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The Determinants of Bank Mergers: A Revealed Preference Analysis

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We provide new estimates of merger value creation by exploiting revealed preferences of merging banks within a matching market framework. We find that merger value arises from cost efficiencies in overlapping markets, relaxing of regulation, and network effects exhibited by the acquirer-target matching. Beyond our findings, the revealed preference method has notable advantages that warrant its application beyond the bank merger market. Notably, we show that the method outperforms reduced form alternatives out of sample, enables sensible counterfactual experiments, and can be used to evaluate private-to-private mergers, which have been understudied because of lack of stock market data.

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1. Introduction

Understanding merger value creation is critically important for the shareholder value at stake, and because how merger value is created has important implications for the nature of competition and consumer well-being (e.g., see Bernile and Lyandres 2010). Unfortunately, the vast majority of mergers involve at least one private company, making it difficult to estimate value creation using changes in stock market value around merger announcements (Bayazitova et al. 2012). This limitation of stock market evidence is especially pronounced in industries where private firms play an important role (e.g., banking, supermarkets, restaurants).

To overcome this difficulty, we develop a novel approach to estimate merger value creation that can be applied even for private-to-private mergers because it relies on the choices of the merging firms directly, rather than stock market responses to the merger announcement.[1] We use the structure of a two-sided matching market to identify outside options for each firm (e.g., see Becker 1973, Roth and Sotomayor 1990) and use characteristics of these outside options in comparison to the actual merger choices to structurally estimate merger value creation. Our approach has three notable advantages relative to reduced form methods that utilize stock market information. First, our method is easily applied to evaluate mergers with private targets or acquirers because it does not rely on stock market information. Second, our structural estimation accounts explicitly for the endogenous matching process by which acquirers match with targets, which is an important source of endogeneity in determining which characteristics matter for merger synergies. Finally, our structural analysis allows for counterfactuals, which are difficult using reduced form methods.

We highlight each of these advantages in an empirical analysis of the bank merger market, employing comprehensive merger-level data from 1995 to 2005 in our study of the determinants of bank merger value. The choice to study bank mergers is natural because it is straightforward to define the scope of the matching market within a narrowly defined industry such as banking. This is especially true during our sample time frame (1995–2005), the decade following the elimination of cross-state branching restrictions (Riegle-Neal

[1] Using a method that is similar in spirit, Devos et al. (2009) use Value Line forecasts of cash flows to produce an estimate of merger value that is linked directly to the underlying fundamentals of the firm. In comparison to their method, our technique does not require analyst coverage or any assumption about the validity of the forecasts. In place of an assumption that the forecasts are reliable, we maintain the assumption that each firm in the merger market reveals a consistent set of preferences by their choice of merger.

Interstate Banking and Branching Efficiency Act 1994).[2] We use this cross-state standardization of merger regulations to motivate our treatment of mergers in the U.S. banking industry as a national merger market that takes place each year.

In our empirical analysis, we recover a structural merger value function that accounts explicitly for the endogenous matching process; thus, it can be used for causal inference. We use our approach to study how features of the acquirer and the target institutions affect the value of the bank merger. According to industry sources, an important reason for banks to merge during our sample was to capitalize on economies of scale. As a 1998 article in the *San Francisco Chronicle* noted, "A bigger bank can acquire customers more cheaply by marketing on a national scale, and can reduce risk by diversifying geographically" (Marshall 1998). In a two-sided matching market, these factors suggest that large banks derive more value from larger target banks, which would generate a positive assortative match in bank size (Becker 1973). Our framework accounts for this cost advantage of large banks by including terms in the match value function that capture the interaction between the size of the acquirer and target banks.

Our main specification quantifies the effect on merger value of cost efficiencies of various types (e.g., merging to a more efficient scale and capturing economies of scope in nearby markets), as well as merger value derived from additional market power. Our structural approach accounts for these explanations by defining a merger value function that explicitly depends on market concentration and the overlap between acquirer and target markets. We also include measures of performance and valuation of the target banks to evaluate how target performance relates to value creation (Maksimovic and Phillips 2001). In effect, this specification allows us to distinguish whether the merger value we recover arises from choices motivated by synergies of different types. The revealed preference method allows the data and the pattern of mergers to speak directly to which of these explanations is consistent with merger decisions and merger value creation.

Throughout our empirical exercise, we find that the mergers we study were primarily motivated by efficiencies, cost reductions, or reducing inefficiencies from previous regulations, and that market concentration (measured by a Herfindahl index) also contributes positively to the value of the merger. On the other hand, we find little evidence that mergers were motivated by high (or low) performing target banks. Consistent with an efficiency rationale for value creation, we find that merger value is greater when there is a greater overlap between acquirer and target markets, and that these gains are greater for mergers between banks regulated by the same agency before the merger. These effects likely represent efficiencies rather than market power because we also control for market concentration in the target's markets in these specifications. The magnitude of these efficiency effects on merger value are sensible, amounting to nearly the annual administrative cost of operating a single bank branch (Radecki et al. 1996). These efficiencies may arise from the ability of the combined bank to pool fixed operating expenses such as advertising and ATM networks across the acquirer and target banks.[3]

Our work also sheds light on the effects of banking deregulation by studying mergers in the post-Riegle-Neal banking industry. Early work on banking deregulation focused on how deregulation affects aggregate measures of economic activity such as state per capita income growth and its volatility (Strahan 2003). More recent work has turned to study deregulation's competitive effects on small-firm finance and innovation (Rice and Strahan 2010, Cornaggia et al. 2015). We deepen existing work on the outcomes of banking competition by studying the value of bank mergers at the merger level. When we aggregate to the entire banking industry, we estimate significant value generated from the increased merger activity during our post-Riegle-Neal sample, a new and novel quantitative indication that the prohibition of banking and branching across state lines was costly.

In addition, we include other features of banking regulation in our specifications for the merger value function. In particular, we allow the merger value function to depend on whether the acquirer and target have different banking charters; thus, they report to different regulatory agencies before the merger. By including this information in the merger value function, we recover the implicit costs of diverse chartering regulations from the pattern of mergers. In this way, our results speak to the effects of inconsistent regulators and are complementary to the evidence presented

[2] The 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act effectively standardized the state-by-state deregulation in branching rules that had been taking place over the previous two decades. After the Riegle-Neal Act, the U.S. banking industry consolidated considerably, in large part due to the merger wave we study. Specifically, the total number of banking institutions in the United States declined from 10,416 to 7,582 in the decade following Riegle-Neal (FDIC Summary of Deposits, 1995–2005). For a complete historical account of this deregulation process as well as a comprehensive empirical analysis of its determinants, see Kroszner and Strahan (1999).

[3] Viewed from the perspective of the banking literature, these findings provide an external check on previous work that evaluated market power versus branching efficiency motives for bank mergers using stock market evidence (Rhoades 1994, Seims 1996). Notably, the existing literature documents a takeover premium for acquired firms, because in the broader merger literature (Rhoades 1994, Eckbo 2009) mergers do not appear to lead to significant changes to market concentration, and there appears to be an efficiency motive for mergers between banks with significant overlap in markets (Seims 1996).

by Agarwal et al. (2014). In a counterfactual exercise, we find that value generated by mergers would be 20%–50% higher per year if all banks were of the same charter type. This result suggests that there are significant frictions in the bank merger market imposed by regulation.[4] Once we rescale our estimates by the fraction of banks that merge in a typical year, our counterfactual-estimated cost of bank chartering regulation equals 1%–2.5% of the value of the entire banking industry. This cost estimate reflects both implicit and explicit costs as revealed by choices of the merging firms and is of the same magnitude as explicit annual supervisory costs (Whalen 2010).

Because our approach uses the matching equilibrium explicitly in a structural model, the estimated match value function we obtain can be used to predict bank mergers, even after the policy environment changes. A structural approach like ours is particularly useful because matching market equilibria are sensitive to small perturbations in payoffs and changes in the policy environment. In these cases, structural estimates can be used to more reliably predict merger outcomes than analogous reduced form approaches. Indeed, the predictive strength of our structural method is borne out in the data. We compare the one-year-ahead predictive accuracy of our structural method to a reduced form predictive regression that uses a binary logit and the predictors that make up our match value function. We find that our revealed preference method dramatically outperforms standard predictive regressions, allowing us to more reliably predict mergers one year ahead than a binary logit approach. Our method represents such a dramatic improvement over reduced form predictive regressions partly because reduced form methods without proper instruments are subject to endogenous matching. Our technique explicitly accounts for the endogenous matching process, thereby providing a more reliable basis for predicting mergers.[5]

[4] These frictions reduce value generated in the bank merger market because we find that—on balance—the mergers in our sample generate value. If the mergers that were obstructed by the frictions were value destroying, the regulatory frictions could actually increase value.

[5] Although our method requires relatively few assumptions, a notable assumption we employ to apply our model to the bank mergers setting is that the bank merger market is national immediately after the Riegle-Neal Act passed. This assumption is not literally true because some states lagged in their official adoption of the law's provisions (see Johnson and Rice 2008). We address this concern about the validity of our assumption and robustness of our method by estimating the match value function in each year of the sample. The predictive accuracy of our structural method outperforms the baseline binary logit predictive accuracy in every year of our sample (even in earlier years), suggesting that to the extent the assumption is violated, the advantages of our structural method outweigh the costs. The online appendix (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2015.2245) presents and reports this exercise.

The fact that we maintain the assumption that managers maximize firm value highlights a limitation of using our revealed preference methodology. By relying on the choices of managers to identify what determines merger value, the revealed preference method recovers the value created from the standpoint of managers, not necessarily shareholders. Thus, whenever agency conflicts are important, revealed preference estimates of value creation are a poor substitute for event study estimates, which more directly recover value created for shareholders. This limitation is important to keep in mind when applying our methodology to study shareholder value or fundamental synergies. Nonetheless, using our structural merger value function to estimate merger value creation, we estimate an annual average of 6.02% of mergers that destroy value from the standpoint of the merged entity. Although our estimates are based on the choices of managers, our magnitudes are similar to recent estimates of merger synergies from the shareholder's perspective (Bayazitova et al. 2012).

Beyond being consistent with recent stock market evidence on merger synergies, several advantages of the revealed preference method are important to emphasize. First, because it does not rely on stock market data, our revealed preference method can be applied to mergers between two private entities when mergers and characteristics data for private-to-private mergers are available, expanding the potential scope of analysis and inference. In a similar vein, other authors have expressed interest in relaxing the dependence of merger value creation measures on stock market data. Maksimovic and Phillips (2001) suggest an alternative method for evaluating the value of mergers that does not rely on stock market information, by using productivity measures. More recently, Devos et al. (2009) produced estimates of merger synergies from Value Line forecasts, which depend more directly on fundamental value creation. Our method shares the advantage of these methods without requiring a reliable measurement of productivity or coverage by Value Line. Second, our structural model accounts for endogenous merger selection directly, which enhances confidence that the characteristics that drive merger values actually drive merger values, rather than a by-product of the merger selection process. Finally, our structural method allows for counterfactual exercises that are robust to changes in the policy environment. This feature of our structural exercise enables a more accurate forecast of merger activity than alternative methods to predict mergers.

More broadly, our approach relates to recent work by Gorbenko and Malenko (2014), who estimate merger valuations by explicitly modeling each merger as an independent auction using observed takeover bids. In contrast, our equilibrium-based approach implies that takeover bids are not independent but are linked across targets because each acquirer in the same merger market can bid on the same set of targets. We infer merger value by the choices forgone by successful bidders, and as a result our method does not require observation of successful and unsuccessful bids by acquirers. This is an attractive feature of our setting when high bids by strong potential acquirers discourage bidding from potential acquirers with slightly lower valuations, or when few formal bids are solicited from strongest potential acquirers.

Our work also relates to a growing literature in industrial organization that employs revealed preference methods (e.g., Aguirregabiria et al. 2012). Notably, Chen and Song (2013) apply the Fox (2010a) estimator to the matching between banks and firms and find evidence of a positive assortative match between banks and firms. To the extent that firms' linkages with target banks are persistent, we should expect that these characteristics of bank-firm matching would be relevant to acquirer-target bank matching, which is our focus. Indeed, that larger targets likely have larger firms as clients is one reason to expect that acquirer and target banks mergers will also exhibit the positive assortative match we document here.

More generally, our paper contributes to an increasingly important segment of the empirical finance literature that explicitly addresses endogeneity in financial markets research (Roberts and Whited 2012). In the last decade, structural approaches have yielded new insight into a wide variety of topics in finance, including debt dynamics, corporate cash holdings, and the role of venture capital firms (Sørensen 2007, Hennessy and Whited 2005, Boileau and Moyen 2016). Relative to existing structural work in finance, our paper employs relatively few assumptions to recover a structural value function. As a result, our method is conceptually straightforward, and similar methods to ours should find fruitful application to address important questions in financial economics.

The remainder of this paper is structured as follows. Section 2 presents our revealed preference method and uses Monte Carlo experiments to evaluate the estimator's small sample properties. Section 3 describes the data and basic summary statistics. Section 4 motivates and describes the form of our specifications. Section 5 is a discussion of the main results on value creation and the determinants of value creation. Section 6 discusses in-sample and out-of-sample performance, compares to relevant alternatives, and presents a counterfactual simulation. Section 7 concludes.

2. The Revealed Preference Model

When analyzing merger value, it is instructive to observe that each acquirer deliberates among a number of viable alternative targets, and each target considers viable offers from a number of alternative acquirers. In practice, targets often entertain multiple takeover bids at the same time (e.g., see Bhagat et al. 2005), but these offers need not be explicit to matter for the merger market decisions of targets and acquirers. Through this equilibrium channel, the values of feasible alternative matches—both implicit and explicit offers—provide a lower bound for the value of each realized merger. Our revealed preference approach formalizes this intuition by explicitly using the characteristics of each bank's alternative matches together with the observed acquirer-target transfers to estimate the value of the mergers that do occur.

In our model of bank mergers as a two-sided matching game (Roth and Sotomayor 1990), the merged acquirer-target pair realizes a joint match value, which is split using an equilibrium transfer from the acquirer to the target. Each bank matches with the bank on the other side of the market that maximizes its individual payoff. In equilibrium, matched banks receive a higher payoff from the observed match partners than they could get from counterfactual partners.

In the model, we construct many possible counterfactual matches to each observed match within a matching market, yielding many inequalities in the structural match value for each observed match. Given these inequalities and a parametric form for the match value function, we choose the parameter vector that maximizes the fraction of inequalities that hold. This is the maximum score estimator, which Fox (2010a) proved to be consistent for matching games given a rank order condition (as in Manski 1975, 1985).[6] Building on Fox (2007; 2010a, b),[7] we develop a maximum score estimator that incorporates acquirer-target transfer data. Transfer data allow the maximum score estimator to produce estimates on an interpretable scale, which is advantageous for understanding the determinants of merger value creation.[8]

[6] Fox (2010a) made separate consistency arguments for one large matching market and many independent matching markets. In the U.S. bank mergers setting for our sample time frame, we have 11 distinct matching markets, one for each year. We view each annual matching market as a large matching market, consistent with the single matching market case in Fox (2010a), and the fact that we observe mergers for multiple years allows us to estimate the match value function with even greater precision. Nevertheless, our year-by-year results rely more explicitly on the assumption of a large matching market that meets each year.

[7] The maximum score estimator proposed by Fox (2007) does not use data on transfers. The fact that the estimator works when transfer data are not available is an advantage if no data on transfers are available, which is true in many matching contexts.

[8] In addition, we demonstrate that for parameters that are identified using the without-transfers estimator of Fox (2010a), our estimator is more precise. We also demonstrate that our method identifies parameters that cannot be identified without transfer data, e.g., the sensitivity of the match value function to a change in some characteristic of the target bank.

2.1. Matching Model

For a total number of M_y matches in matching market y, we denote acquirers by $b = 1, \ldots, M_y$ and targets by $t = 1, \ldots, M_y$. We assume there is one national merger market per year and markets in different years are independent of one another. The merged pair (b, t) realizes a post-merger value $f(b, t)$, which is the summation of the individual payoffs to the acquirer and target, $f(b, t) = V_b(b, t) + V_t(b, t)$.

The payoff to the acquirer $V_b(b, t)$ is the post-merger value minus the acquisition price p_{bt} paid to the target, $f(b, t) - p_{bt}$. The target's payoff $V_t(b, t)$ equals the acquisition price p_{bt}. Each acquirer b maximizes $V_b(b, t)$ across targets. Each target t maximizes $V_t(b, t)$ across acquirers. In the matching equilibrium, every bank derives higher value from the observed acquirer-target match than from any counterfactual match. This revealed-preference insight gives inequalities that we use in our estimation. For example, if acquirer b is matched with target t, whereas target t' could have been acquired by acquirer b, we infer that b derives more value from being matched with t than with t', which gives the following condition:

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

The transfer from acquirer b to target t' $p_{bt'}$ is not available from data on observed matches; however, in equilibrium each target t receives an offer that is the same across acquirers. For acquirer b to acquire target t, the offer p_{bt} from acquirer b must be weakly greater than the offer $p_{b't}$ from a competing acquirer b'. Acquirer b's equilibrium offer will not be strictly greater than the alternative because higher offer prices reduce acquirer b's payoff. Hence, $p_{bt'} = p_{b't'}$ and the inequality in (1). The same logic applies to acquirer b', yielding the following inequalities:

$$f(b, t) - f(b, t') \geq p_{bt} - p_{b't'}, \tag{2}$$

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

The inequalities have a natural interpretation. For example, (2) means that the extra value that acquirer b derives acquiring target t rather than target t' exceeds the extra expense of acquiring target t rather than target t'. Equations (2) and (3) are useful if we have data on transfer amounts, but these data are often unavailable. In the absence of transfer data, we can add these inequalities to obtain a single inequality that does not rely on data from transfers:

$$f(b, t) + f(b', t') \geq f(b', t) + f(b, t'). \tag{4}$$

This inequality implies that the total value from any two observed matches exceeds the total value from two counterfactual matches constructed by exchanging partners.

2.2. Estimation of the Matching Model

Let ε_{bt} be a match-specific error that affects the value to acquirer b matching with target t. Then, acquirers and targets match to one another according to the match value function $F(b, t) = f(b, t) + \varepsilon_{bt}$. Because each acquirer can only acquire one target, the acquirer's choice among targets is a discrete choice. As a simple semiparametric technique to estimate this discrete choice, we turn to maximum score estimation.[9] Fox (2010a) developed a maximum score estimator that makes use of inequality (4). Specifically, given a parametric form for the match value function $f(b, t \mid \beta)$, one can estimate the parameter vector β by maximizing

$$\begin{aligned} Q(\beta) = \sum_{y=1}^{Y} \sum_{b=1}^{M_y - 1} \sum_{b'=b+1}^{M_y} 1\big[& f(b, t \mid \beta) + f(b', t' \mid \beta) \\ & \geq f(b', t \mid \beta) + f(b, t' \mid \beta) \big] \end{aligned} \tag{5}$$

over the parameter space for β. For a given value of the parameter vector $\tilde{\beta}$, $Q(\tilde{\beta})$ is the number of times the inequality (4) is satisfied. The maximum score estimator $\hat{\beta}$, therefore, maximizes the number of times that this inequality holds among the set of inequalities considered.[10]

Although attractive in its simplicity, the maximum score estimator based on (4) does not make use of transfer data, which may significantly improve the performance of the estimator. Moreover, acquirer-specific or target-specific attributes cancel out when we add the inequalities (2) and (3) together to obtain (4). Therefore, any parameters that measure the sensitivity of the match value function to target-specific attributes cannot be identified with maximum score estimation based solely on without-transfers information.[11]

[9] If we assume that the match-specific errors ε_{bt} are distributed i.i.d. Type 1 extreme value, the model reduces to the familiar multinomial logit model. A significant weakness to the multinomial logit approach is that it imposes a restrictive set of substitution patterns, for example, the red-bus blue-bus problem (McFadden 1974, Debreu 1960). An acquirer should be more likely to substitute between similar targets, yet the multinomial logit model does not easily allow for this type of substitution. We explicitly contrast the performance of the multinomial logit to our maximum score technique in the online appendix. The online appendix also considers another alternative, one-sided matching. In both cases, our two-sided matching method that uses maximum score estimation is preferable.

[10] Fox demonstrates that one need not consider all possible inequalities to obtain a consistent estimator, but one need merely form a large subset of all possible inequalities. Fox (2010a) shows that the maximum score estimator $\hat{\beta}$ is consistent if the model satisfies a rank order property (as in Manski 1975, 1985) for matching games; i.e., the inequality in Equation (4) implies $P[b$ acquires t and b' acquires $t'] \geq P[b$ acquires t' and b' acquires $t]$. In addition to providing intuition for conditions under which the maximum score estimator should be used, this strong version of the rank order property is used in the identification arguments given by Fox (2010b).

[11] This point only applies to target-specific attributes. The sensitivity of match value to acquirer-specific attributes is unidentified in

Both to improve the precision of the estimator and to identify the effect of target-specific attributes, we develop a related estimator that uses transfer data, which we call the with-transfer estimator (WT1). We call the maximum score estimator based on Equation (4) the no-transfer-data (NTD) estimator.[12]

For the same pairwise comparisons used to form the objective function for the NTD estimator, the WT1 estimator imposes the inequalities (2) and (3) simultaneously. If both (2) and (3) hold, (4) holds as well, but the converse is not true. The WT1 estimator maximizes the objective function:

$$Q^{tr}(\beta)=\sum_{y=1}^{Y}\sum_{b=1}^{M_y-1}\sum_{b'=b+1}^{M_y}1\big[f(b,t\mid\beta)-f(b,t'\mid\beta)\geq p_{bt}-p_{b't'} \\ \wedge f(b',t'\mid\beta)-f(b',t\mid\beta)\geq p_{b't'}-p_{bt}\big]. \quad (6)$$

In the online appendix, we perform a series of Monte Carlo exercises to evaluate the properties of the WT1, finding that our WT1 performs well relative to a number of notable alternatives.[13] Relative to the without-transfers estimator of Fox (2007), we confirm two main advantages: (1) transfers data allow for much greater precision in estimating determinants of merger value creation, and (2) the with-transfers estimator can identify parameters that are otherwise unidentified without data on transfers—namely, target-specific determinants of merger value creation.

2.3. Interpretation of Estimated Merger Values

It is important to clarify the interpretation of estimated merger values from our framework. Because we rely heavily on manager choices to infer merger value creation, our approach recovers the value created *from the standpoint of the managers of the firm*. Given this, if the managers maximize shareholder value, revealed preference estimates of merger value creation are a good substitute for stock market estimates. On the other hand, when agency problems between managers and shareholders are important (e.g., empire building motives), manager-centric values from a revealed preference approach will correspond less well with changes in shareholder wealth.

In addition, even if there are no agency conflicts between shareholders and managers, greater cross-ownership of acquirer and target firms by institutional investors (as is studied by Matvos and Ostrovsky 2010) reduces the cost of large acquirer-to-target transfers from the standpoint of shareholders. In this context, managers who well represent the preferences of their institutional shareholders view transfers as less costly than they appear from the standpoint of our methodology. In our methodology, a merger that occurs despite a high transfer price is inferred to have high synergy. As such, mergers with a high degree of cross-ownership will tend to have greater merger values inferred from revealed preference. These high estimated merger values arise because of synergies in who owns the firms, not necessarily because of fundamental synergies in the underlying firms.

With these caveats in mind, our revealed preference method is an effective method to use when studying the motives of managers to undertake corporate decisions, but to the extent that there are agency conflicts, future research should be cautious in applying the insights from revealed preference to the value created for shareholders or to fundamental synergies. On the other hand, our revealed preference estimates of merger value creation are manager-centric, which implies that they may be more appropriate for recovering merger synergies that are more salient to managers than to shareholders.

3. Description of Data

3.1. Merger-Deal Data

We study the matching market for banks using comprehensive bank merger and attribute data from SNL Financial (http://www.snl.com/). The data span all bank mergers in the United States between 1995 and 2005 and provide information about acquirer and target banks at the merger-deal level. For the date at which the acquisition is announced, the data provide the asset holdings (A_b and A_t) and number of branches (B_b and B_t) for both acquirer and target bank. We also observe the market value of the transfer (p_{bt}) from the acquirer bank to the target bank upon merging.

SNL Financial's database also provides data on several performance measures of acquirer and target banks. These performance measures are the efficiency ratio (noninterest expense/(net interest income + other income)) and the loan loss reserve coverage ratio (loan

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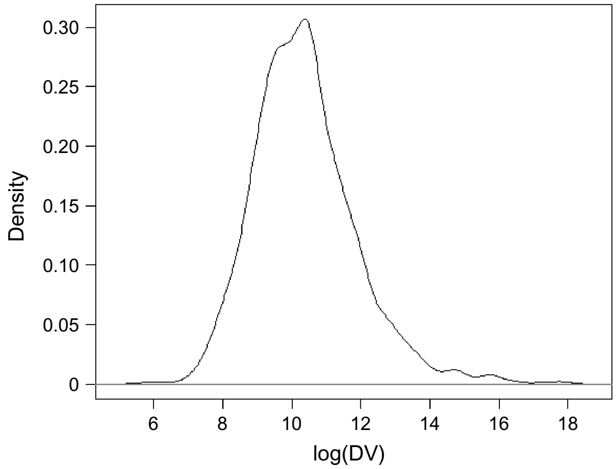
this revealed preference model. This is straightforward to see in Equations (2) and (3). For example, the difference on the left-hand side of (2) refers to the same acquirer; thus, anything characteristic in the value function that is acquirer specific is differenced out of the revealed preference inequalities.

[12] We have also considered an alternative with-transfers estimator (WT2) that imposes inequalities (2) and (3) separately, but this estimator does not perform as well in the Monte Carlo experiments as WT1. In the online appendix, we also describe a quadratic loss specification where differences between target and acquirer are penalized, and a cross-attribute specification in which asset × branches interactions are allowed.

[13] In addition, the online appendix reports a comparison of the with-transfers estimator to a multinomial logit specification along the lines of McFadden (1974), and we find that our structural method has greater precision. We also relax the assumption that mergers occur in a matching market with two sides (acquirers and targets) in favor of a weaker assumption that each bank that merged could be on either side of the merger market. Our method based on two-sided matching exhibits strikingly similar performance as this one-sided matching model.

Figure 1 **Distribution of Deal Values in the Bank Merger Sample**



Notes. This figure portrays the distribution of logged deal values in the sample of observed mergers. Deal value is defined as aggregate price paid for the equity of the entity sold in the transaction, as of the event in question. Where available, deal value is calculated as the number of fully diluted shares outstanding, less the number of shares excluded from the transaction, multiplied by the deal value per share, less the number of "in the money" options/warrants/stock appreciation rights, times the weighted average strike price of the options/warrants/stock appreciation rights. Deal value excludes debt assumed and employee retention pools.

loss reserves/nonperforming loans).[14] Because the information on these performance measures is not available for every merger deal in our sample, we employ these measures in auxiliary specifications that serve to check the robustness of our main findings and to speak directly to managerial motives to merge. In addition, we also construct a measure of deal value at the merger-deal level to use as the equilibrium transfer p_{bt} in our with-transfers estimator.[15] Figure 1 portrays the distribution of deal values in our sample in a density plot of logged deal values. From the figure, the distribution of logged deal values is well behaved and symmetric.

3.2. Bank and Branch Attribute Data

The FDIC Summary of Deposits Banking Database gives the deposit holdings as of June 30th of each

Table 1 **Consolidation in the U.S. Banking Industry (1994 to 2006)**

Year	No. of banks	Average branches	Trimmed average branches	Max
1994	10,416	7.81	2.71	2,024
1995	9,825	8.24	2.81	2,028
1996	9,422	8.64	2.91	2,052
1997	9,110	9.01	3.03	2,643
1998	8,744	9.53	3.14	3,132
1999	8,449	9.98	3.24	4,579
2000	8,324	10.27	3.33	4,510
2001	8,175	10.53	3.43	4,329
2002	8,031	10.78	3.54	4,334
2003	7,877	11.15	3.66	4,296
2004	7,756	11.58	3.74	5,835
2005	7,644	12.04	3.83	5,914
2006	7,582	12.50	3.94	5,789

Source. FDIC Summary of Deposits Database. Trimmed averages are computed by dropping the top and bottom deciles and computing the mean.

year and the location—specifically, metropolitan statistical area (MSA) and state—for each branch of each banking institution in the United States from 1994 to 2006. Table 1 presents summary evidence on the merger-induced consolidation in the banking industry. From 1994 to 2006, the number of banking institutions declined from 10,416 to 7,582, whereas the average number of branches per bank increased from 7.81 to 12.50. The consolidation is not merely taking place among a few large banks, as indicated by trimmed mean of branches per bank, which has increased by nearly 50% over this period.

The Summary of Deposits Database also provides information on the regulatory agency responsible for overseeing each bank, which depends on the bank's charter. Banks can adopt either a national charter or a state charter. If the bank has a national charter, it is regulated federally[16] and must become a member of the Federal Reserve, which adds an additional layer of audits in exchange for the liquidity provided by being a member of the Federal Reserve system. Additionally, the FDIC serves as a backup regulator to all banks with national charters. If the bank has a state charter, the state regulatory agency is responsible for audits and the FDIC is the primary federal regulatory.[17] A number of mergers in our sample took place between acquirer and target banks with different charter types. To empirically assess the importance of this regulatory friction, we

[14] The data also contain the price to book ratio (stock price/book value) of target bank at the time of merger as long as the bank is a publicly traded company. Restricting the sample of mergers to those where the target is publicly traded leaves too few observations to obtain reliable estimates.

[15] We measure deal value as aggregate price paid for the equity of the entity sold in the transaction, as of the event in question. Where available, deal value is calculated as the number of fully diluted shares outstanding, less the number of shares excluded from the transaction, multiplied by the deal value per share, less the number of "in the money" options/warrants/stock appreciation rights, times the weighted average strike price of the options/warrants/stock appreciation rights. Deal value excludes debt assumed and employee retention pools.

[16] Depending on the type of institution during our sample time frame, one of two federal regulatory agencies may be responsible for regulating a bank with a national charter: the Office of Thrift Supervision (OTS), which regulates savings banks and savings and loans associations; or the Office of the Comptroller of the Currency (OCC), which regulates national banks.

[17] State-chartered banks can also become members of the Federal Reserve system, but in practice most state-chartered banks do not. This suggests that there is a trade-off between the benefits provided by the Federal Reserve and the auditing requirements.

construct an indicator variable, $same\_charter_{bt}$, which equals one if the acquirer and target have the same type of charter.

At the MSA level, we construct the market share of each banking institution using its fraction of total deposit holdings in the MSA. Using these market shares, we calculate this MSA-level Herfindahl Hirschman Index (HHI) before and after each merger, which allows us to assess whether a merger meets the criteria for additional scrutiny under the U.S. Antitrust Guidelines ($HHI > 1{,}800$ and $\Delta HHI > 200$). We compute each MSA's HHI by taking the sum of squared market shares. Using this information, we construct a merger-deal level covariate $HHI\_violate_{bt}$, which equals the fraction of target t MSAs for which a merger with acquirer b would lead to antitrust scrutiny under the Department of Justice's merger guidelines.

Finally, for acquirer and target branches within MSAs, the FDIC geography identifiers allow us to construct a merger-deal level covariate $overlap_{bt}$, which equals the fraction of overlapping MSA markets for the acquirer and target banks. We construct this variable for each potential merger and estimate its contribution to the match value function.

4. Estimation

4.1. Determinants of Match Value

During our sample period (1995–2005), bank mergers were potentially motivated by some combination of efficiencies,[18] merging to acquire and exploit market power, and acquiring better performing branches to improve the bank's overall performance.[19] Together with our data on institution size and performance (see §3.1 for details on performance measures), we estimate how efficiencies and market power separately affect the bank merger match value function. A number of these determinants of bank merger value are target specific. Thus, the ability of the with-transfers estimator to identify target-specific determinants of merger value is important.

After the 1994 Riegle-Neal Act, mergers were often motivated by creating national banking networks that are less sensitive to local economic shocks and more valuable to consumers. To this end, there are obvious advantages to banking with a bank with a wider geographic footprint, as Anil Kashyap noted in 1998, "If you are a BofA customer, you won't have to pay transaction fees at ATM machines since there'll be one in every city you go to" (Marshall 1998). As an alternative to opening new branches, mergers are an effective way for a bank to achieve a large, national banking network. We account for this large-banking-network motivation to merge by including interactions between target and acquirer banking attributes (assets and branches) in our specification of the match value function.

A merger between two banking institutions will also generate cost efficiencies (or inefficiencies) unrelated to the size of the network of branches. If economies of scale are easier to capture in banking markets familiar to the acquiring bank, the match value between an acquirer bank and a target bank will tend to increase with the fraction of overlapping markets (captured by $overlap_{bt}$). On the other hand, Aguirregabiria et al. (2012) document significant potential to diversify geographic risk post-Riegle-Neal by expanding into new markets. Thus, the effect of overlap on bank merger value will tend to be negative to the extent geographic diversification of risk is an important motive for bank mergers. Thus, the ex ante relationship between $overlap_{bt}$ and match value is an empirical question that speaks to whether geographic risk or economizing on local efficiencies is more important.

To address the extent to which the degree of market concentration increases merger match value, we include the average HHI of the target bank's markets as a component of our match value function. Moreover, to the degree that antitrust regulation tempers this incentive to merge, we also include the fraction of target markets that would warrant antitrust scrutiny ($HHI\_violate_{bt}$) in our match value specifications. In the middle of this merger wave, however, industry experts did not consider market power to be an important explanation for the large number of mergers during our sample period.[20] Nevertheless, including these terms in the match value function allows us to assess the market concentration hypothesis directly.

[18] Using data from the pre-Riegle-Neal era, Kroszner and Strahan (1999) demonstrate that new banking technologies for both deposit-taking and lending increased the geographic scale of banking. Our sample time frame (1995–2005) occurs during a period of rapid innovation in Internet technology, which increases the efficient scale of banking beyond the ATM and credit history technologies described by Kroszner and Strahan (1999). Thus, economies of scale are as relevant for bank mergers in our time period as they were for the geographic scale of banking in Kroszner and Strahan (1999).

[19] At the time of our sample, industry experts pointed to efficiencies (or reductions in inefficiencies) from cross-state mergers and deemphasized the role of market power as a motivator for merging (Marshall 1998). Nevertheless, we consider this hypothesis by including market power terms in the match value function. In a 1998 newsletter to the Federalist Society, Rockett (1998) makes the point that the purported merger mania after the Riegle-Neal Act was—in part—motivated by achieving better stock market performance and improving balance sheets. To the extent that we observe measures of financial performance of targets and acquirers, we can assess whether these were primary motivators.

[20] "Most experts believe a merger between two huge banks operating in different parts of the country—such as NationsBank and BofA—is unlikely to harm consumers by reducing competition, unlike a consolidation of banks in one local market" (Marshall 1998).

4.2. Functional Form for the Match Value Function

To use the maximum-score estimator, we specify a parametric form for the value of a match between target t and acquirer b.[21] For the match-value function, we follow existing empirical work on matching markets (e.g., Fox 2007, Chen and Song 2013) and evaluate the degree and direction of assortative matching using interactions between acquirer and target attributes. Exploiting the ability of our estimator to identify non-interacted parameters, we also extend the specification to include target-specific attributes:

$$F(b,t) = \beta_1 W_b W_t + \gamma_1' \mathbf{X}_t + \boldsymbol{\gamma}_2' \mathbf{X}_{bt} + \varepsilon_{bt}, \qquad (7)$$

where W_b is an attribute of acquirer b and W_t is the same attribute for target t, $\mathbf{X}_t$ contains target-specific covariates, $\mathbf{X}_{bt}$ is a vector of match-specific covariates, and ε_{bt} is an unobserved match-specific error term that we assume is independent across matches in our data set. We estimate several variations on this basic specification, adding to the match function in (7) interaction terms for additional attributes. Using the transfers data with our with-transfers estimator allows us to identify γ_1, which is unidentified in the without-transfers estimator.

4.3. Subsampling Confidence Intervals

We generate point estimates by running the differential evolution optimization routine from 20 different starting points and selecting the coefficient vector that yields the highest value for the maximum score objective function.[22] For valid inference, we generate the confidence intervals using the subsampling procedure described by Politis and Romano (1992) and Delgado et al. (2001) to approximate the sampling distribution. For the entire data set, we set the subsample size to be 500—approximately 1/3 to 1/4 of the total sample size. Of all samples of size $n_s = 500$ drawn from the original data set (N observations), we select at random 100 of these samples for use in constructing the confidence bounds.

For each of the $S = 100$ subsamples, we compute the parameter vector that maximizes the objective function in (6). Call the estimate from the sth subsample $\hat{\beta}_s$ and the estimate from the original full sample $\hat{\beta}_{full}$. The approximate sampling distribution for our parameter vector can be computed by calculating $\tilde{\beta}_s = (n_s/N)^{1/3}(\hat{\beta}_s - \hat{\beta}_{full}) + \hat{\beta}_{full}$ for each subsample. This procedure accounts for the $\sqrt[3]{N}$ convergence of the maximum score estimator (Politis and Romano 1992, Delgado et al. 2001). We take the 2.5th percentile and the 97.5th percentile of this empirical sampling distribution to compute 95% confidence intervals for all of our estimates.

[21] Because different specifications for this functional form focus on different features of the matching between acquirer and target, we evaluate the robustness of our conclusions to several related specifications for the match value function in the maximum-score estimation in the online appendix.

[22] Fox (2007) argues that the maximum score estimator is consistent if we randomly sample a sufficiently large number of inequalities to impose rather than the full number of inequalities (which is often intractably large). Relying on this insight, for each specification we run in this paper, we sample 40 acquirer-target pairs from each year and form the $\binom{40}{2}$ inequalities implied by their matching.

5. Main Findings

This section presents the results from estimating several specifications of the match value function to better understand the determinants of value creation in the merger market. The most robust determinants of merger value creation are lower regulatory frictions, cost efficiencies from overlapping markets, and network effects exemplified in the assortative matching between acquirers and targets.

5.1. Bank Size, Market Concentration, and Overlap of Markets

Table 2 presents results from estimating the revealed preference model with merger value function given by Equation (7). In every specification in Table 2, the coefficient estimates on the interactions between acquirer and target assets (branches) are positive and statistically significant.[23] This finding suggests that large acquirer banks tend to match with larger target banks, and that this pattern of matching is revealed to be valuable by the pattern of potential mergers that did not occur. For example, the estimate on the interactive term in column (2) implies that a 10% increase in the number of acquirer branches is associated with a \$408,000 increase in the effect of an additional target branch on merger match value. This interactive effect remains significant whether or not the match value function includes target assets and the interactive term between acquirer and target assets. Although the magnitudes vary across specifications, the interpretation in the context of the observed match is that the matching equilibrium exhibits a strong positive assortative match on both branches and assets, a finding that is consistent with the conventional understanding that mergers during this time period (from 1995 to 2005) were motivated by taking advantage of large national networks.

Across specifications in Table 2, the estimates for the own effect of target assets and branches is negative across specifications, and these own effects tend to be statistically significant. This finding, together with the consistently significant interactive effects, suggests that a larger number of assets and branches in the target bank contributes positively to the match value, but not

[23] We take statistical significance to mean that the 95% confidence interval from subsampling does not contain zero.

Table 2 Maximum Score Estimates of Match Value Function

	(1)	(2)	(3)	(4)	(5)
$Assets_t$	−360.36**		−211.02**	−2.33**	−392.33**
	(−443.09, −225.19)		(−395.02, −126.96)	(−82.92, −0.92)	(−725.27, −99.00)
$\log(Assets_b) \times Assets_t$	47.88**		24.84**	0.30**	151.12**
	(29.32, 59.88)		(15.02, 48.69)	(0.13, 9.98)	(91.28, 375.88)
$Branches_t$		−32.71**	−151.29**	−7.94	−7.11
		(−44.27, −25.21)	(−389.08, −111.15)	(−121.00, 33.37)	(−83.60, 3.55)
$\log(Branches_b) \times Branches_t$		40.80**	644.79**	13.86**	10.04**
		(28.45, 44.60)	(372.68, 811.83)	(5.53, 137.94)	(5.56, 67.57)
MSA overlap				967.44**	1,210.45**
				(729.42, 984.44)	(1,098.15, 1,397.11)
HHI violation fraction				366.91	463.97
				(−200.73, 761.48)	(−440.10, 1,146.41)
Target HHI					0.15**
					(0.05, 0.42)
Number of observations	1,484	1,484	1,484	1,484	1,484
Percent of inequalities (%)	43	37	44	78	79

Notes. This table presents estimates of the match value function $F(b,t) = \boldsymbol{\beta}'\mathbf{X}_{bt} + \boldsymbol{\varepsilon}_{bt}$ using maximum score estimation. Subsampling-based 95% confidence intervals are in parentheses. Point estimates are generated by running the differential evolution optimization routine using R's DEoptim package (Mullen et al. 2011). For differential evolution, we use 100 population members, scaling parameter 0.5, and we employ the classical differential evolution strategy (strategy = 1). For point estimates, we run the optimization routine for 20 different starting points (seeds) and select the run that achieves the largest value of the objective function. For confidence intervals, we use the subsampling procedure described in Politis and Romano (1992). We set the subsample size to be 500 (approximately 1/3 to 1/4 the total sample size) and randomly generate 100 replications of the routine to obtain confidence bounds.

**Indicates significance at the 5% level; i.e., 95% confidence interval does not contain 0.

independently of the size of the acquirer bank. Taken together, the results suggest that a network of branches and customers is more valuable on average as the size of the network grows, suggesting that an acquirer with many branches and customers would derive disproportionately more value from a large target, ceteris paribus. On the other hand, there is a cost to managing more assets and branches. This cost shows up in the coefficient estimates on target attributes, which are consistently negative and statistically significant.

In the final two columns of Table 2, the positive and significant estimates for $overlap_{bt}$ suggest that banks derive significantly more match value if the acquirer and target have more overlapping markets. Relative to having no overlap in MSA markets, the estimate in column (4) implies that an acquirer and target with complete overlap in MSA markets will realize a nearly \$1 million (\$967,440) increase in the merger match value. Because our specifications account for market concentration, this finding suggests that the merging banks can realize operating efficiencies better when the target and acquirer banks have branches in the same MSA. The magnitude of this estimate is sensible given previous estimates to operate a bank branch. In a different context, Radecki et al. (1996) estimate that the total costs of operating a branch are around \$1.4 million annually with indirect costs (e.g., advertising, and computing systems) amounting to half of that. Given this estimate holds constant the number of branches as another predictor in the match value function, these efficiencies more likely represent cost savings on indirect costs like advertising that can be spread across multiple branches than cost savings from branch closures.

To the role of market concentration, the positive estimate on target bank's average HHI suggests that greater market concentration increases the match value, consistent with greater market concentration allowing the combined bank to extract additional profit. On the other hand, having a higher fraction of MSA-level markets that would justify antitrust scrutiny (i.e., greater HHI violation fraction) does not seem to either detract from the match value or add to it. As column (5) demonstrates, this finding on insensitivity of the match value function to the HHI violation fraction is robust to controlling for the target bank's average HHI. Taken together with the results on assortative match and overlapping markets, the results from these specifications indicate that both efficiency and market power rationales to merge create value for the merger.

5.2. The Role of Premerger Target Performance

We also allow the match value function to depend on performance measures of targets: the efficiency ratio (noninterest expense/income) and the loan loss reserve coverage ratio (loan loss reserves/nonperforming loans).[24] We include these performance measures to

[24] These measures are available from SNL Financial, but not for the same set of banks. As such, including all measures at once reduces the number of observations in the specification to the point where identification is questionable. Thus, we evaluate the contribution of each of these categories in isolation of the other.

Table 3 Maximum Score Estimates of Match Value Function with Performance Measures

	(1)	(2)	(3)	(4)
Assets$_t$	−318.25**	−2.07**	−371.12	−1.43**
	(−441.91, −203.95)	(−312.79, −0.67)	(−456.99, 231.99)	(−241.62, −0.16)
log(*Assets*$_b$) × *Assets*$_t$	41.97**	0.28**	48.20**	0.17**
	(26.98, 59.82)	(0.09, 41.17)	(29.99, 58.91)	(0.03, 29.61)
Branches$_t$	−312.00	−1.79	−265.30	2.76
	(−442.11, 377.21)	(−241.74, 500.10)	(−415.28, 521.83)	(−166.48, 411.50)
log(*Branches*$_b$) × *Branches*$_t$	73.23	0.75	58.97	0.02
	(−97.77, 134.66)	(−159.91, 140.23)	(−134.86, 286.71)	(−70.79, 59.97)
Efficiency ratio target	−5.80	4.26		
	(−62.07, 10.20)	(−46.86, 22.21)		
LLR ratio target			1.72	−0.03
			(−2.45, 6.00)	(−1.58, 1.04)
MSA overlap		757.89**		886.86**
		(335.91, 933.89)		(655.64, 958.27)
HHI violation fraction		933.42		411.92
		(−42.09, 943.88)		(−169.98, 757.19)
Number of observations	1,269	1,269	765	765
Percent of inequalities (%)	39	78	38	81

Notes. This table presents estimates of the match value function $F(b,t) = \boldsymbol{\beta}'\mathbf{X}_{bt} + \boldsymbol{\varepsilon}_{bt}$ using maximum score estimation. Subsampling-based 95% confidence intervals are in parentheses. Point estimates are generated by running the differential evolution optimization routine using R's DEoptim package (Mullen et al. 2011). For differential evolution, we use 100 population members, scaling parameter 0.5, and we employ the classical differential evolution strategy (strategy = 1). For point estimates, we run the optimization routine for 20 different starting points (seeds) and select the run that achieves the largest value of the objective function. For confidence intervals, we use the subsampling procedure described in Politis and Romano (1992). We set the subsample size to be 500 (approximately 1/3 to 1/4 the total sample size) and randomly generate 100 replications of the routine to obtain confidence bounds. These specifications were also estimated with acquirer-specific efficiency ratio and LLR ratio, which are not reported here because they are unidentified. In separate Monte Carlo exercises, we show that the revealed preference method performs well on identified parameters (e.g., interaction terms and target-specific terms) when the value function also includes unidentified terms.

**Indicates significance at the 5% level; i.e., 95% confidence interval does not contain 0.

assess the importance of efficiency and distress in merger value creation. Given existing work on agency and merger activity, this is a natural line of inquiry. Although merger value could depend on the target's operational performance for efficiency reasons (e.g., see Maksimovic and Phillips 2001), the performance characteristics of targets could proxy for agency frictions in the acquirer and thus be related to merger value creation through that channel.

In Table 3 we report specifications for merger value that include these measures of performance, and across specifications, there is not a significant relationship between merger value and premerger target performance. Nonetheless, the qualitative findings of §5.1 remain true regarding assortative matching and overlap of markets. These matching and branching efficiency motives to merge appear to be robust, whereas performance measures do not appear to systematically affect merger value. Thus, it appears that the consolidation of banking institutions during our sample reflects the relaxation of regulation and efficiency motives (e.g., assortative matching and greater geographic overlap of markets).

5.3. The Role of Bank Regulation

We now use our model to quantify the implicit costs of bank chartering through frictions in the bank merger market. To evaluate these implicit costs, we allow the merger value function to depend on a dummy variable, *same_charter*$_{bt}$, that equals one if the acquirer and target have the same type of charter and thus are regulated by the same regulator. We also include an interaction between *same_charter*$_{bt}$ and *overlap*$_{bt}$. The interactive effect is reasonable if having different charters complicates dealings with multiple types of regulators, especially if the regulation impacts the cost efficiencies realized in overlapping markets. Agarwal et al. (2014) study a similar regulatory friction in the context of small state chartered banks that are audited on a rotational basis, finding there are costs to adjusting to different types of regulators. Agarwal et al. (2014) document costs of inconsistent regulators in the context of rotational regulation, suggesting in that context that window dressing for the regulator can be costly because it leads to artificial variability in operations. In the merger context, we evaluate whether there are implicit costs of having to adapt to a new regulatory regime that are reflected by the choices of the merging banks.

Table 4 presents evidence on the role of bank charter type in determining merger value creation. When we include the *same_charter*$_{bt}$ dummy variable, the coefficient estimate is large and positive but not statistically significant. The estimate implies an increase in merger

Table 4 Estimates of the Match Value Function Using Bank Chartering Information

	(1)	(2)
MSA overlap	934.98**	878.21**
	(700.21, 976.72)	(661.52, 957.71)
Same charter	158.45	37.60
	(−85.41, 331.96)	(−211.71, 306.30)
(*Same charter*) × (*MSA overlap*)		743.28**
		(117.42, 901.26)
Number of observations	1,484	1,484
Percent of inequalities (%)	75	75

Notes. This table presents estimates of the match value function $F(b,t)=\boldsymbol{\beta}'\mathbf{X}_{bt}+\boldsymbol{\varepsilon}_{bt}$ using maximum score estimation. Subsampling-based 95% confidence intervals are in parentheses. As in Table 5, the specifications in this table include (but do not report for the sake of brevity) own-effects and interactions for assets and branches as well as HHI violation fraction. Point estimates are generated by running the differential evolution optimization routine using R's DEoptim package (Mullen et al. 2011). For differential evolution, we use 100 population members, scaling parameter 0.5, and we employ the classical differential evolution strategy (strategy = 1). For point estimates, we run the optimization routine for 20 different starting points (seeds) and select the run that achieves the largest value of the objective function. For confidence intervals, we use the subsampling procedure described in Politis and Romano (1992). We set the subsample size to be 500 (approximately 1/3 to 1/4 the total sample size) and randomly generate 100 replications of the routine to obtain confidence bounds.

**Indicates significance at the 5% level; i.e., 95% confidence interval does not contain 0.

Table 5 Evaluating the Extent and Impact of Value-Destroying Mergers

Year	No. of mergers	% *value destroying*	% *unmatched in optimum*	*Match value*	% *of value lost*
1995	168	5.95	4.17	190.445	0.27
1996	146	4.79	3.42	356.079	0.30
1997	152	4.61	3.29	189.349	0.38
1998	221	5.88	1.81	549.745	0.21
1999	158	6.96	1.90	264.840	0.21
2000	109	2.75	1.83	210.457	0.13
2001	121	8.26	4.13	326.746	0.43
2002	93	5.38	3.23	93.517	0.24
2003	95	6.32	2.11	122.004	0.27
2004	120	8.33	2.50	1,957.699	0.07
2005	101	6.93	3.96	114.253	0.98

Notes. Match value measured in millions of dollars is the sum across mergers in that year of the estimated match value for merged acquirer-target pairs. % *value destroying* is the fraction of mergers with negative merger value creation. *% of value lost* is the total (negative) merger value of these value-destroying mergers divided by the overall match value. Unmatched acquirers and targets occur in the solution to the linear programming problem if mergers involving these acquirers and targets would be value destroying under the recomputed optimal configuration of mergers.

match value of $158,450, on average, if the target and acquirer banks have the same charter. When we include the interaction of this dummy variable with the percentage of overlapping markets, the coefficient is large and statistically significant. This finding suggests that the match between banking charters is more important for geographically overlapping banks. More concretely, for a target and acquirer whose MSA markets completely overlap, having the same charter increases match value by $743,000, and this increase is statistically significant. More generally, this finding suggests that a match between bank charters can contribute to the value of the merger by avoiding these regulatory frictions, especially because a bank has branches in more markets and thus greater overlap with potential targets.

5.4. Evidence on Merger Value Creation

The fitted values from our merger value function provide merger-specific estimates for value creation from the perspective of the merging banks. Thus, subject to the caveat that our measure of merger value is from the perspective of the firm's managers, this section takes our estimated merger value function to reflect underlying shareholder value.[25] As evidence on the degree to which unmeasured characteristics (e.g., agency frictions) destroy merger value, Table 5 presents summary

[25] In addition, the online appendix presents an analysis of acquirer-specific value, which nets out the transfer from the overall value created. The fraction of mergers that destroy acquirer-specific value is greater than discussed in the main text but is not strikingly greater (fraction of value destroying mergers rises to 6.93% instead of 6.02%).

Table 6 **Year-by-Year Measures of Fit**

Year	No. of mergers	*Same match*	*Highest value*	*Average rank*	*Price* ρ	*% of optimal value*
1995	168	0.274	0.15	0.81	0.947	84.4
1996	146	0.171	0.03	0.74	0.996	88.4
1997	152	0.237	0.12	0.72	0.945	83.2
1998	221	0.118	0.10	0.73	0.994	86.5
1999	158	0.241	0.18	0.81	0.994	72.1
2000	109	0.303	0.06	0.70	0.941	85.0
2001	121	0.331	0.12	0.78	0.981	84.0
2002	93	0.355	0.19	0.82	0.792	83.3
2003	95	0.253	0.27	0.84	0.984	85.8
2004	120	0.283	0.17	0.79	0.988	97.1
2005	101	0.307	0.04	0.79	0.715	85.4

Notes. *Same match* is the fraction of acquirers that are matched to the same target in the optimal pattern of mergers, *highest value* is the fraction of acquirers whose realized target produces the highest match value of any possible target, *price* ρ is the correlation between the equilibrium transfers and the transfers implied by the equilibrium solution. *Highest value* equals the fraction of matches where the observed match had the highest estimated match value for the acquirer among all counterfactual mergers, and *average rank* equals the average percentile of match value for the observed match relative to all counterfactual matches. *% of optimal value* is the percentage of merger value that the observed mergers create relative to the merger value created in the solution to the linear programming problem.

statistics on the fraction of mergers that we compute to have negative merger value. On average, only 6.02% of mergers in a given year yield negative match value, and in every year of the sample, the lost value from these mergers is less than 1% of overall merger value creation. These estimates indirectly yield insight into scope for value-reducing agency problems in the merger market. For example, if a merger appears to reduce value according to our measure—accounting for cost efficiencies, market power, or network-enhancing benefits—this could indicate a manager-shareholder agency problem (e.g., see Harford et al. 2012).

Our revealed preference estimate of merger synergies may either overstate or understate the true fraction of value of synergies. On one hand, this measure could overlook some value-destroying mergers in which the transfer appears less costly to the merging firms because of significant overlap in ownership of acquirer and target (Matvos and Ostrovsky 2010).[26] On the other hand, our specification for merger value creation may not capture some types of merger-specific synergies. To the extent these synergies are unmeasured and enhance the profitability of mergers that look unprofitable according to our measures, our revealed preference method will tend to understate the frequency of value-destroying mergers because it will classify some of these mergers as negative value when they create value for unmeasured reasons. The fact that these estimates of value destruction in mergers are close to recent estimates using stock market evidence provides additional confidence in the validity of these estimates (Bayazitova et al. 2012).

6. Robustness and Extensions

6.1. In-Sample Performance of Merger Value Function

Our framework allows us to compute a number of measures that allow us to evaluate the in-sample performance of the revealed preference method. To evaluate our revealed preference model, we benchmark against the optimal computed match as we did in evaluating the extent of merger value creation in the bank merger sample. We compute five measures of fit for our merger value function: (i) the fraction of mergers for which the realized match has the highest computed match value (*highest value*), (ii) the fraction of mergers for which the realized match is the same as the optimal pattern of mergers (*same match*), (iii) the average percentile rank of the observed matched target in the rank-order list of acquirers (*average rank*), (iv) the correlation coefficient between the actual deal values and the equilibrium transfers computed from the linear programming problem described in Shapley and Shubik (1971) (*price* ρ), (v) the fraction of realized merger value relative to the merger value created in the solution to the linear programming problem (*% of optimal value*). Greater values for each of these measures implies better performance of the estimated merger value function in sample.[27]

For each year in our sample, Table 6 summarizes these measures of performance. *Same match* ranges

[26] Despite this being an important consideration, there is less concern arising from potential cross-ownership for mergers that involve private banks (the typical case) because these kinds of mergers have less cross-ownership. The number of merger observation drops by 22% ((1,484 − 1,158)/1,484) when requiring the acquirer to be publicly traded. Targets are even more likely to be privately held, with about half of the sample of targets being private.

[27] In the online appendix, we describe how to implement these linear programming measures in greater detail.

from 0.118 to 0.355, but it is relatively stable across years with an average of 0.261. Contrast *same match* with the *highest value* (a naive measure of fit), which ranges from 0.03 to 0.27 during our sample time frame and averages 0.13. The *highest value* fraction is lower for in-sample predictions because some targets would generate the highest value for multiple acquirers, but this is not possible in equilibrium. Our equilibrium measure of fit (*same match*) accounts for this, and as a result, the model correctly predicts observed matches where the acquirer-target match does not generate the highest value for the acquirer (but where that acquirer's highest value target is assigned to another acquirer who values the target more highly), as indicated by the greater success rate of *same match*.

Using average rank in the acquirer's rank order list, we observe a measured *average rank* ranging from 0.70 to 0.84 across years, with an average of 0.79. Thus, when the estimated match value is not precisely at the top for the observed match, it is very often near the top of match values. By this measure, the fit of the model appears to be quite good. The advantage of an out-of-equilibrium measure of fit like *average rank* is that it is easy to compute, but the disadvantage is that it does not account for the effect of small perturbations in value on the matching market equilibrium.

Given the closer link to the underlying equilibrium of *same match*, one way to evaluate the relative validity of these out-of-equilibrium measures of fit is to compute their correlation across years with *same match*. The correlation between the *highest value* and *same match* is only 0.209, whereas the correlation between *average rank* and *same match* is greater at 0.396. On this basis, we may prefer *average rank* to *highest value* for in-sample measures of it.

In our fourth assessment of the performance of the estimates from the revealed preference model, we compute the correlation between the actual transfer amounts to the equilibrium transfer prices from the dual of the linear programming problem. Regardless of the year considered, the high correlation between actual transfer amounts and the transfers from the linear programming problem, ranging from 0.715 to 0.996 indicates that our model replicate the transfer amounts quite well.

Finally, we contrast the observed set of mergers with this computed optimal pattern of mergers by computing the total match value under the observed equilibrium and compare it to the total match value in the solution to the linear programming problem. The implied value of mergers for the observed matching is meaningful, ranging from \$93 million in 2002 to \$1.96 billion in 2004. By this metric, the actual mergers produce 72.1%–97.1% of the optimum of the linear programming problem with an average of 85.0%. This small scope (15%) for the amount of value destroyed is a conservative estimate of the amount of value left on the table from agency issues and optimization error because the optimal solution to the linear program may overfit the particular characteristics of the sample, whereas the realized mergers may account for merger-specific synergies that, in reality, create value. From this standpoint, the merger value function we estimate fits quite well.

6.2. Comparison to Binary Logit Regression

Another way to assess our revealed preference method is to compare its predictive accuracy to the performance of a binary logit regression that uses the same set of regressors. To implement the binary logit regression, we need to construct a data set of counterfactual and observed mergers with all of the information we used in our revealed preference model. On this data set, we use binary logistic regression to predict whether an acquirer-target pair was an observed merger using the features of our match value specification as the right-hand side of the logistic regression.

We use the fitted values from the logistic regression to predict which target the acquirer will acquire. For each acquirer, the target with the largest fitted value is predicted to merge with the acquirer. Using this rule, we find that logistic regression performs dramatically worse than our revealed preference method. As the fraction of successful predictions in Table 7 indicate, binary logistic regression successfully predicts slightly greater than 1% of observed mergers, compared to a yearly average of 26% using our reduced form method (see Table 6). We attribute the significantly better performance of our method to the fact that we explicitly take into account the nature of equilibrium in the bank

Table 7 **Comparison of Predictive Accuracy with Binary Logistic Regression**

Year	No. of mergers	Revealed preference	Binary logistic
1995	168	0.274	0.006
1996	146	0.171	0.014
1997	152	0.237	0.007
1998	221	0.118	0.014
1999	158	0.241	0.019
2000	109	0.303	0.009
2001	121	0.331	0.033
2002	93	0.355	0.011
2003	95	0.253	0.021
2004	120	0.283	0.008
2005	101	0.307	0.010

Notes. The "revealed preference" column indicates the fraction of successful predictions using revealed preference method to estimate match value for each acquirer-target pair and then using those estimated match values to solve for the matching market equilibrium. The "binary logistic" column indicates the fraction of successful predictions using the maximum fitted value from a logistic regression (with the same set of predictors as enters into the match value function) for each acquirer as the prediction of the acquirer-target match.

Table 8 **Predicting Mergers One Year in Advance**

Year	*Same match*	*Highest value*	*Average rank*	*Unmatched*	No. of observed mergers	*Price* ρ
1996	0.089	0.16	0.78	28	146	0.995
1997	0.092	0.07	0.77	28	152	0.939
1998	0.041	0.05	0.69	82	221	0.988
1999	0.013	0.12	0.77	79	158	0.997
2000	0.018	0.15	0.78	44	109	0.941
2001	0.025	0.06	0.70	81	121	0.979
2002	0.011	0.17	0.78	16	93	0.625
2003	0.000	0.21	0.84	18	95	0.994
2004	0.025	0.17	0.79	47	120	0.989
2005	0.010	0.15	0.79	69	101	0.916

Notes. The estimated match values are obtained by running the maximum score estimator the previous year's sample of merger deals. To compute the *same match* fraction, compute the matching equilibrium assuming these estimated match values, and calculate the fraction of matches that are the same as observed. Based on this matching equilibrium, *unmatched* is the number of acquirers-targets that are not assigned to one another, and *price* ρ is the correlation between the equilibrium transfers and the transfers implied by the equilibrium solution. As for nonequilibrium measures, *highest value* equals the fraction of matches where the observed match had the highest estimated match value for the acquirer among all counterfactual mergers, and *average rank* equals the average percentile of match value for the observed match relative to all counterfactual matches. Because the estimated match values are computed for the year ahead, computing *match value* and *% of optimal value* makes less sense than in the in-sample case.

merger market. Not only does this provide our method with an improved ability to relate our estimates to economic theory, the comparison to predictive logistic regression suggests that we achieve significant gains in predictive accuracy.

6.3. Out-of-Sample Fit and Predicting Mergers

A notable extension of our framework is to estimate a merger value function and use it to predict mergers that will subsequently take place. The year-by-year estimates suggest that we could estimate the merger value function using observed and counterfactual mergers from year $T-1$, then roll forward our estimated merger value function to date T to predict the mergers that are most likely to take place.

With an estimated match value function, we can evaluate the match value for realized mergers as well as for counterfactual mergers (a hypothetical merger between the acquirer and another target). To evaluate the ability of the model to predict mergers, we estimate the match value using the estimates from the previous year and then assess the model fit using the measures of fit we discussed in the previous section.

Table 8 summarizes our ability to predict mergers out of sample. As expected, the *same match* column indicates that our ability to predict mergers out of sample is worse than the in-sample fit. Specifically, the average fraction of correct predictions across years is 0.032. This fraction of correct predictions as well as the drop-off in out-of-sample predictability is comparable[28] with other recent work on the ability to predict mergers in and out of sample (Cremers et al. 2009). In addition, the correlation of the prices from the dual of the linear programming problem with actual prices remains high (ranging from 0.625 to 0.997). That is, the model appears to predict the pattern of transfers better than the identity of the participants.

Table 8 also illustrates why it is unwise to use nonequilibrium measures of fit (*highest value* and *average rank*) in the two-sided matching setting. Using the *highest value* fraction and *average rank* as our measures of fit, the out-of-sample fit appears to be on par with the in-sample fit. Nevertheless, these measures do not account for the fact that small perturbations in the payoffs can lead to large changes in the observed match. Even if the differences in match value do not reorder the preference ordering for each particular acquirer, they can change the intensity of preference, and this can change the allocation. Our equilibrium measure of fit accounts for this kind of reordering; hence, it is more realistic about the out-of-sample validity of the model.

6.4. Counterfactual Evidence

As we saw in our bank charter specifications, an important aspect of the bank merger market is the match between type of banking regulation that applies to target and acquirer banks. Our specifications in Table 4 implied that acquirer and target banks with the same type of charter experience a premium in their match value. This premium reflects a cost of multiple types of bank charters. In this section, we report the findings from a counterfactual simulation where we impose that all banks have the same charter. Our findings suggest a sizable cost of the dual chartering

[28] For example, Cremers et al. (2009) construct a takeover factor, which together with the market factor, exhibits a cross-sectional R^2 of 0.1339. When the authors consider out-of-sample predictions similar to what we do in this section, their R^2 drops to 0.0403.

Table 9 The Effect of Eliminating Dual Bank Chartering Regulation on Bank Merger Match Value

Year	No. of observed mergers	*Same match*	*Not matched*	*Match value* ($ millions)	*% increase in match value*
1995	168	0.232	6	294.825	54.8
1996	146	0.205	4	443.008	24.4
1997	152	0.270	1	272.677	44.0
1998	221	0.113	2	677.061	23.1
1999	158	0.215	2	359.794	35.9
2000	109	0.330	1	277.520	31.9
2001	121	0.355	3	398.945	22.1
2002	93	0.516	3	152.552	63.1
2003	95	0.316	1	187.534	53.7
2004	120	0.342	2	2,028.748	3.6
2005	101	0.347	3	176.175	54.2

Notes. Match value is the sum across mergers in that year of the estimated match value for merged acquirer-target pairs assuming those acquirers and targets have the same bank charter. Unmatched acquirers and targets occur in the solution to the linear programming problem if mergers involving these acquirers and targets would be value destroying.

system, which manifests itself in fewer mergers between banks of different chartering types.

Table 9 reports the results from our counterfactual simulation. Relative to the baseline where banks may have different charters (and hence different regulatory agencies), the number of acquirer-target pairs that go unmatched declines slightly, and the total match value is significantly larger when there is no distinction between the charter types, typically a 20%–50% increase in the total estimated match value of bank mergers for any given year.

Despite its large magnitude relative to banks that merge in a particular year, our estimated magnitude of 20%–50% of the match value reflects a much smaller fraction of the banking industry as a whole. We observed approximately 200 mergers per year relative to a total number of banks from 7,000 to 10,000.[29] Rescaling our estimate by the fraction of banks that merge in a typical year in our sample, our counterfactual-estimated cost of bank chartering regulation equals 1%–2.5% of the value of the entire banking industry. To put this estimate in context, 1%–2.5% is slightly larger, but on the same order as the annual supervisory fee paid by national banks. For example, see calculations in Whalen (2010, Table 1), which report that supervisory fees for national banks average $21,000 for a bank with $25 million in assets, and $48,000 for a bank with $100 million in assets. In percentage terms, this amounts to approximately 0.5% to nearly 1%.

The implied effect reflects direct costs of additional regulation and the costs imposed by compliance with diverse chartering rules, as well as foregone opportunities when these costs stand in the way of a merger between a state bank and a national bank. Consider the example of a state acquirer bank and a national target bank with branches in multiple states. The potential merger may be advantageous because of an otherwise large overlap of markets and similarity of assets and branches, but the national bank has branches in another state. In this case, the state bank must decide whether it will learn and comply with federal charter regulations (either for the acquired branches or for the bank as a whole), or if upon acquisition of the national bank, it will divest holdings in other states to bring the entire bank under the original state charter. In either case, this is a significant friction in the bank merger market.

[29] For this calculation, take 400 merging banks from 200 mergers and use 8,000 banks as the size of the overall industry.

7. Conclusion

In the context of bank mergers, this paper develops a novel technique to estimate merger value creation without relying on stock market information. We do so by exploiting the features of a matching market equilibrium between acquirer and target banks. The fact that our approach does not rely on stock market information to recover estimates of value creation is particularly advantageous when at least one of the parties involved with the merger is private. When we evaluate the determinants of merger value creation, bank mergers appear to be motivated by branching efficiency and competitive concerns, rather than premerger performance of the target or the threat of antitrust regulation.

Despite its simplicity, our method is useful for predicting mergers. We obtain a structural estimate of the match value function that allows us to forecast the value of potential bank mergers based on characteristics of the target and acquirer bank. Our analysis shows how to use the revealed preference methodology to forecast which mergers will occur. In our sample of bank mergers, we find that the revealed preference method outperforms relevant alternatives (e.g., binary logit) partly because reduced form analysis without proper instruments is subject to endogenous matching, whereas our structural method explicitly accounts for matching endogeneity.

Consistent with recent work by Agarwal et al. (2014), our specifications suggest that significant implicit costs are imposed on banks through regulation. The fact that banks with national charters are subject to different regulatory procedures than banks with state charters imposes a friction in the bank merger market that prevents mergers between banks of different charter types. From our counterfactual exercise, we estimate that the cost of bank chartering regulation amounts to 20%–50% of the value created by bank mergers in a typical year. Rescaled by the number of banks that merge in a given year, this amounts to a cost of chartering regulation of 1% to 2.5% of the value of the banking industry. The regulatory friction from dual chartering is costly because the mergers it prevents are value creating, on average. In settings where mergers are value destroying, similar frictions in the merger market could be beneficial, rather than harmful, because they would prevent value destroying mergers at the margin.

This paper is part of an emerging literature that uses the structure of matching markets and networks in research on financial markets (Sørensen 2007, Akkus et al. 2013, Chen and Song 2013, Ahern and Harford 2014). Because matching processes are ubiquitous in financial markets and endogeneity frequently confounds finance research (Roberts and Whited 2012), we expect techniques that leverage the structure of matching in financial markets will play an increasingly important role in finance research going forward.

Supplemental Material

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References

Agarwal S, Lucca D, Seru A, Trebbi F (2014) Inconsistent regulators: Evidence from banking. *Quart. J. Econom.* 129(2):889–938.

Aguirregabiria V, Clark R, Wang H (2012) Diversification of geographic risk in retail bank networks: Evidence from the bank expansion after the Riegle-Neal Act. Working paper, University of Toronto, Toronto, ON.

Ahern KR, Harford J (2014) The importance of industry links in merger waves. *J. Finance* 69(2):527–576.

Akkus O, Cookson JA, Hortacsu A (2013) Assortative matching and reputation in the market for first issues. Working paper, Nathan Associates, Arlington, VA.

Bayazitova D, Kahl M, Valkanov R (2012) Value creation estimates beyond announcement returns: Mega-mergers versus other mergers. Working paper, University of North Carolina at Chapel Hill, Chapel Hill.

Becker GS (1973) A theory of marriage: Part I. *J. Political Econom.* 81(4):813–846.

Bernile G, Lyandres E (2010) The effects of synergies on competitors, customers, and suppliers in horizontal mergers. Working paper, Singapore Management University, Singapore.

Bhagat S, Dong M, Hirshleifer D, Noah R (2005) Do tender offers create value? New methods and evidence. *J. Financial Econom.* 76:3–60.

Boileau M, Moyen N (2016) Corporate cash savings: Precaution versus liquidity. *Internat. Econom. Rev.* Forthcoming.

Chen J, Song K (2013) Two-sided matching in the loan market. *Internat. J. Indust. Organ.* 31(2):145–152.

Cornaggia J, Mao Y, Tian X, Wolfe B (2015) Does banking competition affect innovation? *J. Financial Econom.* 115(1):189–209.

Cremers KJM, Nair VB, John K (2009) Takeovers and the cross-section of returns. *Rev. Financial Stud.* 22(4):1409–1445.

Debreu G (1960) Review of R.D. Luce's individual choice behavior: A theoretical analysis. *Amer. Econom. Rev.* 50(1):186–188.

Delgado MA, Rodríguez-Poo JM, Wolf M (2001) Subsampling inference in cube root asymptotics with an application to Manski's maximum score estimator. *Econom. Lett.* 73(2):241–250.

Devos E, Kadapakkam P-R, Krishnamurthy S (2009) How do mergers create value? A comparison of taxes, market power, and efficiency improvements as explanations for synergies. *Rev. Financial Stud.* 22(3):1179–1211.

Eckbo BE (2009) Bidding strategies and takeover premiums: A review. *J. Corporate Finance* 15(1):149–178.

Fox JT (2007) Semiparametric estimation of multinomial discrete-choice models using a subset of choices. *RAND J. Econom.* 38(4):1002–1019.

Fox JT (2010a) Estimating matching games with transfers. Working paper, Rice University, Houston.

Fox JT (2010b) Identification in matching games. *Quant. Econom.* 1(2):203–254.

Gorbenko AS, Malenko A (2014) Strategic and financial bidders in takeover auctions. *J. Finance* 69(6):2513–2555.

Harford J, Humphery-Jenner M, Powell R (2012) The sources of value destruction in acquisitions by entrenched managers. *J. Financial Econom.* 106(2):247–261.

Hennessy CA, Whited TM (2005) Debt dynamics. *J. Finance* 60(3):1129–1165.

Johnson CA, Rice T (2008) Assessing a decade of interstate bank branching. *Washington Lee Law Rev.* 65(1):73–128.

Kroszner RS, Strahan PE (1999) What drives deregulation? Economics and politics of the relaxation of bank branching restrictions. *Quart. J. Econom.* 114(4):1437–1467.

Maksimovic V, Phillips G (2001) The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *J. Finance* 56(6):2019–2065.

Manski CF (1975) Maximum score estimation of the stochastic utility model of choice. *J. Econometrics* 3(3):205–228.

Manski CF (1985) Semiparametric analysis of discrete response. *J. Econometrics* 27(3):313–333.

Marshall J (1998) Why banks feel the urge to merge. *San Francisco Chronicle* (April 14), http://www.sfgate.com/business/article/Why-Banks-Feel-Urge-To-Merge-3009357.php.

Matvos G, Ostrovsky M (2010) Cross-ownership, returns, and voting in mergers. *J. Financial Econom.* 98(1):90–112.

McFadden D (1974) The measurement of urban travel demand. *J. Public Econom.* 3:303–328.

Mullen K, Ardia D, Gil D, Windover D, Cline J (2011) DEoptim: An R package for global optimization by differential evolution. *J. Statist. Software* 40(6):1–26.

Politis DN, Romano JP (1992) A general theory for large sample confidence regions based on subsamples under minimal assumptions. Technical Report 399, Department of Statistics, Stanford University, Stanford, CA.

Radecki LJ, Wenniger J, Orlow DK (1996) Bank branches in supermarkets. *Current Issues Econom. Finance* 2(13):1–6.

Rhoades SA (1994) A summary of merger performance studies in banking, 1980–93, and an assessment of the "operating performance" and "event study" methodologies. Technical report, Board of Governors of the Federal Reserve System, Washington, DC.

Rice T, Strahan PE (2010) Does credit competition affect small-firm finance? *J. Finance* 65(3):861–889.

Roberts MR, Whited TM (2012) Endogeneity in empirical corporate finance. Simon School Working Paper FR 11–29, University of Rochester, Rochester, NY.

Rockett J (1998) The urge to merge: Trends in bank mergers. *Financial Services & E-Commerce Newsletter* 2(2), http://www.fed-soc.org/publications/detail/the-urge-to-merge-trends-in-bank-mergers.

Roth A, Sotomayor M (1990) *Two-Sided Matching: A Study in Game-Theoretic Modelling and Analysis*. Econometric Society Monographs, Vol. 18 (Cambridge University Press, Cambridge, UK).

Seims TF (1996) Bank mergers and shareholder wealth: Evidence from 1995's megamerger deals. Financial Industry Studies, August 1996. http://ssrn.com/abstract=7892.

Shapley LS, Shubik M (1971) The assignment game I: The core. *Internat. J. Game Theory* 1(1):111–130.

Sørensen M (2007) How smart is smart money? A two-sided matching model of venture capital. *J. Finance* 62(6):2725–2762.

Strahan PE (2003) The real effects of U.S. banking deregulation. Technical report, Federal Reserve Bank of St. Louis, St. Louis.

Whalen GW (2010) Why do de novo banks choose a national charter? OCC Economics Working Paper 2010-2, Office of the Comptroller of the Currency, Washington, DC. http://www.occ.treas.gov/publications/publications-by-type/occ-working-papers/2015-2009/wp2010-2.pdf.