For a number of M markets, I denote a two-sided merger market with externalities using two finite disjointed sets of firms : Merging group by $\mathcal{A}$=$\{a_1$,...,$a_m\}$ and target group by $\mathcal{T}$=$\{t_1$,...,$t_m\}$. In a two-sided matching game with an assignment E, consider two merging banks a_i, $a_j \in \mathcal{A}$, two target banks t_i, $t_j \in \mathcal{T}$. I denote an observed assignment $\mu_m(\cdot|E) : \mathcal{A} \to \mathcal{T}$, an observed bijection assigning each merging bank to a particular target partner in a market m. The match reference function is $\mu_m(a_i|E) = t_i$ and $\mu_m(a_j|E) = t_j$, all in a matching market m.

For any assignment $\mu(\cdot|E)$, I denote by $\mu_{a_i}^{a_j}(|\tilde{E})$, the counter-factual assignment derived from $\mu(\cdot|E)$ by exchanging the match partner of a_i and a_j.

$$\mu_{a_i}^{a_j}(x|\tilde{E}) := \begin{cases} \mu(a_j|E) & \text{if} \quad x = a_i \\ \mu(a_i|E) & \text{if} \quad x = a_j \\ \mu(x|E) & \text{otherwise.} \end{cases} \tag{4.14}$$

It implies that $\tilde{E}$ be the assignment E except that $\{a_i, \mu_m(a_j)\}$ and $\{a_j, \mu_m(a_i)\}$ match and $\{a_i, \mu_m(a_i)\}$ and $\{a_j, \mu_m(a_j)\}$ do not match .

Definition 4.3. *(Pairwise Stability with Externalities) An assignment μ is pairwise stable if it is individually rational and is not blocked by any matching pair, i.e. for every pair $(a_i, t_i) \in A \times T$, $t_i \in \mu_m(a_i)$. And the matches (a_i, t_i) and (a_j, t_j) satisfy local production maximization, that is,*

$$f_m\Big(a_i, \mu(a_i|E)\Big) + f_m\Big(a_j, \mu_m(a_j|E)\Big) \geq f_m\Big(a_i, \mu_{a_i}^{a_j}(a_i|\tilde{E})\Big) + f_m\Big(a_j, \mu_{a_i}^{a_j}(a_j|\tilde{E})\Big). \tag{4.15}$$

Further, I assume that the post-merger value with externalities take the following form.

$$f_m\Big(a_i, \mu_m(a_i)|E\Big) = P_m\Big(a_i, \mu_m(a_i)\Big) + \zeta R_m\Big(a_i, \mu_m(a_i)|E\Big) \tag{4.16}$$

The first term is a function of match, buyer-target only, in absence of market structure. In my model, buyer-specific ,target-specific attributes and match covariates are included in the first term. The second term accounts for the effects of externalities induced by assignment E. In fact, $R_m\Big(a_i, \mu_m(a_i)|E\Big)$ is an externalities function of effects of market competition and rival banks' merger activities.

Bacarra *et al.* (2012) give proofs that pair-wise stable assignment exists when match value function is such that target-specific attributes are common to all mergers and the effects of externalities are separably additive. Throughout my analysis, I assume that market competition linearly depends on the average number of all commercial banks in which counties that a_i banks engages. Also, rival banks' merger activities rely on matches of other banks in same market. Then, equation (1.18) can be written as following

$$f_m\Big(a_i, \mu_m(a_i)|E\Big) = P(a_i, \mu_m(a_i)) + \sum_{h=1}^{h=H} \zeta_h k_m\Big(a_i, \mu_m(a_i)|E\Big) \tag{4.17}$$

It is general in that externalities are additive separability and the coefficients ζ_h are not restricted in sign so that effects can be either positive or negative. This formulation allows for banks in close proximity to compete with other banks including merging and unmatched, and to influence post-match values of rival banks.

5 Findings

In this section, I test several hypotheses regarding the matching between merging banks and target banks, and discuss the implications of my findings.

5.1 The Determinants of Mergers

I compare the motivations for mergers with ex-ante analysis of the characteristics of the banks. I define a discrete variable(Event) that can take three values: merging banks, un-matched banks and target banks. Following Focarelli *et al.* (2002), I estimate multinomial logit estimation

$$Prob(Event = i, \quad for \quad i = 0, 1, 2) = F(Assets, Branches, Costs, Risk) \qquad (5.1)$$

where the function F is the logistic distribution. The coefficients are to be interpreted as affecting the odds ratio with respect to the baseline case, not the marginal probability. Table 6 reports the summary of merging banks(active), target banks and unmatched banks. As expected, merging banks are big and target banks are small. Target banks have higher risk (net charge-off rate) and low ROA (performance). Table 7 presents the multinomial logit estimation results. Coefficients in column (1) show that the characteristics of merging banks respect to the target banks. The results is consistent with summary statistics that merging banks are larger and have higher quality. The positive and significant coefficients of number of employee per branch, ROA and negative net charge-off rates imply that banks with high profitability want to broaden customer services. Also, column (2) shows that merging banks are more profitable than unmatched banks.

5.2 Empirical Analysis

To check the matching pattern between merging banks (active) and target banks (passive) in the data, Table 8 reports the results of regressing merging bank characteristics on matched target bank characteristics. It presents five specifications using different characteristic measures: log value of assets, number of branches, cost measures, risk measures for loan loss provision and the number of employees per branch.

The coefficients on the five relevant interaction terms are all positive and significant. For example, the asset size of the merging bank is positively and significantly related to the asset size of the target bank. This results indicate that positive assortative matching exists in the bank merger market. Off-diagonal intersection terms, such as between asset and risk measure, turn out to be insignificant.

These results imply that sorting and matching pattern exists but it cannot disentangle whether certain attributes contribute match value and whether target attributes affect characteristics of merging bank after merger.

5.2.1 Profit Estimation

Post-merger value affects merging bank's revenue in following merger period. I run primitive OLS regression of profit after merger on buyer-target attributes. I can compute market level profit of bank j in market m,

$$\pi_{jmt} = M_m s_{jm}(r_j^{loan} - r_j^{dep} + r_j^{ser}) - cost \tag{5.2}$$

where M_m is market-size, total deposits from market m, s_{jm} is the market-share of bank j in market m, r_j^{loan} is the loan-interest rate, r_j^{dep} is the deposit-interest rate and r_j^{ser} is the service-fee rate. Then bank a_i's bank-level profit can be summed up market-level revenue $R_{a_i mt}$. Bank revenue after merger between target bank t_i can be estimated by match-specific attributes.

$$\Pi(a_i, t_i|E) = \alpha_0 + \alpha_1 W_{a_i} + F_m(a_i, t_i) + \xi_{a_i}, \tag{5.3}$$

$$\begin{aligned} F(a_i, t_i|E) = &\ \beta W_{a_i} W_{t_i} + \xi Covariates(a_i, t_i) \\ &+ \omega_1 Mkt_{competition}(a_i, t_i|E) + \omega_2 Rival(a_i, t_i|E) + \varepsilon_{a_i,t_i}. \end{aligned}$$

Table 9 presents the results of regressing bank-level profit on merging bank and target bank' attributes and match specific covariates and market externalities. But, it's hard to extract the match synergy value $F_m(a_i, t_i)$ from bank profit. The coefficient on the interactive assets is positive and significant. And the coefficients of cost and risk interaction terms are negative. I can see the market externalities affected negatively and significantly revenue of merging bank. However, I cannot draw strong inferences from this reduced form analysis. For example, I cannot conclude yet that there's substitutability between cost and risk interaction terms.

To draw match-specific synergy effects, I estimate first difference log revenue estimation. Table 9 reports the estimation results for the following specification.

$$\begin{aligned} \Delta log(R_{a_i,t_i}) = &\ \beta_0 + \beta W_{a_i} W_{t_i} + \gamma_1 X_{a_i} + \gamma_2 X_{t_i} + \xi Covariates(a_i, t_i) \\ &+ \omega_1 Mkt_{competition}(a_i, t_i|E) + \omega_2 Rival(a_i, t_i|E) + \xi_{a_i,t_i}. \end{aligned}$$

Compared to Table 8, the coefficients on the relevant interaction terms are positive. But, I can not extract the effects of market externalities with log difference estimation.

5.3 Hypotheses

In section 6, I will test several hypotheses presented here regarding the matching between bank mergers.

Hypothesis 5.1. *Large banks tend to merge with large banks and small banks tend to merge with small banks.*

I include bank size as measured by the natural logarithm of the bankâĂŹs total assets and number of branches. This pattern is called positive assortative mathching of sizes. To test for positive assortative matching, two OLS regressions are run and column (1) and (2) in Table 8 show this pattern. The main reasons for positive assortative matching are as follows. First, considerable consolidations were observed after 1994 Riegel-Neal Act. Consumers prefer big banks with high branch networks. Expanding branch networks is a key motives to induce mergers. Also, large and small banks typically use different criteria in service and bank products. Therefore, large target banks are better match for large merging banks, whereas small target banks are better match for small merging banks.

Hypothesis 5.2. *The more overlapped are markets that merging and target banks serve before merger, the higher post-merger value will have the merging bank. And this market overlap match-specific covariates play an important role in matching.*

From the prior studies, it is likely that the potential for cost efficiency and market power depends on the geographic overlap of markets between the merging and target banks. The market overlap between mergers indicates that the proportion of in-market bank mergers is higher. In section 3.3, it is explained that in-market mergers have much more potential than out-of market mergers for exercising market power and creating cost efficiency gains.

Hypothesis 5.3. *The operating cost measure of target banks is complementary to the merging bank's cost efficiency.*

Operating cost measure is defined in section 3.2.1. Following the regression of merging bank's cost attributes on matched target attributes in Table 8, I find cost measures are positively related each other in matching. Dick (2006) regressed the effect of branching deregulation on cost measure and shows that this cost measure appears to increase by one percentage point following deregulation. Banks provide better service through more extensive branching and ATM networks as well as paying higher salaries to their employees. Throughout the mergers, increased geographic network enables banks to exploit high service to customers.

Hypothesis 5.4. *The proxies for risk of target banks is complementary to the merging bank's risk proxies.*

This hypothesis is consistent with regression between merging and target attributes in column (4) in Table 8. Maksimovic and Phillips (2001) show that merger value depend on operational performance for efficiency reasons. But, Dick (2006) shows that credit risk appears to increase by o.4 percentage point following deregulation. Thus nationwide branching can enhance banks to control credit risk only through geographic diversification.

Hypothesis 5.5. *Market competition that each bank faces gives negative externalities on match value.*

Measures of market competition are studied in section 3.2.2. There has been several attempts to revel the relationship between market concentration and prices after merger(Sapienza 2002, Erel 2011). Thus, deposit interest rate is lower and loan interest rate is higher in high concentrated markets. I find that post-merger revenue is lower in highly competitive markets from Table 9.

Hypothesis 5.6. *Rival banks' merger activities as externalities affect match value.*

There has been several papers to study rivals' reactions following mergers. Kim and Singal (1993), Hannan and Prager(1998) show that merging banks do not pass efficiency gain to customers so merging banks lower deposit interest rate after merger. And non-merging banks sharing same overlapping markets lowered deposit rates,too. Prior research shows that rival banks behave similarly to consolidated banks. Also, rivals increase price when the size of the merger is large. Thus, it is natural to expect that post-match value depends on the size of merger activities of rival banks.

6 Estimation Results

6.1 Results from matching model

In the estimation, I include the following the interaction terms as explanatory variables for the two-sided matching: Assets, number of branches, loan loss provision and operating cost measures. Market overlap between matches are used for match-specific covariates.

Since matching estimations are conducted without transfer data, I need to normalize the match value. Based on the evidence that I described above for the positive assortative matching of size, I use $\text{Branch}_{Mer} \times \text{Branch}_{Tar}$ as the normalized variable. I estimate first fixing the coefficient at +1 and then fixing it at -1. The final estimates for all parameters correspond to the sign of the coefficient of $\text{Branch}_{Mer} \times \text{Branch}_{Tar}$ with the highest objective function value. The estimate of this normalized variable is super-consistent.

Table 11 shows that match value estimation results when only matched cases are included. The coefficients on the interactions between merging and target assets and branches are positive and statistically significant. It suggests that larger merging bank tends to merge with larger target banks. This result is consistent with the conventional understanding that most mergers were motivated by expanding branch networks and confirms hypothesis 5.1.

The coefficient of merger geographical overlap term is positive and significant in terms of 95% confidence interval. It indicates that a match value is higher when a match occurs between highly market-overlapped banks. An implication of this finding is that the potential for cost saving and market power depends on the geographical overlap of markets between merging and target banks. As the number of branches of merging banks that completely overlapped with target banks increases, market overlap contributes the value of post-match

I also allow the match synergy function to depend on cost and risk measures. The coefficient of cost measures is positive and significant, indicating that merging banks with higher quality prefer to match with partners with relatively good service quality. This supports hypothesis 5.3. Another possible reason is that rigidity of labor market.

However, the interaction term on risk measures turn out to be insignificant. In other words, the risk measures doesn't seem to be contributed on merger value. One possible explanation is that banks might have used their greater geographic diversification as a hedge against risk. Since nationwide branching through mergers and acquisitions allowed banks to have different risk preferences, the interaction between merging and target banks' loan loss provision measures is not a significant factor in the matching.

Finally, I incorporate market externalities into a matching model. Market competition and rival banks' merger activities give significant and negative impacts on merging banks. It is consistent with *ceteris paribus*, a bank's profit increases with the number of its own branches, and decreases with the number of competing rivals. When banks are exposed to merger activities of rivals in the same markets, then gains from increased cost efficiency can be minimized and it is hard for banks to exercise market power. I can infer that increased competitive rivals can lessen the post-match values.

In Table 12, I expand analysis to unmatched banks. In this case, each bank can choose whether to merge or stay unmatched. I show that results have similar sign with Table 11. However, the impacts of rivals on un-matched banks' merger are different from merging banks. Multiple merger activities in the same markets will rather enhance competition. Thus the coefficient of rivals merger activities on unmatched is positive. But, these effects are relatively weaker.

6.2 Impact of Mergers on Price Changes and branch networks

I test the price changes and branch networks after the merger are consistent with the results in the matching model.

6.2.1 Deposit interest rate

An ownership change in a market might influence non-merging rival banks that operates in the regions affected by consolidation. After a merger happens, the pricing policy of the merging bank affects the policies of the rival banks, too. To analyze the effects of mergers on price and performance, I estimate the following fixed effect regressions.

$$\begin{aligned} r_{k,t}^{deposit} - r^{ff} = \tau_1 Merge_{k,t}^{t=0,-1,-2,-4} + \tau_2 M_{k,t}^{overlap} + \tau_3 Bank_{k,t} \\ + \lambda_1 Mkt_{k,t}^{comp} + \lambda_2 Rival_{k,t}^{Mer} + d_t + \nu_{kt} \end{aligned} \tag{6.1}$$

where $r^{deposit} - r^{ff}$ is the relative deposit interest rate[22] charged at time t by bank k, measured by the difference between bank's deposit rate and the three month federal funds

[22] The deposit, loan interest rates and service fee rates are calculated as one-year rates

rates.[23] $M_{k,t}^{overlap}$ measures the fraction of geographically overlapped markets between mergers. $Bank_{k,t}$ is a vector of bank specific control variables. To measure bank size effects, I add natural logarithm of bank $k's$ asset. To avoid simultaneity, all variables are lagged one year. In particular, I distinguish rival banks from the other non-merging banks. In order to examine whether rival banks' activities affect interest rates, I create $Rival_{k,t}^{Mer}$ measured by average rivals' merger activities exposed in the same market that bank k engages. Focarelli and Panetta (2003) finds strong evidence that the full price effects of mergers can be revealed after 3 years following mergers. Thus, time dummy variables are added. $Merge_{k,t}^{t=0,-1,-2,-4}$ are dummy variables that is equal to 1 if bank k is involved in merger activities in year t, t+1, t+2, t+4.

Table 13 presents the estimates of equation (6.1)[24]. It shows that in the transition period the deposit interest rate of the merging(consolidating) banks decreases, while in the completion period it increases by 11-14 basis points. This pattern is consistent with Focarelli and Panetta (2003) that in the short run mergers cause consumer-adverse changes but that their long-run effect is beneficial. The coefficients of the bank characteristics are all significant and have the expected sign. Deposit interest rates are lower for banks with high ratio of cost measures. First, a large part of the increase in costs is accounted for by the rise in salary expenses. High quality is negatively related to deposit rate. These interpretation is consistent with many previous papers of consumer demand estimation. Loan loss provision or net charge-off rate(bad loans) are used for proxies of credit risk.

Also, deposit interest rates are higher for larger and inefficient(low ROA) banks. As expected, market competition enhances rivalry and lower the deposit rates. If The markets are more overlapped, the effects of market power dominate cost efficiencies and interest rate changes unfavorably to consumers.

6.2.2 Loan Interest Rates

Loan interest rates can be estimated by the following equation similar to deposit interest rates.

[23]Radecki (1999) suggests federal funds rates as an approximation of foregone income for deposit balances. However, London Inter Bank Offer Rate (LIBOR) also used for loan spread in Erel (2011).

[24]Note that the number of observations differs across columns because of some missing data.

$$
\begin{aligned}
r^{loan}_{k,t} - r^{ff} = \tau_1 Merge^{t=0,-1,-2,-4}_{k,t} + \tau_2 M^{overlap}_{k,t} + \tau_3 Bank_{k,t} \\
+ \lambda_1 Mkt^{comp}_{k,t} + \lambda_2 Rival^{Mer}_{k,t} + d_t + \nu_{kt}
\end{aligned}
\tag{6.2}
$$

Table 14 shows that the estimation results. Different from deposit interest rate, determining loan rates is more related to loan portfolio risks than merger effects. Rather, I find that the favorable effect of mergers on loan rates starts after first year following the merger, but becomes significant after 4 years. Larger and high risky banks have lower loan interest rates.

6.2.3 Service Fee Rate

Service fee rates can be estimated by following equation.

$$
\begin{aligned}
log(r^{ss}) - log(r^{ss}_{lag}) = \tau_1 Merge^{t=0,-1,-2,-4}_{k,t} + \tau_2 M^{overlap}_{k,t} + \tau_3 Bank_{k,t} \\
+ \lambda_1 Mkt^{comp}_{k,t} + \lambda_2 Rival^{Mer}_{k,t} + d_t + \nu_{kt}
\end{aligned}
\tag{6.3}
$$

Table 15 presents how characteristics of banks and merger activities affect service fee rates. Service fee rates change after mergers hasn't been investigated in banking industry. It's because of the scarcity of available data and service rate hasn't been an interest for researchers. But, service fee rate becomes the most compelling factor for customers since deposit rates stay low after 2000s. I find that larger banks with high quality have higher rates.

Service fee rates are more vulnerable to merger activities of banks. As the fraction of market overlap between mergers increases, service fee rates increase unfavorably to consumers in the short term. In the long term after 2 years service fee reversed beneficially to consumers. Market externalities also influence the service fee change. The coefficients of merger activities of rivals are different for merging banks and unmatched banks. Merger activities of rivals lower service fee of merging banks but increase unmatched banks. It is consistent with the results of matching model. Moreover, banks set low service fee in less concentrated and competitive markets.

6.2.4 The impact of merger activities of rivals on Branch Density

Even though characteristics and prices are available only on bank level, the change of number of branches is observable in market level. Branch density reflects not only bank's quality but also market mobility. It can be a good indicative for merger effects of rivals on market. The number of branches owned by bank k in market h is estimated by following equation

$$\begin{aligned} Log(Branch_{k,h}) = \tau_1 Merge_{k,t}^{t=0,-1,-2,-4} + \tau_3 Bank_{k,t} \\ + \lambda_1 Mkt_{k,t}^{comp} + \lambda_2 Rival_{k,t}^{in} + \lambda_3 Rival_{k,t}^{out} + d_t + \nu_{kt} \end{aligned} \tag{6.4}$$

where $Rival_{k,t}^{out}$ and $Rival_{k,t}^{in}$ are dummy variables that take the value of 1 when out-of-market and in-market mergers of rivals occur. Estimation results are presented in Table 16. I find the evidence that in-market merger and out-of-market mergers affect rivals differently. When in-market merger happens in the same market, merging banks have more opportunities for cost saving. At first, the least efficient branches can be eliminated. Then rival banks correspond to remove inefficient branches to offer better service for consumers. However, when new banks enter into the market through out-of-market mergers, then competition is enhanced and rival banks increase branch density to compete new banks.

I can also see the long-term change of mergers. Consolidated banks gradually increase branch density to exert cost-efficiencies obtained by mergers. The effects of bank characteristics and market structure is corresponding with other analysis. Larger and less risky banks have higher branch density. And market competition gives negative effects on the number of branches.

7 Conclusion

In this paper, I identify the key sources of match-specific characteristics to determine post-merger synergy values in a competitive assignment framework. I investigates a two-sided matching model in the banking merger market using U.S Texas branch location data from 1994-2005. Match synergy is determined by observable attributes of merging banks (active) and target banks (passive) and match-specific covariates. The results show that bank size and cost measures have positive assortative matching: Larger banks prefer to match with large target banks, and banks with high cost quality tend to match with banks with high cost to asset ratio. Moreover, I find the evidence of match-specific covariates such as market overlap between matches play important roles in determining the match value.

Since the match synergy depends not only on the match between merging and target banks but also on the activities of other banks in the market, I extend matching model with externalities. Market competition and rival banks' merger activities are regarded as externalities. These externalities depend on all the banks in assignment and are additively separable, so the maximum score estimator is applicable. I find that effects of externalities are not negligible. I show that banks have lower match values in competitive markets. Also merger activities of rival banks weaken the merger effects of merging banks. However merger activities of rival banks that exert market power give positive effects on un-matched banks.

Even though I opened up potential to apply externalities on matching model, there are many issues left for a future research regarding bank mergers and a matching model. One issue I could not address was about dynamic market competition. Also, the model used in this paper assumes one-to-one matching. An interesting extension of my model would be applying one-to-many matching. Another set of extensions to this work should consider unobservable incentives into matching model. Future research in this direction will likely prove fruitful[25].

[25]Bajari, Fox and Ryan (2006) and Fox and Yang (2012) studied the identification of the distribution of unobserved complementaries in matching games.

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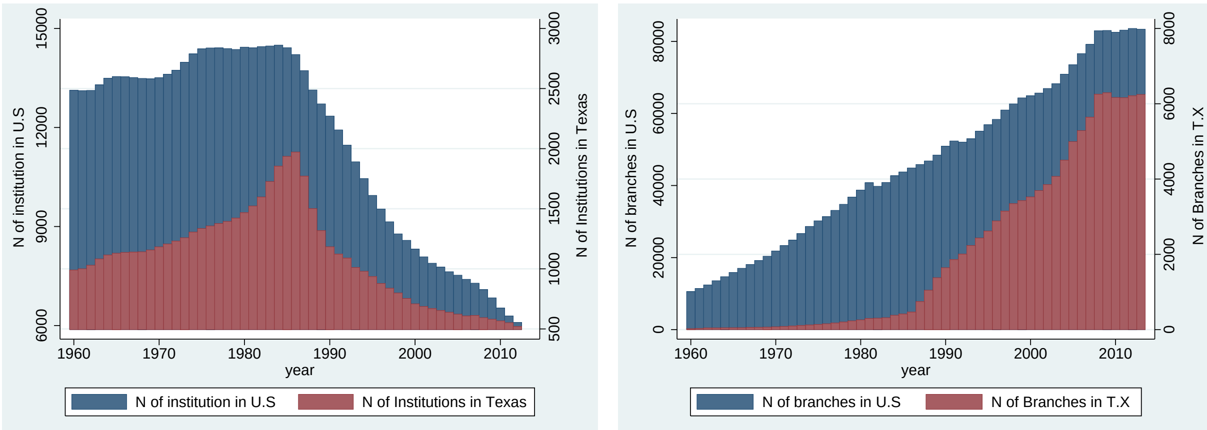
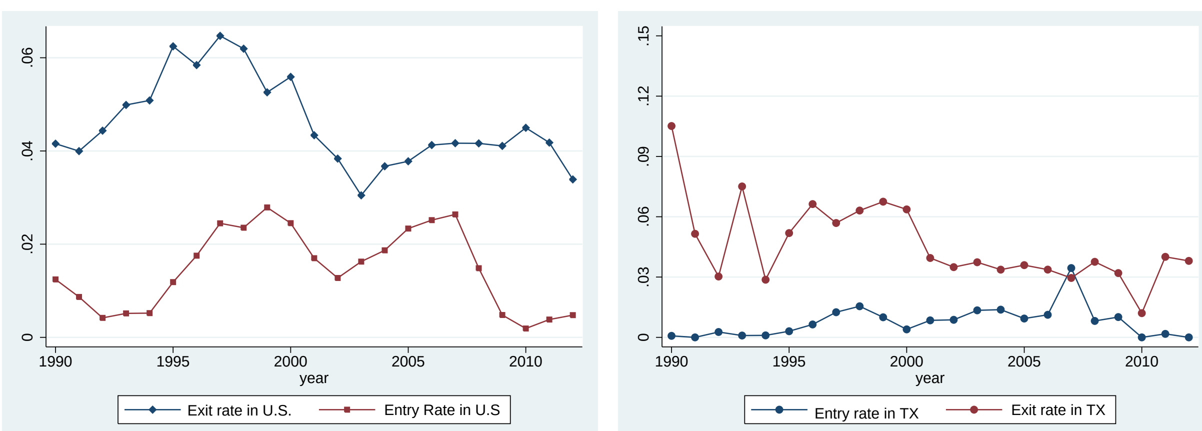


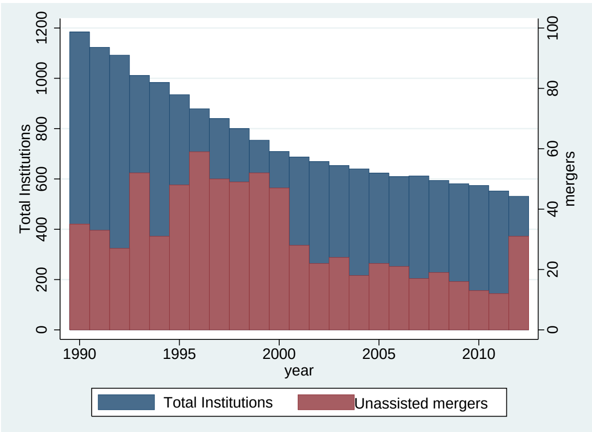
Figure 1: Changes of the number of banking institutions and Branches in U.S. and Texas from 1960-2013



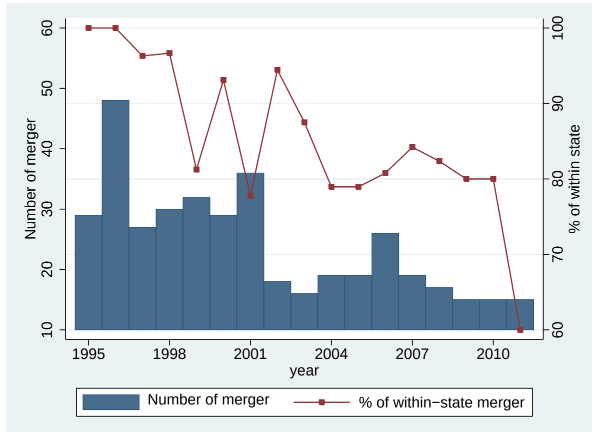
(a) (b)

Figure 2: Changes in Entry rate and Exit rate in Banking Industry

Notes: Entry corresponds to new additions and conversions. Exit corresponds to unassisted mergers and failure.

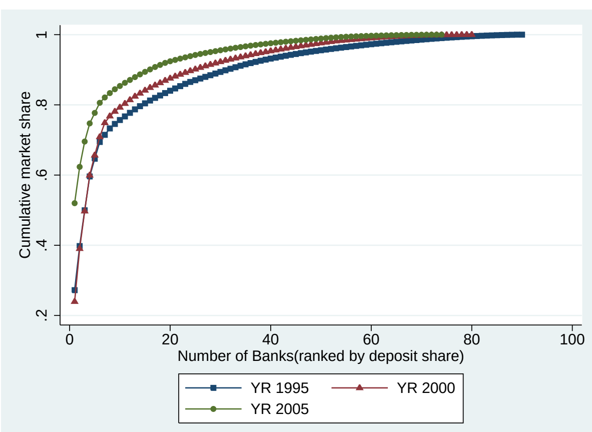


(a) Changes of total Institutions and Unassisted mergers in TX from 1990-2012

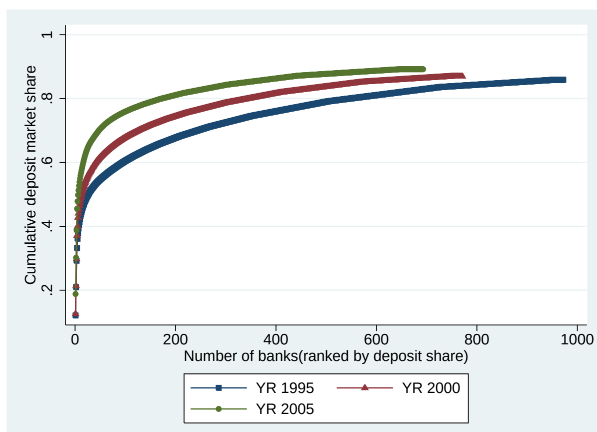


(b) Number of Mergers and % of within-state merger in TX from 1995-2011

Figure 3: Number of Merger changes in TX



(a) Harrison County, Houston city in TX



(b) Texas

Figure 4: Lorenz curve for deposit market share in TX

Table 1: Number of Commercial Banking institutions and Market share by asset size in Tx

Number of Commercial Banks				Year	Market Share (%)			
Mega(%)	big(%)	Medium(%)	small(%)		Mega	big	Medium	small
7 (0.72)	41 (4.22)	190 (19.54)	734 (75.51)	1995	39.36	14.95	15.37	16.2
8 (0.87)	47 (5.16)	182 (20.00)	673 (73.95)	1996	41.75	15.7	14.25	14.66
10 (1.15)	52 (5.96)	190 (21.78)	620 (71.10)	1997	44.4	16.69	13.78	12.9
10 (1.19)	62 (7.37)	192 (22.35)	539 (69.08)	1998	46.39	16.5	13.01	11.91
15 (1.87)	57 (7.09)	192 (23.91)	539 (67.12)	1999	47.68	16.26	13.04	10.89
17 (2.20)	63 (8.17)	182 (23.60)	509 (66.01)	2000	49.47	15.64	11.49	10.39
19 (2.59)	71 (9.67)	192 (26.15)	452 (61.58)	2001	52.31	17.8	10.68	7.98
22 (3.06)	72 (10.01)	190 (26.42)	435 (60.50)	2002	54.49	16.3	10.29	7.33
25 (3.52)	85 (11.97)	196 (27.60)	404 (56.90)	2003	57.27	16.46	9.31	6.08
28 (4.00)	87 (12.44)	198 (28.32)	386 (55.22)	2004	58.23	16.35	8.81	5.46
30 (4.33)	91 (13.13)	203 (29.29)	369 (53.24)	2005	61.71	14.64	8.17	4.67

Notes: Mega, Big, Medium and small banks are categorized by asset size over 3 Billon, between 300 million and 3 billion, between 100 million and 300 million and less than 100 million dollars

Table 2: Summary statistics of Commercial banks in Texas

Variables	Year 1995				Year 2005			
	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Assets ($ million)	20.7	172.5	.23	4.46E+03	521.0	5.92E+03	.27	1.05E+05
N of Branches	3.63	16.00	1	290	7.86	34.86	1	537
N of counties	1.60	3.35	1	70	2.60	5.41	1	78
Loan interest rate(%)	4.94	.82	.30	16.16	3.53	.68	.06	8.91
Deposit interest rate(%)	1.52	.32	.08	2.78	.66	.22	0.02	1.48
Service fee rate(%)	.41	.47	.002	13.18	.39	.60	0.01	10.38
Operating Cost Efficiency(%)	1.81	.67	.12	9.39	1.74	.87	.01	12.20
Loan loss provision(%)	1.74	1.08	.13	8.82	1.41	1.07	.13	22.44
Net Charge-off rate	.14	.93	−10.29	15.87	.21	1.05	−20.54	7.60
Employees per branch	19.73	13.39	2.5	136	17.32	30.65	2.33	760.5
ROA	1.28	.74	−7.78	5.58	1.14	1.04	−6.57	5.61
Market Share(%)	.09	.58	0.01	12.09	.12	.94	0.01	18.81
N of Observations	972				693			

Notes: Operating Cost Efficiency and Loan loss provision ratio is defined in Section 3.2.1. Operating cost efficiency is the ratio of non-interest expenses over assets. Loan loss provision is the ratio of total loan loss provisions over total loan size. Deposit, loan interest rate and service fee rate are calculated by interest expenses to totoal domestic deposits,interest-revenue to net loan sizes and service charges on deposit accounts to total deposits.

Table 3: Entry, Exit, Expanding and Shrinking behaviors of Banks in Tx between 1995 and 2011

Year	Number of Banks						Total
	Exit	Entry	Expanding	Shrinking	Merging	Entry by Merger	
1995	42	2	64	11	29	0	1021
1996	72	5	84	13	48	0	954
1997	57	14	69	7	27	1	911
1998	50	18	68	13	30	1	879
1999	63	20	67	10	32	6	836
2000	42	10	61	9	29	2	804
2001	54	16	56	10	36	8	766
2002	25	10	58	13	18	1	751
2003	23	13	32	11	16	2	741
2004	28	15	67	15	19	4	728
2005	26	19	65	4	19	4	721
2006	33	13	67	13	26	5	701
2007	24	27	70	13	19	3	704
2008	23	20	71	9	17	3	701
2009	21	11	56	8	15	3	691
2010	21	6	42	10	15	3	676
2011	28	10	33	15	15	6	658

Table 4: Example of Bank History in FDIC

	Prosperity Bank (FDIC: 16835) in Edna, TX
Date	Event
9/13/1949	Institution established: Original name:First National Bank of Edna (16835)
10/3/1977	Changed name to First Bank of Edna (16835)
1/2/1981	Changed name to Allied First Bank (16835)
4/4/1984	Changed name to First Bank (16835)
7/28/1988	Acquired First Capitol Bank (11146) in WEST COLUMBIA, TX
8/31/1990	Acquired Citizens National Bank (25301) in EL CAMPO, TX
8/22/1991	Acquired Buchel Bank and Trust Company (14421) in CUERO, TX
6/18/1992	Moved bank headquarters from EDNA, TX to EL CAMPO, TX
6/18/1992	Changed name to First Prosperity Bank (16835)
6/25/1992	Acquired American National Bank - Post Oak (26420) in HOUSTON, TX
7/23/1992	Acquired 1st National Bank of Texas (26676) in WEBSTER, TX
10/1/1998	Acquired Union State Bank (10713) in EAST BERNARD, TX
10/1/1999	Acquired The Commercial National Bank of Beeville (3096) in BEEVILLE, TX
2/23/2001	Acquired Heritage Bank (1221) in WHARTON, TX
2/23/2001	Changed name to Prosperity Bank (16835)
5/8/2002	Acquired Texas Guaranty Bank, National Association (25739) in HOUSTON, TX

Table 5: Federal Deposit Insurance Corporation(FDIC) Merger Decisions

Applicant Institution			Other / Target Institution						
Institution Name	Total Assets	Cert No.	Institution Name	Total Assets Acquired	Offices	Cert No.	Action Approved	DOJ Reply Date	Application Number
Alpine Bank GLENWOOD SPRINGS, CO	$1,581,294	23091	First National Bank TELLURIDE, CO	$149,335	4	33699	11/22/2005	11/18/2005	20052966
NewAlliance Bank NEW HAVEN, CT	$6,465,577	18261	Cornerstone Bank STAMFORD, CT	$ 230,230	7	26006	9/21/2005	7/15/2005	20051719
Bank of the West SAN FRANCISCO, CA	$40,955,966	3514	Commercial Federal Bank OMAHA, NE	$10,384,663	199	30341	10/6/2005	8/23/2005	20051945

Table 6: Summary Statistics

Variables	Mean	St.Dev	Min	Max	Obs.
	Panel A: Active Banks in Mergers				
Assets($ million)	1.11e+03	5.42e+03	1.68	6.55e+04	289
N of branches	21.86	53.77	0	451	289
Loan loss provision(%)	1.50	1.20	.22	14.72	289
ROA	1.22	.71	-4.34	4.15	289
Net-charge off rate(%)	.12	.62	-2.24	8.88	289
Cost measure	1.73	.6	.09	6.90	289
Employees per branch	22.90	13.87	6	123.01	289
Rival merger activity	.32	.32	0	1	289
	Panel B: Target Banks in Mergers				
Assets($ million)	301.4	2.43E+03	.69	3.23E+04	289
N of branches	14.56	52.89	1	487	289
Loan loss provision(%)	1.67	1.27	.29	13.57	289
ROA	.91	1.29	-12.65	3.75	289
Net-charge off rate	.44	1.66	-1.47	22.39	289
Cost measure	1.91	.74	.31	9.75	289
Employees per branch	17.23	9.53	0	92	289
	Panel C: Unmatched Banks				
Assets($ million)	124.63	492.17	1.20	5.90E+03	936
N of branches	11.19	21.63	1	226	936
Loan loss provision(%)	1.33	.55	.19	5.25	936
ROA	1.22	.97	-4.31	9.51	936
Net-charge off rate(%)	.25	.61	-4.32	10.81	936
Cost measure	1.90	.67	.04	8.25	936
Employees per branch	18.63	12.37	2.67	156.77	936
Rival merger activity	.61	.28	0	1	936

Table 7: Multinomial Logit Regression

	Merging Banks	
	(1)	(2)
Explanatory Variables	(vs. Target)	(vs. Unmached Banks)
log(Asset)	.26(.15)*	.38(.06)***
log(Branch)	.32(.24)	$-$.53(.11)***
N of Counties	$-$.02(.01)	.04(.01)***
Empbranch	.59(.23)***	.80(.17)***
Loan loss provision	2.67(4.99)	37.01(9.77)***
ROA(%)	.18(.10)**	$-$.08(.08)
Net Charge-Off Rate(%)	$-$.23(.14)*	$-$.24(.14)*
Observations	1512	
Pseudo R-squared	.21	

Notes:***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8: Regression of Target characteristics on Merging bank characteristics

Characteristics of Target Banks	Characteristics of Merging Banks				
	(1)	(2)	(3)	(4)	(5)
	log(Asset)$_{Mer}$	Branch$_{Mer}$	Cost$_{Mer}$	Risk$_{Mer}$	Empbranch$_{Mer}$
log(Asset)$_{Tar}$	.88(.07)***	.11(.03)***	$-$.04(.02)*	.03(.04)	.05(.04)
Branch$_{Tar}$	.36(.20)*	.24(.09)***	.02(.05)	$-$.14(.11)	.05(.07)
Cost$_{tar}$	.41(.35)	.14(.11)	.14(.08)*	-.01(.20)	$-$.17(.10)*
Risk$_{Tar}$	$-$.23(.16)	$-$.04(.07)	.03(.04)	.21(.06)***	$-$.04(.06)
Empbranch$_{Tar}$	.14(.19)	.22(.08)***	$-$.04(.08)	$-$.06(.14)	.15(.08)*
Fixed Effects	Year	Year	Year	Year	Year
Observations	289	289	289	289	289
R-squared	0.55	0.24	0.08	0.10	0.09

Notes: Heteroskedasticity robust standard errors are reported in parentheses next to each coefficient. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Cost measure is a variable that the natural logarithm of the ratio, non-interest expenses to asset. Risk measure is a variable that loan loss provision ratio. Empbranch is a variable that number of employee per branche. Empbranch and cost measure are in logs.

Table 9: OLS Analysis of Bank Profit Function : Match only

Variables	*Profit*		
	(1)	(2)	(3)
logAsset_{mer}		$-.71(.40)^{*}$	$-.78(.40)^{*}$
Branch_{mer}		.38(.30)	.38(.30)
Cost_{mer}		$.47(.27)^{*}$	.41(.26)
Risk_{mer}		$-2.43(1.30)^{*}$	$-1.67(1.21)$
$\text{logAsset}_{mer}\times$ logAsset_{tar}	$.07(.01)^{***}$	$.10(.02)^{***}$	$.10(.02)^{***}$
$\text{Branch}_{mer}\times$ Branch_{tar}	.24(.30)	.12(.14)	.13(.14)
$\text{Cost}_{mer}\times$ Cost_{tar}	$-.10(.04)^{***}$	.40(.26)	.35(.26)
$\text{Risk}_{tar}\times$ Risk_{mer}	$-.16(.04)^{***}$	$-.18(.05)^{***}$	$-.18(05)^{***}$
Merger Overlap	$.10(.01)^{***}$	$.11(.04)^{***}$	$.13(.02)^{***}$
Market Competition	$-.78(.31)^{**}$	$-.62(.21)^{***}$	
Rival's Merger activities	.67(.60)		$-.81(.43)^{*}$
Observations	289	289	289
R-squared	0.65	0.70	0.69

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 10: OLS Analysis of Bank profit (2): Match only

Variables	Δ_t $\log(profit)$			
	(1)	(2)	(3)	(4)
logAsset_{mer}	$-.291(.06)^{***}$			.062(.12)
Branch_{mer}	$-.172(.06)^{***}$			$-.205(.07)^{***}$
Cost_{mer}	$-1.53(.53)^{***}$			$-.299(.48)$
Risk_{mer}	$-.264(.10)^{***}$			$-25.69(3.11)^{***}$
logAsset_{tar}		$.481(.05)^{***}$		$.394(.15)^{**}$
Branch_{tar}		$.312(.12)^{***}$		.169(.12)
Cost_{tar}		.151(.10)		.133(.09)
Risk_{tar}		$.325(.11)^{***}$		$-6.39(3.23)^{**}$
$\text{logAsset}_{tar}\times$ logAsset_{mer}	$.016(.01)^{***}$	$.015(.01)^{***}$	$-.007(.01)$	$.030(.01)^{*}$
$\text{Branch}_{tar}\times\text{Branch}_{mer}$	.005(.01)	$-.064(.01)^{***}$	$.088(.02)^{***}$	$-.014(.02)$
$\text{Cost}_{tar}\times$ Cost_{mer}	$-.10(.05)^{*}$	$.057(.01)^{***}$	$.084(.02)^{***}$	$.152(.07)^{**}$
$\text{Risk}_{tar}\times$ Risk_{mer}	$-.009(.01)$	$.06(.01)^{***}$	$-.020(.01)$	$-.036(.02)$
Merger Overlap	.15(.11)	.08(.12)	$.201(.09)^{**}$	.114(.12)
Market Competition	$-.075(.04)^{*}$	$-.05(.05)$	.058(.12)	$-.108(.15)$
Rival's merger activity	.100(.12)		.112(.13)	$-.097(.12)$
Observations	289	289	289	289
R-squared	0.62	0.54	0.37	0.66

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 11: Maximum Score Estimates of Match Value Function: Match only

Explanatory Variables	Match Function Estimate				
	(1)	(2)	(3)	(4)	(5)
$\text{Branch}_{tar} \times \text{Branch}_{mer}$	1 (superconsistent)	1 (normalized)	1 (normalizedt)	1 (normalized)	1 (normalized)
$\text{logAsset}_{tar} \times \text{logAsset}_{mer}$	1.58 (0.22, 2.12)	2.04 (0.53, 3.22)	3.89 (2.41, 6.46)	2.88 (0.97, 4.60)	1.82 (0.65, 3.28)
Merger Overlap	5.58 (0.86, 8.67)	7.26 (3.16, 11.40)	11.73 (8.12, 17.82)	11.05 (3.48, 16.68)	5.07 (2.21, 9.04)
$\text{Risk}_{tar} \times \text{Risk}_{mer}$		46.75 (-0.58, 122.97)	66.04 (-108.04, 152.19)	26.85 (16.16, 84.75)	
$\text{Cost}_{tar} \times \text{Cost}_{mer}$	2.15 (0.31, 2.92)	2.73 (-0.63, 7.63)	4.76 (0.47, 12.81)	5.22 (0.71, 13.49)	1.72 (1.47, 5.36)
Market Competition			-0.51 (-5.27, 12.73)	-2.46 (-5.63, 2.88)	-5.35 (-15.85, -3.45)
Rival's Merger Activities				0.04 (-0.14, 0.19)	-9.17 (-22.51, -1.07)
Observations of Match	289	289	289	289	289
N of Inequalities	4114	4114	4114	4114	4114
Percent of Inequality	0.83	0.89	0.93	0.90	0.96

Notes : I run the differential evolution(DE) algorithm in Mathmatica
95% confidence intervals are reported in parentheses below each coefficient.
For confidence intervals, I follow the sub-sampling procedure described in Politis, Romano, and Wolf (1999) and use subsample size equal to 1/4 of the total sample size

Table 12: Maximum Score Estimates of Match Value Function: Unmatched included

	Match Function Estimates	
Explanatory Variables	Point Estimate	95% Confidence Interval
$\text{Branch}_{tar} \times \text{Branch}_{mer}$	1	superconsistent
$\text{logAsset}_{tar} \times \text{logAsset}_{mer}$	1.22	(0.009, 1.77)
$\text{logCost}_{tar} \times \text{log Cost}_{mer}$	0.58	(-0.76, 1.02)
Merger Overlap	5.19	(0.24, 8.71)
Rival's merger activity; Unmatched	4.08	$(-0.25, 13.70)$
Rival's merger activity ; Match	-7.24	$(-12.83, -1.25)$
Market Competition	-0.20	$(-0.36, -0.04)$
Observations	1225	
N of Inequalities	23417	
Percent of Inequality	0.88	

I run the differential evolution(DE) algorithm in Mathmatica.
95% confidence intervals are reported in parentheses below each coefficient.
For confidence intervals, I follow the subsampling procedure described in Politis, Romano, and Wolf(1999) and use subsampe size equal to 1/4 of the total sample size

Table 13: Effects of M&As on Deposit Interest Rates on Tx bank between 1995 and 2005

Explanatory Variables	$\log(r^d)$ $-log(r^{ff})$			
	Merging Banks Only		All Banks	
	(1)	(2)	(3)	(4)
logAssets	.008(.01)	.041(.04)	.023(.01)***	.16(.01)***
Cost efficiency	$-$.193(.05)***	$-$.017(.03)	$-$.157(.01)***	$-$.034(.01)***
ROA	$-$.044(.02)	$-$.001(.02)	$-$.024(.01)***	$-$.007(.01)***
Net Charge-Off rate	.030(.01)**	.084(.07)	.014(.01)**	.002(.01)
Loan Loss Provision	$-$1.11(.81)	$-$4.14(4.92)	$-$2.52(.32)***	$-$.57(.33)***
Merger overlap	$-$.074(.03)**	.047(.04)	$-$.078(.02)***	$-$.005(.03)
Concentration		$-$1.55(.63)**	.114(.04)***	$-$.014(.05)
market competition	$-$.084(.02)***	$-$.268(.07)***	$-$.041(.01)***	
Rival Merger :Match	$-$.023(.05)	.089(.05)	$-$.115(.05)**	$-$.064(.04)
Rival Merger:Unmatch			$-$.043(.01)***	
1+ Year After Merger	$-$.052(.06)	.032(.04)	$-$.030(.01)**	$-$.044(.01)***
2+ Year After Merger	$-$.111(.08)	$-$.122(.06)*	$-$.040(.02)**	$-$.044(.01)**
4+ Year After Merger	.116(.05)**	.142(.06)**	$-$.010(.03)	$-$.013(.03)
Fixed Effects	Year	Bank,Year	Year	Bank,Year
Observations	264	264	8560	8560
R-squared	0.68	0.53	0.59	0.42

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 14: Effects of M&As on Loan Interest Rates on Tx Banks between 1995 and 2005

Explanatory Variables	$log(r^l)$ -$log(r^{ff})$			
	Merging Banks Only		All Banks	
	(1)	(2)	(3)	(4)
log Assets	$-.022(.01)^{**}$	$-.034(.03)$	$-.043(.01)^{***}$	$.004(.01)$
Cost efficiency	$-.006(.03)$	$-.020(.03)$	$.042(.01)^{***}$	$.001(.01)$
ROA	$.006(.01)$	$-.011(.01)$	$.042(.01)^{***}$	$.018(.01)^{***}$
Net Charge-Off rate	$.014(.01)^{*}$	$.017(.05)$	$.039(.01)^{***}$	$.017(.01)^{***}$
Loan Loss Provisions	$2.79(.80)^{***}$		$2.02(.32)^{***}$	$1.08(.28)^{***}$
Merger overlap	$.029(.02)$	$.022(.04)$	$-.009(.01)$	$.021(.02)$
Concentration	$.407(.20)^{**}$			$.052(.05)$
Market competition		$-.172(.05)^{***}$	$-.004(.01)^{*}$	
Rival Merger :Match	$-.020(.05)$	$.068(.04)$	$-.020(.05)$	$-.029(.03)$
Rival Merger :Unmatch			$.003(.01)$	$.001(.01)$
1+ Year After Merger	$.009(.02)$	$.004(.03)$	$-.015(.01)$	$-.015(.01)$
2+ Year After Merger	$.059(.02)^{**}$	$.024(.03)$	$-.014(.014)$	$-.012(.02)$
4+ Year After Merger	$-.065(.04)$	$-.092(.05)^{**}$	$.010(.01)$	$-.036(.01)^{**}$
Fixed Effects	Year	Bank,Year	Year	Bank,Year
Observations	264	264	8560	8560
R-squared	0.81	0.74	0.84	0.88

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 15: Effects of M&As on Service Fee Rates on Tx Banks between 1995 and 2005

Explanatory Variables	$log(r^{ss}) - log(r^{ss}_{lag})$			
	Merging Banks Only		All Banks	
	(1)	(2)	(3)	(4)
log Assets	.027(.01)*	.158(.21)	.018(.01)***	.064(.01)***
Cost efficiency	.657(.10)***	.711(.26)***	.350(.03)***	.344(.01)***
ROA	.067(.02)**	.129(.10)	.043(.00)***	.052(.01)***
Net Charge-Off rate	.009(.01)	.350(.18)*	.010(.01)**	.005(.01)
Loan Loss Provisions	11.13(4.02)***	21.10(17.8)	1.94(.93)**	1.68(.60)***
Merger overlap	.057(.04)	.431(.13)***	.079(.04)**	.088(.04)**
Concentration	.977(.39)**	3.94(1.7)**		
Market competition			−.024(.01)***	−.037(.01)***
Rival Merger : Match	−.121(.07)	−.220(.15)	−.169(.06)*	−.128(.06)**
Rival Merger : UnMatch			.003(.01)	.043(.01)***
N of county	.194(.07)***	.159(.01)***	.025(.01)***	.026(.01)***
1+ Year After Merger	.030(.05)	-.080(.09)	.030(.01)*	.027(.02)
2+ Year After Merger	−.182(.08)**	−.295(.12)**	−.036(.02)	−.048(.02)*
4+ Year After Merger	−.172(.05)***	−.300(.17)*	−.049(.02)**	−.060(.03)*
Fixed Effects	Year	Bank,Year	Year	Bank,Year
Observations	288	288	8560	8560
R-squared	0.54	0.46	0.19	0.23

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 16: The Effects of mergers on Changes of Branch Density of Tx Banks between 1995 and 2005

	Explanatory Variables	log N of branches (1)	(2)
Bank Characteristics	logAsset	.171(.01)***	.177(.01)***
	log N of Counties	−.275(.01)***	−.278(.01)***
	Cost Efficiency	.056(.01)***	.073(.01)***
	Loan Loss Provisions	.209(.20)	−1.247(.34)***
	ROA	.015(.01)***	.023(.01)***
Merger Effects	Rivals' out-of-mkt merger	.003(.01)	.059(.01)***
	Rivals' In-mkt merger	−.124(.01)***	−.022(.01)*
	1+ Year After Merger	.063(.03)*	.049(.02)***
	2+ Year After Merger	.095(.03)**	.046(.02)***
	4+ Year After Merger	.134(.05)**	.053(.02)***
Market Structure	log(N of Banks)	−.506(.01)***	−.391(.04)***
	log County Pop 2000	−.064(.01)***	
	log Per capita	−.074(.02)***	
	MSA Index	.012(.01)*	
	Fixed Effects	Year	County, Year
	Observations	16765	16765
	R-squared	0.35	0.31

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively