The Determinants of Bank Mergers: A Revealed Preference Analysis

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Abstract

This paper analyzes bank mergers in a two sided matching framework with endogenous transfers. The two sides are formed by buyers and targets. When a buyer is matched with a target, there is a value created by this match. We impose a functional form for this value and estimate it by employing two maximum score estimators, one using transfer data, the other not using the transfer data. Our semi-parametric estimates show that relative sizes of both assets and branches for each side of the match do matter. The closer these values for a matching pair are, the more value is created. Secondly, geographical proximity, such as buyer's and target's branches being in the same markets or in the neighboring markets, increases the value. Moreover, same market mergers obtain higher values than neighboring market mergers. Lastly, at the time of the announcement of the merger, mergers resulting Antitrust violation of the post merger local market concentration have lower values.

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1 Introduction

Bank mergers has been a hot topic for economists during the past few decades. Merger activity in the US reached its peak point during mid 90's after the Riegle-Neal Interstate Banking and Efficiency Act of 1994, allowing banks to operate nationwide. Banking industry has changed a lot after this substantial merger activity. Total number of banking organizations decreased from 10,500 to 7,500 in the period 1994-2004 according to Federal Deposit Insurance Corporation data set.

There is a huge literature on analyzing bank mergers. **?**) gives an extensive review of banking industry under the influence of mergers. The motivations for the mergers are summarized as increasing the cost efficiency, increasing the geographic scope of operations to diversify the risks, or merging with one of the competitors operating in the same market to increase market power. Another triggering factor for mergers are improvements in technology (**?**)), allowing the banks to coordinate the distant branches, and to offer new products.

This paper analyzes mergers in a different perspective, asking what attributes of banks play role in banks' decisions to merge or not, and with whom to merge. We model bank mergers as a competitive two sided one to one matching market with endogenous transfers. The two sides are labeled as buyers and targets. Once a buyer matches with a target, they attain a post merger value. For a particular match, agents share this value through transfers that the buyer pays to the target. Upon merging, target bank's operations will be carried on by the buyer. The payoff for the buyer is the post merger value net of transfer paid to the target, and the target's payoff is the transfer received from the buyer.

In this framework banks pick their partners from among the banks in the merger market to maximize their payoffs. The equilibrium notion is characterized by single agent best responses. Matched banks receive higher payoff from the observed match partners than they could get from counterfactual partners.

Single agent best response and transferable payoffs give the condition called local production maximization, which is introduced in **?**). This condition implies that for any two pairs of observed matches the sum of the post merger value created by these matches exceeds the sum of the value that can be created if these pairs exchange their partners. This condition allows us to use a consistent maximum score estimator to estimate the post merger value function. The estimator simply makes pairwise comparison for observed matches. This estimator uses the observed matches as the dependent variable, and the attributes of the banks as the explanatory variables. It does not use the transfer information. It is proven to be a consistent estimator in **?**).

We propose an alternative maximum score estimator that uses the transfer data for each merger. The condition used in the presence of transfer data is stricter than the one used in the local production maximization. We make comparison on two pairs of observed matches. To justify the equilibrium in the observed matches, we require for each of the buyer that the increase in buyer's payoff switching from its observed target to counterfactual target should be less than the additional amount of transfer required to convince the counterfactual target. The convincing transfer is equal to the amount received from the counterfactual target's observed buyer. Simply, we want the buyers lose when they deviate from their observed targets. This condition implies the local production maximization, however, the reverse is not true.

In order to see validity of alternative maximum score estimator in finite samples, we perform Monte Carlo experiments. It turns out to have less bias and less variance than the estimator not using the transfer data. For the time being, the formal consistency proofs are not provided.

In estimating the post merger value function, we propose two different functional forms. Both functions calculate the degree of sorting in the matched banks attributes. One is just the summation of cross products of attributes, while the other gives penalties for the gap between the matched banks attributes. Since we want to see the effect of bank size in merger decisions, we use two size variables; amount of assets and number of branches. Assets measure the bank's capital while branches serve as a proxy for labor. Moreover we add match specific covariates in both functional forms. These are dummy variables measuring the geographic proximity of the matched pairs. These variables for a particular match indicate if the buyer's and target's branches are in the same market or if there is partial overlap in markets, or no overlap at all, meaning that the buyer is geographically expanding its market. As stated in **?**) the market definition can go as large as state levels because of single pricing employed by geographically expanding big banks. So we define market in two ways, Metropolitan Statistical Area (MSA) level and state level. We also add the degree of neighboring of the buyer's and target's branches and post merger local market concentration violations for each observed and counterfactual matches.

The estimates show that there is a positive sorting in the level of assets and branch numbers in bank mergers. The closer these values for a matching pair are, the more post merger value is created. The sorting in assets is more important that sorting in branch numbers. However, for the mergers of banks operating in the same MSA, the importance of sorting in branches decreases even further. The geographical proximity coefficients indicate that mergers of banks operating in neighboring states have more value than those not sharing a neighboring state borderline. However, the biggest value is obtained when both buyer and target are operating in the same market, whether it is defined as a state or an MSA. In the same MSA mergers we see that post merger local market concentration violations decreases the value. This result points out that Antitrust regulation does indeed restrain banks to merge via buying one of its competitors in a local market. If Antitrust restrictions are less strict, we will observe more and more in-market mergers which will occur in buyers intentions to get more market power.

The rest of the paper is organized as follows. Section 2 describes the matching model, introduces maximum score estimators and reports Monte Carlo experiments results. Section 3 provides sources of the data sets used and explains variables used in estimation. Section 4 puts forward functional form specifications and interprets the estimation results. Section 5 discusses the future work.

2 Econometric Model

2.1 Matching Model

We model the merger process as a two sided one to one matching process with endogenous transfers. It is based upon the assignment model introduced in **?**). We denote buyers by $b = 1, ..., M_y$ and targets by $t = 1, ..., M_y$, where M_y is the number of matches observed in market y. We assume there is one national merger market per year and markets in different years are independent of each other. Once a buyer b and a target t merge, they realize a post merger value, denoted by $f(b,t)$. The matched banks share this value in a way that b pays t a transfer, p_{bt}, which is a purchase price of the target. So we can decompose the value into two parts;

$$f(b,t) = V_b(b,t) + V_t(b,t)$$

where

$$
\begin{aligned}
V_b(b,t) &= f(b,t) - p_{bt} \\
V_t(b,t) &= p_{bt}
\end{aligned}
$$

$V_b(b,t)$ is the buyer's payoff, and similarly, $V_t(b,t)$ is the target's payoff. Buyer maximizes $V_b(b,t)$ over potential targets, likewise, target maximizes $V_t(b,t)$ over potential buyers. In equilibrium, all the banks in each side make their single-agent best responses. Each bank's payoff from its observed partner is higher than the payoff if the bank matches with a counterfactual bank. Transferable payoff structure and single agent best responses imply local maximization of the post merger value functions. Local maximization lets us derive inequalities that are necessary conditions that we use in the estimation. For two pairs of observed matches (b,t) and (b',t'), b is matched with t instead of t', meaning that b gets more payoff when matched with t than the payoff it could get if matched with t'. Therefore we can write the following condition:

$$
\begin{aligned}
V_b(b,t) &\geq V_b(b,t') \\
f(b,t) - p_{bt} &\geq f(b,t') - p_{bt'} \qquad (1)
\end{aligned}
$$

In order for b to convince t', the offer $p_{bt'}$ shouldn't be less than what b' offers to t', $p_{b't'}$. Moreover it shouldn't exceed $p_{b't'}$ because any price greater than that value still convinces t' to match with b however it decreases b's payoff. So

$$
p_{bt'} = p_{b't'} \qquad (2)
$$

Then inequalities (1) and (2) give

$$f(b,t) - f(b,t') \;\; \geq \;\; p_{bt} - p_{b't'} \tag{3}$$

In words, extra payoff that b gets from matching with t rather than matching with t' should be greater than the extra transfer b has to pay to convince t. Similarly, for b' we write the following inequality:

$$f(b',t') - f(b',t) \;\; \geq \;\; p_{b't'} - p_{bt} \tag{4}$$

In the absence of transfer data, we add the inequalities (3) and (4) to get the local value maximization condition:

$$f(b,t) + f(b',t') \;\; \geq \;\; f(b',t) + f(b,t') \tag{5}$$

This condition says that for any two observed match pairs the total post merger value created should be greater than that gained if they were to exchange partners.

2.2 Maximum Score Estimators

?) introduces a consistent maximum score estimator that make use of inequality (5). For a given function parameter it makes all pairwise comparisons of observed matches by evaluating the inequality (5). The score is increased by one when a given pairwise comparison satisfies the inequality. Then we pick the parameter values bringing the highest score. Since this estimator does not use the transfer data in matches, we call it ”without transfer estimator” henceforth. So the without transfer estimator maximizes the following score function:

$$Q(\beta) = \sum_{y=1}^{Y} \sum_{b=1}^{M_y} \sum_{b'=b+1}^{M_y} 1[f(b,t|\beta) + f(b',t'|\beta) > f(b,t'|\beta) + f(b',t|\beta)] \tag{6}$$

where t and t' are observed matches of b and b', respectively, and 1[.] is an indicator function taking value of 1 if the inequality in the brackets hold and 0 otherwise.

This estimator has two limitations. One is that there is no use of transfer data. We would lose information if we do not make use of transfer data in case of its availability. The other point is in the identification of the post merger value function. If the function involves buyer specific or target specific variables non interacted with the matched partner's variables, coefficients for those variables can not be identified.

In this study, by keeping those shortcomings in mind, we propose an alternative maximum score estimator that uses transfer data, which we call "with transfer estimator" henceforth. For pairwise comparisons, the estimator requires the observed matches to satisfy the inequalities (3) and (4) at the same time. It should be noted that (3) and (4) implies (5), but (5) does not imply (3) and (4) at the same time. So this new estimator, which requires stricter conditions than the without transfer estimator, maximizes the following objective function:

$$Q^{tr}(\beta) = \sum_{y=1}^{Y} \sum_{b=1}^{M_y} \sum_{b'=b+1}^{M_y} 1[f(b,t|\beta) - f(b,t'|\beta) > p_{bt} - p_{b't'} \wedge f(b',t'|\beta) - f(b',t|\beta) > p_{b't'} - p_{bt}] \tag{7}$$

To see how this new estimator works in finite samples, we perform Monte Carlo experiments. We follow **?**) closely in conducting the experiments. We introduce two valuation functions, one with only interaction terms, the other with not only interaction terms but also a non-interaction term for one side of the match. We use two attributes that interact, say A and

B, each having mean of 10 and standard deviation of 1, and they have a covariance of 0.5. We define the true function as

$$f(b,t) = A_b A_t + 1.5 B_b B_t \tag{8}$$

including only the interaction terms. We add match specific errors for each possible match, with (1/9)th and (2/3)rd of standard deviation of the true valuation function. We first solve the social planner's problem to determine the matched pairs. Then, in order to get the transfer data, we use the duality theorem of the linear programming. So we have both the assignment and transfer data, along with the attributes for each agents. This allows us to compare the two maximum score estimators. We performed 100 iterations with 100 agents for only 1 market.

Table 1: Monte Carlo Results, interaction terms only

Estimators	# iterations	Error Std Dev	Bias	RMSE
Without	100	3.68	-0.0817	0.6104
With	100	3.68	0.0074	0.0262
Without	100	22.09	-0.3017	1.4519
With	100	22.09	0.0787	0.1584

Table 1 reports the bias and root mean squared error (RMSE) of the estimates for both types of estimators under both low and high variance. We see that "with transfer estimator" has significantly lower bias and lower RMSE than "without transfer estimator" has in both low and high error structure.

For the second specification, we define the true function as

$$f(b,t) = A_b A_t + 1.5 B_b B_t + 2C_t \tag{9}$$

Noninteracted term is the variable C of the target, with a mean of 10 and a standard deviation of 1, and it is independent of A and B. The error structure is the same as used in the previous experiment, match specific errors but here we use low variance. Here our concern is whether "with transfer estimator" can identify the non-interacted term's coefficient. When we rewrite the inequality (3) and substitute the functional form, we see that we can identify the non interacted term's coefficient for the target.

$$\begin{aligned}
f(b,t) - f(b,t') &> p_{bt} - p_{b't'} \\
A_b A_t + \beta_1 B_b B_t + \beta_2 C_t - A_b A_{t'} - \beta_1 B_b B_{t'} - \beta_2 C_{t'} &> p_{bt} - p_{b't'} \\
A_b(A_t - A_{t'}) + \beta_1 B_b (B_t - B_{t'}) + \beta_2 (C_t - C_{t'}) &> p_{bt} - p_{b't'}
\end{aligned}$$

Table 2 reports bias and RMSE for coefficients for both interacted and non interacted terms. The first two rows are calculated by estimating the functional form including the non interacted term. The last two rows reports the results using estimators with a misspecified functional form, considering only the interacted terms.

Table 2: Monte Carlo Results, non interaction terms included

Estimators	# iterations	Error Std Dev	Bias β_1	Bias β_2	RMSE β_1	RMSE β_2
Without	50	3.52	0.0967	1003.01	0.7289	45371.1
With	50	3.52	0.0112	-0.0015	0.0269	0.2118
Without	50	3.52	0.0744		0.5654	
With	50	3.52	0.0199		0.0315	

Correctly specified "with transfer estimator" does a pretty good job in estimating the coefficients because bias and RMSEs are low. When we use "without transfer estimator" we get a good estimate for the interacted term's coefficient while we can not identify the non interacted term's coefficient. Even if we fail to specify the functional form correctly in estimation, we get good estimates for the interacted term's coefficient with both estimators.

To sum up, we get the idea that "with transfer estimator" works well in finite samples. It has less bias, less RMSE, and we can identify more parameters than using "without transfer estimator". Another advantage of the with transfer estimator is that the estimates will be in dollar values. Because right hand sides of the inequalities (3) and (4) are the difference of the two transfers which are in dollars.

3 Data

The data used in this study come from two sources; Federal Deposit Insurance Corporation (FDIC) and SNL Financial.

FDIC collects branch level data from each banking institution and bank holding company in the US, including its territories, once a year. Our FDIC data set is for years from 1994 to 2005. We use the following variables: amount of deposit holdings, and the physical location of each branch, ie. in what state and in what MSA the branch is located. There are 59 states and 369 MSAs.

We calculate the local market concentrations, ie. Herfindahl Hirschman Index (HHI), in each MSA by using the deposit holding information. HHI is the sum of squared market share percentages for each banking institution in a given market. If there are two or more banking institutions under the same bank holding company, we consider only the bank holding company as an entity in calculating the local market HHI. For each possible merger of buyer and target banks we calculate both pre and post merger HHI levels to determine if there will be any Antitrust violations after the merger. The location information is used in calculating the match specific geographical proximity covariates, which will be explained in detail in the estimation part.

SNL Financial offers extensive bank merger data. In this study for each bank merger transaction, we use the identities of the buyer and target banking institutions, the announcement and completion dates, amount of assets, deposits, core deposits, and number of branches for buyer and target banks, and the transfer that the buyer pays to the target. These attributes are as of the announcement date of the merger transaction.

The data we use in the estimation is the combination of these two data sets. For each merger transaction that we have in SNL data set, we add market existence information of each bank that we capture from the FDIC data set. We considered two market definitions, state level and MSA level, so we can see how many branches each bank has in each of these market definitions.

4 Estimation

4.1 Functional Form Specification

In this study we are looking for what attributes of the banks are important in merger decisions. We classify the attributes into two categories; physical attributes and geographical branch location attributes. We investigate whether these physical attributes are interacted, and if they are, how they are sorted in the post merger value functions. We also calculate the effect of geographical proximity of the buyer to the target for each merger.

Figure 1 shows the relationship between asset sizes of buyers and targets for the observed matches. We observe that as the size of the buyer increases the target size also increases. But another striking fact is that the the targets' assets are smaller than buyers' assets most of the time. In Figure 2 we observe more or less the same pattern as seen in the asset sizes. Number of targets' branches are smaller than buyers' number of branches, and buyers with higher number of branches merge with targets with higher number of branches. We could use the deposit and core deposit data as well, however they are strongly correlated with the amount of asset. To avoid multi collinearity problem we do not use them.

So we use amount of assets and branch numbers to calculate the degree of positive assortative sorting, and to find out for which one of these attributes sorting is more important. We propose two different functional form specifications for the post merger value function.

Specification 1:

$$f(b,t) = A_b A_t + \beta_B B_b B_t + \sum_{(b,t)} \text{covariates} \tag{10}$$

Specification 2:

$$
\begin{aligned}
f(b,t) &= 1[A_b > A_t] + \beta_{A1} 1[A_b > A_t](A_b - A_t)^2 + \beta_{A2} 1[A_b < A_t](A_b - A_t)^2 \\
&\quad + \beta_{B0} 1[B_b > B_t] + \beta_{B1} 1[B_b > B_t](B_b - B_t)^2 + \beta_{B2} 1[B_b < B_t](B_b - B_t)^2 \\
&\quad + \sum_{(b,t)} \text{covariates}
\end{aligned} \tag{11}
$$

A_b and A_t are asset sizes for buyer b and target t respectively. Likewise Bs denote the branch numbers. Asset variables are in natural logarithm of thousands of dollars, while branch variables are in natural logarithms of actual branch numbers. In the first specification we can estimate the relative importance of branch sorting to asset size sorting. In the second one, we can estimate the severity of punishments in increasing the gap between target's and buyer's asset or branch levels.

In both specifications we create some match specific covariates to calculate the geographical proximity. We use the branch existence information in two different market definition, state level and MSA level. For each of these market definitions, we create three dummy variables. "InSameMarket" shows that if the target's branches are located in the same markets as the buyer's branches are, ie. there is a complete overlapping of markets. "PartialOverlap" takes value of 1 if some of the target's markets overlap with buyer's markets. "Expansion" is for the buyers and targets that have no overlapping at all. We want to see what kind of market overlapping brings most value to the mergers.

Tables 3 and 4 gives the summary of data for each market definition we use in the estimation. We can see the number of mergers, and the proportions of mergers for each market overlapping type. We have less number of mergers in MSA markets since we discard the banks operating in non MSA markets.

When defining the state level market, we calculate the neighboring proportion of the target's states to buyer's state. It is calculated as the ratio of the sum of target's states that are neighbor to any one of the buyer's states to the sum of all target's states. We multiply this ratio, which we call "Neighbor", by the above mentioned dummy variables to see whether neighboring ratio increases the post merger value.

MSA level market analysis allows us to calculate pre and post merger HHIs in each of the overlapping market for a merger. We create a variable called HHIViolation by calculating the proportion of target's markets violating the Antitrust guidelines. For an overlapping market to have a violation, post merger HHI exceeds 1800 and the change in HHI is greater than 200, or the total market share of the merged entity exceeds 35%. In case of violation Antitrust challenges the merger case. Buyers may be willing to increase market power in local markets by buying one of the competitors in that market. However Antitrust guidelines discourages banks to buy its competitors in a local market which will be more concentrated. We want to learn if the violations decreases or increases the post merger value. If the coefficient is positive, the buyers get more value although there will be violations in a market that Antitrust will challenge. This value comes from the increased market power in that particular market. If the coefficient is negative, that implies buyers are precluded to do so by Antitrust guidelines.

Estimation is performed by using a global optimization routine called differential optimization, which is introduced in **?**), to maximize the objective functions (6) and (7). These estimators are semi parametric because we do not impose any functional form for error distribution in the model.

4.2 Estimation Results

We estimate the model by using both of the specifications and by employing both of the estimators. The results are reported in Tables 5, 6, 7, and 8 in the Appendix. This study currently gives only the point estimates, we do not have the 95% confidence intervals for the coefficient estimates yet. Therefore, we focus on the relative sizes and signs of the estimates in interpreting.

The columns differ in the market definitions and the variables used in the estimation. Columns starting with 'S' denotes when market is defined as state level, while 'M' stands for MSA markets. The last row provides the percentage of correct predictions in objective function for each estimation.

In estimation of specification 1 by using the "without transfer estimator", we have to normalize the asset coefficient by 1. Then the coefficient of the branch interaction variable shows the relative importance of sorting in branches to sorting in asset sizes. All estimation types give the result that sorting in branch sizes is less important than sorting in assets. (S2) shows that merged entities in the same market and having partial overlap have more value than if they are in totally separate markets. This additional value is higher for the ones in the same state. When we give weights to the market expansion dummies (S3), we see that as target has more neighboring states the higher value the merged entity will get, for all kinds of expansion. Again the highest extra value is brought by in the same state mergers. We get the same result if we consider the market in MSA levels, in (M2), that in same market has the highest extra value. However, MSA analysis (M3), which is performed by using the pairwise comparisons only in the same market, gives us a negative coefficient on the HHIViolation meaning that having a post merger violation in a local market which will end up with a challenge by Antitrust authorities, decreases the post merger value. This shows the unwillingness of the buyers to buy any of its competitors in the local market to increase its market power resulting violation. Put differently, if there is a deregulation or even decreasing the severity of the restriction, merger banks will no longer have negative effect in post merger valuations so we will observe more and more in same market mergers.

When we perform the estimation of specification 1 by the "with transfer estimator", we get the same qualitative results. Since we do not have 95% confidence levels for the estimates, we prefer not to make any inference in the levels of these estimates even if these values correspond to dollar values.

Estimation of specification 2 tells us that punishment for the gap in branch levels are less severe than that for the gap in asset sizes. So we can conclude that sorting in assets is more important. If we compare the different market expansion coefficients, we see that in same state mergers have significantly higher extra value than partial overlap in states merges. These coefficients for the MSAs are nearly the same. There is no significant extra value in merging a target operating in the buyer's MSA markets. We should note that signs of (M3) coefficients, especially HHIViolation, are the same as we get in the first specification. So we have consistency in our results.

5 Future Work

One task to be done for the current analysis is to calculate the standard deviation of the estimates by performing subsampling. This will allow us to obtain 95% confidence intervals for the estimates. Then, we can interpret monetary value estimates obtained by "with transfer estimator". Furthermore, we can enrich the interpretation of the results by calculating marginal rate of substitution for the buyer so that we can describe the buyer's preferences.

We define an alternative estimator, ie. "with transfer estimator". We only check its validity by Monte Carlo experiments, resulting with a less bias and a less variance than the "without transfer estimator". However a formal consistency proof should be made.

When we use MSA level market we have to discard bank mergers in non MSA markets. This results in losing information. To use merger data in these areas as well, we can keep track of branch locations in county level for those banks.

We model the merger market as a two sided one to one matching market. We empirically study the market by classifying banks as buyers or targets according to what we observe in the data. We do not impose any clear cut definitions to be a target or a buyer bank in this framework. This can cause a problem in predicting which banks will merge. Any given bank can be either a target or a buyer depending on the market. If it receives a good offer, it can be a target. If it comes up with a target that can be convinced with a transfer such that it increases its payoff post merger, it can end up being a buyer. Thus, the current model analyzed in this paper should be extended to one to many matching, and furthermore, to one sided matching framework, ie. roommate problem. However the results that we obtain in this study will form a benchmark in our later analysis.

6 Appendix

Figure 1: Buyer vs. Target Assets (in logs)

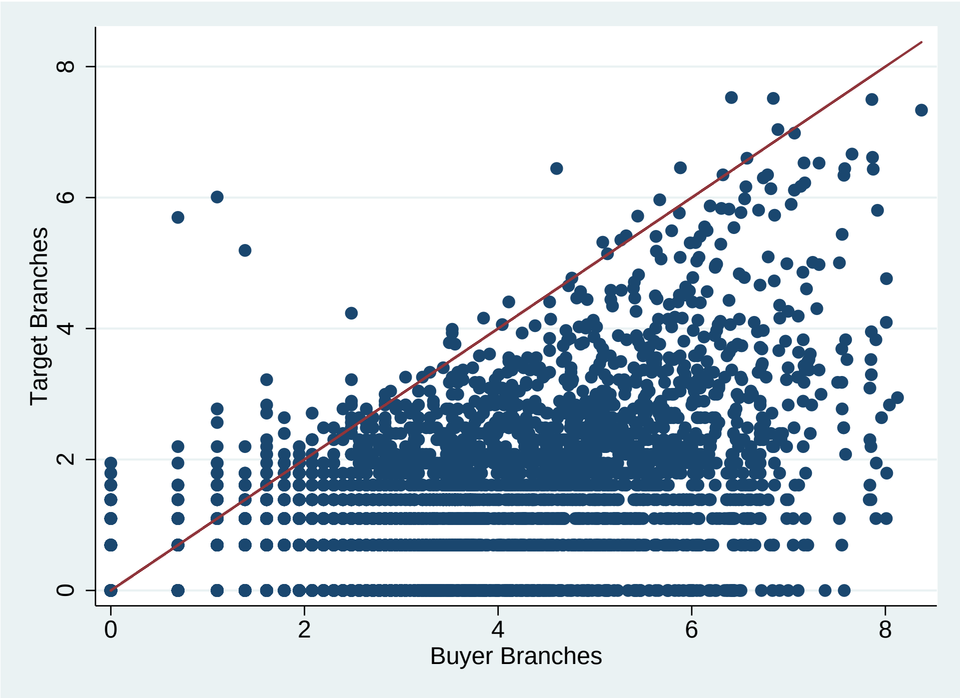

Figure 2: Buyer vs. Target Branches (in logs)

Table 3: Market Definition: State

Year	# of mergers	InSameMarket	PartialOverlap	Expansion
1995	268	0.8993	0.0112	0.0896
1996	224	0.8973	0.0089	0.0938
1997	224	0.8393	0.0000	0.1607
1998	304	0.8289	0.0362	0.1349
1999	217	0.8157	0.0553	0.1290
2000	168	0.8869	0.0298	0.0833
2001	156	0.8333	0.0577	0.1090
2002	128	0.8438	0.0313	0.1250
2003	117	0.8889	0.0342	0.0769
2004	160	0.7875	0.0625	0.1500
2005	130	0.8538	0.0308	0.1154

Table 4: Market Definition: MSA

Year	# of mergers	InSameMarket	PartialOverlap	Expansion
1995	168	0.6488	0.0774	0.2738
1996	146	0.6027	0.0616	0.3356
1997	152	0.6184	0.0592	0.3224
1998	221	0.4661	0.1086	0.4253
1999	158	0.5443	0.0886	0.3671
2000	109	0.5138	0.1284	0.3578
2001	121	0.5950	0.1570	0.2479
2002	93	0.5699	0.0538	0.3763
2003	95	0.6842	0.0947	0.2211
2004	120	0.4667	0.2083	0.3250
2005	101	0.6040	0.0396	0.3564

Table 5: Specification 1, without transfer estimator

Variables	(S1)	(S2)	(S3)	(M1)	(M2)	(M3)
Asset	1	1	1	1	1	1
Branch	0.6764	0.4864	0.4365	0.6767	0.6649	-0.0854
InSameMarket		7.8	8.44		11.05	
PartialOverlap		6.82	5.67		10.983	
Expansion			4.64			
HHIViolation						-9.578
% of success	74	95.5	96.2	74	93	69

Table 6: Specification 1, with transfer estimator

Variables	(S1)	(S2)	(S3)	(M1)	(M2)	(M3)
Asset	0.0161	0.0441	0.0635	0.01619	0.0287	0.07
Branch	0.1851	0.083	0.0392	0.1851	0.1428	0.1189
InSameMarket		2.562	3.2158		3.508	
PartialOverlap		1.744	2.4238		3.264	
Expansion			1.5159			
HHIViolation						-14.532
% of success	21	78	85	21	68	12

Table 7: Specification 2, without transfer estimator

Variables	(S1)	(S2)	(S3)	(M1)	(M2)	(M3)
Asset, β_{A0}	1	1	1	1	1	1
Asset, β_{A1}	-0.1003	-0.095	-0.0962	-0.3373	-0.2064	-2.977
Asset, β_{A2}	-25.234	-10.28	-4.07	-22.33	-17.288	-2.381
Branch, β_{B0}	0.995	0.93	0.393	0.9714	0.2113	1
Branch, β_{B1}	-0.0733	-0.0463	-0.0484	-0.2276	-0.1383	0.197
Branch, β_{B2}	-1.2203	-0.845	-2.086	-4.058	0.5575	4.074
InSameMarket		9.05	10.414		5.73	
PartialOverlap		4.49	7.122		5.71	
Expansion			5.675			
HHIViolation						-18.094
% of success	74	95.5	96.3	74	93	69

Table 8: Specification 2, with transfer estimator

Variables	(S1)	(S2)	(M1)	(M2)	(M3)
Asset, β_{A0}	0.4024	0.2911	0.4024	1.3197	0.1567
Asset, β_{A1}	-0.2672	-0.3717	-0.2672	-0.2059	-0.3325
Asset, β_{A2}	-1.596	-3.3971	-1.597	-7.483	-0.4627
Branch, β_{B0}	0.7687	0.1850	0.7687	2.158	0.3474
Branch, β_{B1}	-0.043	0.0199	-0.043	-0.1888	0.1274
Branch, β_{B2}	-1.369	-2.181	-1.369	-0.0951	-0.1418
InSameMarket		5.6188		6.3266	
PartialOverlap		3.781		5.1047	
HHIViolation					-1.625
% of success	43	83	48	74	29