

# Multiple Bank Mergers and Rational Foresight

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## Abstract

This paper presents evidence of foresight in bank merger programs. Using a search-theoretical model as a basis for estimation, the paper finds that banks that merge only once choose different partners, in rational ways, than those that merge more than once. Prior empirical research on merger patterns, efficiency, etc. has relied on the assumption that all mergers are a priori equivalent. We find evidence to the contrary: rational foresight should be incorporated into theoretical and empirical analyses. As well, we show that once foresight is incorporated, relative asset size now appears sufficient to explain variation previously described by a range of controls.

**JEL Codes:** G2, G34, D83

**Keywords:** bank mergers, multiple mergers, merger programs, foresight, search and matching

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# 1 Introduction

A couple of recent papers (Rosen 2004, Gorton et al. 2007) have addressed the strategic behavior of firms involved in repeated mergers. We follow and extend this line of research. In particular, we extend current merger research in two ways. One, we provide a method for the evaluation of a sequence of mergers. Two, we enable this evaluation over a full distribution of agents.

Our focus is on bank merger programs. Banks have engaged in 20 years of unparalleled merger activity that provides an outstanding laboratory for the investigation of merger, and sequential merger, behavior. As recently as 1975, there were about 14,000 banking institutions in the United States. By this year, the number had fallen to fewer than 7,000. Since the mid 1990s, bank failures have been very rare, and we attribute much of the decline in the number of institutions to merger activity. Enabling much of the volume of transactions was the passage of the Riegle-Neal (Interstate Banking and Branching Efficiency Act of 1994), which permitted almost unfettered interstate mergers.

Our primary tool will be a multi-stage model of matching that incorporates a bank's incentives to evaluate long run outcomes when deciding on a current merger opportunity. In particular, this model will allow us to look at whether an institution considers the impact of *future* merger considerations in its current decision. We find evidence both that banks have a long-run perspective in mind when making merger decisions and that the relative position of a bank vis-a-vis its competitors is significant. These manifest in a couple of ways. First, the relative size of mergers change over time. A bank that merges twice tends to buy a relatively *smaller* one second. Second, the patterns of assortative matching change. That is, a bank at the 75th quantile of the asset distribution may merge with a bank from a different point in the distribution in the first and second mergers.<sup>1</sup> Finally, these characteristics appear to parsimoniously capture much of the variance of merger decisions that has previously been attributed to other characteristics.

Over the past 10 years, the country has witnessed the emergence of a number of national-scale institutions. Many of these grew out of a dozen or more acquisitions; it is the relative frequency of "repeat" mergers that inspired this study. Existing literature has looked in great depth at the motivations for a single transaction. The manner of doing so typically involves making the assumption that each merger event is identical up to the selection of controls; this allows one to place the full range of merger events into some type of regression and evaluate the coefficients. While appealing, this amounts to an assumption of error exchangeability that is probably unjustified in this context. While the results have been, at times, compelling and confirming of intuition for merger motivation, one must question the logic of including Bank of America's or Citibank's first

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<sup>1</sup>Note that this is different than the first point as relative sizes can change as the overall industry distribution changes. Positive assortative matching implies that the largest bank will merge with the largest, etc.

and tenth transactions as equivalent events.<sup>2</sup> Does an institution pick a small target in order to bid on a big one at a later date? If not, does it instead pick a large initial target to have more leverage in subsequent transactions? We find the latter, which we discuss in greater detail below.

To evaluate this problem, one needs a general framework that incorporates two features. One, each agent faces a potential multi-stage decision. Two, after a merger, subsequent decisions are influenced by the new combination of interests; the initial merger decision is made exclusively by the original bank. To address this, we use a multi-period search model developed in Cohen-Cole (2006) as the basis for our analysis. In addition to addressing these concerns, the model has clear and testable conclusions about the patterns of mergers that should be observed if agents have farsighted considerations.

As an example, the model predicts that mergers should show an increasing relative size (defined as the buyer asset size divided by the target asset size). Figure 1 illustrates this result. It shows the distribution of merger ratios (the ratio of asset sizes) for institutions that merged only once and institutions that merged more than once. This chart displays the ratio only for the first merger in a series. Similarly, evidence of differences between single mergers and planned merger programs can be seen in Figure 2. This shows the ratio for the 'final' merger in the series for banks that merged one, two, or three times, and we can again see possible evidence of foresight in merger planning. Notice that the distributions reflect the prediction; firms that have three mergers in the time period evaluated show larger relative merger ratios than those with fewer mergers. It is not difficult to see that the assumption of exchangeability within existing merger studies is difficult to support; in these studies, all of the three distributions in Figure 2 would be aggregated into a single distribution for analysis.

For some intuition on this result, the model used finds that the share of the acquisition surplus (to both acquirer and target) is exponentially declining in the number of future mergers. That is, if one merges with an equal today, any surplus from future acquisitions will accrue to both parties. One could imagine two possible strategies to combat this. A firm might prefer to acquire a sequence of very small firms prior to a large acquisition, thus ensuring that the surplus from the initial acquisition accrues to the firm and that negotiating authority for the final acquisition is large. Alternatively, a large acquisition might be followed by small ones such that the subsequent surplus, though shared with the initial target, would otherwise belong principally to the firm.

This paper will review the relevant literature on financial mergers and acquisitions in section 2. In the subsequent section 3, the paper will highlight the search-theoretical model and discuss how we test its principal conclusions. Section 4 discusses econometric implementation. After a review

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<sup>2</sup>Most studies include each merger as a single observation. Thus, a bank that merges twice would have two observations in the dataset - effectively as two different institutions reflecting the then-current characteristics at the time of each merger.

of the data in section 5, we show results in section 6 and discuss and conclude in section 7.

## 2 Literature Review

There is a long and thorough literature on why banks merge, which banks merge and with whom, as well as on the economic impact of mergers.<sup>3</sup> Perhaps the most prominent lines of thought relate merger decision-making to potential efficiency gains and/or to market power. Additional research has come from exploration of the incentives created by regulatory goals and from discussions of managerial agency issues. We depart slightly from these lines of research to discuss patterns of merger activity. Simply, this paper will describe the patterns of past mergers by looking at how agents evaluate *sequential* decisionmaking.

The efficiency motivation for mergers can be subdivided into three strands: economies of scale, economies of scope, and managerial efficacy. While communications technology has removed barriers to operating a truly national or global bank, it has also made it easier for small banks to reduce overhead and function profitably. A number of papers support the conclusion that cost economies of scale only exist for relatively small banks,<sup>4</sup> necessitating alternative explanations for large bank mergers. One such explanation is the ability of large banks to offer a wider range of financial services under a single brand. That is, economies of scope can enable banks to capture higher market share. The scope arguments are strongest for mergers between banks and nonbanks, and therefore less applicable to this study which only examines mergers between banks. As well, there is little agreement within the banking industry on the ability of universal banks to add value. Simply, the managerial efficacy motivation dictates that superior management can create value by acquiring the assets of poorly managed institutions. Since the inferior management could not realize the bank's "true" inherent worth, the bank was perpetually undervalued. A plausible story, this explanation is very difficult to prove or disprove empirically.

Similarly, while the theory behind market power enhancing profitability is straightforward, empirical analyses have shown unclear results from increased concentration. Some existing papers demonstrate that local loan rates often increase alongside decreasing deposit rates following mergers that boost market share;<sup>5</sup> others find no relationship between concentration and profitability, loan rates, or deposit rates.<sup>6</sup> Choice of control variables on both the demand and supply side drive these conflicting conclusions. This highlights the difficulty of separately identifying market power and efficiency effects and is perhaps an area for future research.

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<sup>3</sup>For a more comprehensive summary of bank M&A literature, see Berger *et al.* (1999).

<sup>4</sup>See Berger *et al.* (1987) for one example.

<sup>5</sup>See Berger & Hannan (1989) and Hannan (1991).

<sup>6</sup>See Brewer & Jackson (2004) for a recent example.

Regulatory institutions continue to have significant influence on merger and acquisition activity, even in the wake of Riegle-Neal. While that piece of legislation was not the only explanation for the large number of merger and acquisitions in the late 1990s, it epitomized the deregulatory trend. Bank holding companies have increased their out-of-state deposit holdings from 2 percent to 28 percent between 1979 and 1994, a dramatic structural shift (Berger *et al.* , 1995). In addition to Riegle-Neal, a belief in the existence of a "too-large-to-fail" threshold and an aversion to allowing high market share are the main aspects of regulation in the United States. There is some evidence that banks merge in an attempt to reach the perceived "too-large-to-fail" threshold (Saunders & Wilson, 1999). In support of this market share hypothesis, Hannan and Pilloff (2006) finds that high market share increases the likelihood of being acquired from outside the market but decreases the likelihood of being acquired by another bank in the same market. Finally, the Community Reinvestment Act (CRA), established in 1977, plays a limited role in bank mergers (Bostic *et al.* , 2002).

Existing discussion of managerial motives generally centers on empire building. By increasing bank assets, CEOs can often increase personal compensation dramatically. Managerial hubris is a more recently posited agency issue. While, as pointed out above, mergers can be legitimized by efficient management taking over inefficient management, the hubris hypothesis is that the optimism of managers leads to incorrect beliefs about their own abilities (Roll, 1986).

We change tact slightly to focus on the patterns of mergers. There are various theories on the patterns of bank mergers, however, all of them look at a current decision and the immediate consequences of that decision. In contrast, this paper looks at the long run motivations of merging firms by evaluating how banks consider not only the current merger but also its *potential* subsequent ones. Rosen (2004) examines the implications of these "merger programs" in the context of all firms and finds that the consequences of consecutive acquisitions differ markedly from those of one-off or idiosyncratic mergers. While his focus is on executive compensation, Rosen also notes that when a firm acquires multiple targets, the early acquisitions tend to increase market returns much more than later acquisitions. These results may be applicable to the financial sector, and, if so, may contribute to our understanding of bank merger behavior whether it be myopic or farsighted.

A second paper, Gorton, et al. (2007), discusses strategic merger behavior with multiple firms. Their model evaluates the decision dynamics of a small number of firms by backward induction. Even in this simple structure, they find incentives for complicated merger strategies that depend in part on the sizes of the other firms in the market. In empirical evaluation, they confirm the finding of the importance of the distribution of firms.

Using our catalog of the components needed in a comprehensive model, one can relate this

paper to the prior literature. The two components, a multi-stage model and an integrated decision mechanism, respond to set of existing models and reduced form approaches that rely on the assumption of a single type of merger. That is, there are no existing empirical strategies that challenge the fundamental assumption that all mergers events are equivalent.<sup>7</sup>

### 3 Theoretical Model

In this section, we outline the structure of the multi-stage search model. We think a search model is an appropriate framework as the cost of exploring a merger with a possible partner is non-zero. Merger negotiations take time, during which other mergers are harder or impossible to consider. A search model incorporates the time-cost of looking for partners into an evaluation of decision making. For the sake of brevity, we abstract from Cohen-Cole (2006), but do not copy the model in its entirety. Broadly, the model will specify a value function for the payoffs from a merger. Merging produces an option value due to the possibility for a subsequent merger; the merged bank moves to a new position in the industry distribution. Remaining unmerged produces the option value of merging with a different firm at a later date. The subsequent merger can also be represented by a value function with similar tradeoffs. The challenge is to nest these value functions into a single framework and then to extract the implications of the second merger on the decision to undertake the first.

Begin with a continuum of banks of three types  $(x_a, x_b, y)$ . Type  $y$  agents can merge only with the outcome of an  $x_a, x_b$  match (denoted  $x$  for simplicity). Thus, in order to form a two-stage merger,  $x_a$  and  $x_b$  match into  $x$  in "stage one." Once matched, the new type  $x$  may now match with type  $y$  (stage two) to produce a larger firm. This partitioning of banks is done for mathematical tractability, though the intuition is unchanged in the more general case. Firms must agree for a match to take place and surplus is divided per Nash Bargaining. This bargaining structure appropriates match surplus according to relevant size. Match-making is time consuming and thus costly. Agents face a Poisson arrival of potential partners.

A match between  $x_a$  and  $x_b$  prevents additional search of this type, creates a type  $x$ , and enables search for  $y$ . This is the fundamental setup that allows us to discuss a multiple-stage merger decision. For  $x_a$  and  $x_b$ , by backward induction, the process includes the problem from the second stage – a trade off between the immediate benefits of merging and the opportunity cost of further search. It also includes a similar first-stage trade-off – some immediate flow payoffs and the opportunity to participate in the second period game versus the opportunity cost of further first-stage search.

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<sup>7</sup>Gorton, et al (2007) include a variable in their regression for recent merger activity (whether the entity had had a merger in the prior 12 months). In a non-structural sense, this accounts for prior activity.

Take a continuum of agents indexed on some publicly observable variable  $x \in [0, 1]$ . In the empirical work, we will use total assets as the key variable. Normalize the mass to one, and let  $L : [0, 1] \rightarrow [0, 1]$  be the type distribution and  $l$  be the positive, finite, and bounded density function ( $0 < l_{\min} < l(x) < \infty$ ). Agents belong to the graph in  $\mathbb{R}^2$  with Lebesgue measure  $\{(x, i) \mid x \in [0, 1], 0 \leq i \leq l(x)\}$ . There are two types of agents with exogenously given type distributions:  $x_a, x_b$ . There is one type of agent,  $x$ , with an endogenously given distribution based on the matching result of the first stage.

Normalize the flow output of agents  $x_a, x_b$ , and  $y$  to zero. When agents  $x_a$  and  $x_b$  are matched, they produce an endogenous flow output and merge to form an agent of type  $x$ . Agent  $x$ 's type is thus endogenously determined by the first-stage matching process between  $x_a$  and  $x_b$ . At any instant of continuous time, an agent,  $x_a$  or  $x_b$ , is unmatched, matched into  $x$ , or fully matched with  $y$ . All unmatched agents engage in search: this includes all  $x_a, x_b, y$ , as well as the matched  $x_a$  and  $x_b$  (a new agent  $x$ ). Type  $y$  meets only type  $x$ , and  $x_a, x_b$  meet only each other. Upon meeting, two agents each observe the other's type prior to the match decision.

The outcome of the first stage match  $(x_a, x_b)$  is a production function  $g : [0, 1]^2 \rightarrow [0, 1]$ . The outcome of the second stage  $(x, y)$  is  $f : [0, 1]^2 \rightarrow \mathbb{R}$ . Having laid the foundations, we can move to discussion of the payoffs.

### 3.1 Payoffs

Each agent maximizes expected value of payoffs, discounted at rate  $r > 0$ . Output of matches  $f(x, y)$ , and  $g(x_a, x_b)$  is shared. Further,  $x$ 's share of match output is shared between types  $x_a, x_b$  in proportion to their initial distribution. Essentially, the relative sizes at the time of the initial merger will determine the share of payoff in the second merger. This is akin to a stock appropriation in the merged institution that is equal to the original relative asset shares. For example, assume that stock holders in  $x_a$  got 30% of the combined  $x_a, x_b$  firm. Then, 30% of the surplus from the  $x, y$  merger will be given to  $x_a$ .

Each type  $x, y$  earns endogenous flow payoff  $\pi(x|y)$  when matched, and each  $x_a, x_b$  earns flow payoff  $\pi(x_a|x_b)$  when matched. It is assumed that  $\pi(\cdot)$  is continuous, differentiable, non-negative, and Lipschitz. Because payoffs exhaust output  $\pi(x|y) + \pi(y|x) = f(x, y)$  or  $f(g(x_a, x_b), y)$ ; and  $\pi(x_a|x_b) + \pi(x_b|x_a) = g(x_a, x_b)$ .

#### 3.1.1 Steady State and Surplus from Matches

It can be shown that there exists a steady-state search equilibrium in which (i) every firm maximizes expected payoff, taking all other strategies as given, (ii) if either matching weakly increases payoffs, the two agents involved accept the match, (iii) all unmatched rates are in steady state.

Let  $V(x_a)$  and  $W(x)$  denote the expected values of unmatched agents  $x_a, x$  respectively. Let  $W(x|y)$  be the present value of  $x$  when matched with  $y$ ; similarly for  $V(x_a|x_b)$ . Thus, note that  $V(x_a|x_b) = W(x)$  by construction. Let  $S(x|y) \equiv W(x|y) - W(x)$  be surplus for  $x$  when matched with  $y$ . Similarly, let  $s(x_b|x_a) = s(x_a|x_b) \equiv V(x_a|x_b) - V(x_a) = W(x) - V(x_a)$  be  $x_a$ 's surplus when matched with  $x_b$  into  $x$ . Surplus for agent  $x_a$  when matched twice (with  $x_b$  and  $y$ ), is  $S(g(x_a, x_b)|y) = S(g(x_a, x_b)|y) + s(x_a|x_b) = W(g(x_a, x_b)|y) - W(g(x_a, x_b)) + W(g(x_a, x_b)) - V(x_a)$ .

While unmatched, agents  $x_a, x_b$  earn nothing. The flow rate of  $x, y$  matches is  $\rho \int_{M(x)} u(y) dy$ . The density of unmatched  $x$  is  $u(x)$ . If  $x$  fails to match, then at rate  $\delta$  the match breaks and reverts to  $x_a$ : incurring capital loss  $s(x_a|x_b)$ .  $x$  earns flow profits of  $\pi(x_a|x_b)$  in each period. Letting  $S(x|y) = S(y|x)$ , and  $S(x_a|x_b) = S(x_b|x_a)$  by the Nash Bargaining solution, then noting the resource constraints:  $\pi(x|y) + \pi(y|x) = f(x, y)$  and  $\pi(x_a|x_b) + \pi(x_b|x_a) = f(x_a, x_b)$ , we have the single-stage result:

$$S(x|y) = \frac{f(x, y) - rW(x) - rW(y)}{2(r + \delta)}. \quad (1)$$

In addition, we have

$$s(x_a|x_b) = \frac{g(x_a, x_b) - rV(x_a) - rV(x_b) + k}{2(r + u(x)\delta)}, \quad (2)$$

where  $k = \rho \int_{M(x)} S(x|y) u(y) dy$ . Substituting from above and rearranging yields

$$S(x|y) = \frac{f(x, y) - rW(y) - rV(x_a)}{2(r + \delta)} - \frac{r}{2(r + \delta)} \left[ \frac{g(x_a, x_b) - rV(x_a) - rV(x_b) + k}{2(r + u(x)\delta)} \right].$$

Bank surplus from a merger is the difference between two terms. The first term is half the excess of flow match output (once discounted) over  $y$ 's and  $x_a$ 's unmatched value. That is, given some match output  $f()$ , the share is computed by deducting the unmatched value. Thus matching must show an improved output over remaining unmatched in order to accept a merger. The second term is one quarter the excess of flow match output over  $x_b$ 's and  $x_a$ 's unmatched value (twice discounted at the appropriate rates). The logic is that an unmatched  $x_a$  must share his match output *twice* – initially sharing half the first-stage match, then subsequently sharing both this initial match and the new surplus with  $y$ .

This leads to a intuition that match surplus is exponentially declining in the number of matches. Note that in the theory section of this paper, we do not restrict the payoff function from mergers to any given form. Conditional on the mergers producing non-negative payoffs and payoffs being increasing in asset size, we can make a set of claims.

## 3.2 Testable Implications

This model has a number of implications that we will test for in the following sections. This subsection will detail the rationale behind each of them. Effectively, the model in this paper suggests that firms make their current decisions based on how those decisions impact their future opportunity set. This is somewhat akin to agents making pricing decisions based on future inflation expectations; the key distinction is that in this context agents are basing current actions on expectations of their own behavior (rather than exclusively on an aggregate).

What can we use as a parsimonious representation of market power? To illustrate the efficacy of the approach, we look at firm total assets.<sup>8</sup> For each, we look at the ratio of these measures between the larger of two merging banks and the smaller.<sup>9</sup> Consider the ratio of measures - these give a simple measure of the relative types involved in a merger. Using one of these ratios, we can comment on optimal merger strategy as implied by this model. We have two matched sets of initial results: first, we can comment on how future expectations drives current behavior. Second, we can discuss merger patterns conditional on first-period behavior. Disentangling these two effects seems bound to be confounded by endogeneity concerns; in fact, in this model, the decisions of the first and second stages of a merger program are inextricably linked. Thus, our econometric implementation in the next section will identify the presence of what we call "regimes." Effectively, the decision to undertake a particular merger restricts the agent to a given regime in the next round. The choice of a merger is linked to the possibilities of the next round; thus we are concerned not with the direction of causation in this model but the presence of the patterns predicted by the model. Regardless, we discuss an IV exercise to identify causation in the Results section.

## 4 Econometric Implementation

Our goal in this section is to evaluate the degree to which the conclusions of the model are upheld in the data. We approach this question with a relatively straightforward methodology. Our goal will be to assess the presence of the regimes indicated in the above paragraph. This allows us to use a very simple reduced form to look for the presence of a handful of key directional indicators.

To summarize, we will search for the following:

### **Conjecture 1** *role of future mergers on current decisions*

- The asset ratio of the 2nd merger should be a positive predictor of the asset ratio of the current merger.

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<sup>8</sup>We also replicated our main results using firm equity, but this analysis is omitted for brevity.

<sup>9</sup>We do not consider acquirer or acquired designations.

- The asset ratio of the 3rd merger should be a positive predictor of the asset ratio of the current merger.

**Conjecture 2** *the pattern of future mergers conditional on the current one*

- The asset ratio of the current merger should be a positive predictor of the asset ratio of the subsequent merger.
- The asset ratio of the current merger should be a positive predictor of the asset ratio of the 3rd merger.

We evaluate as follows. First define

$$ratio_{kt} = asset_{it}/asset_{jt},$$

where  $asset_i$  is the asset size of firm  $i$ , the acquiring bank, and  $asset_j$  is the asset size of the target bank. The subscript  $t$  indexes time. Though this is not a panel model, the time index will be useful in tracking merger order below. We also define  $ratio_k$  as the asset ratio for the  $k$ 'th merger in a series of mergers for bank  $i$ .

Our claims can then be evaluated as follows. For conjecture 1 above, we use:

$$ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 E_t ratio_{3it''} + \varepsilon_i \quad (3)$$

$$ratio_{2it'} = \alpha + \beta_4 E_t ratio_{3it''} + \eta_i, \quad (4)$$

where  $E_t$  is the time  $t$  expectations operator. Note the time subscripts on  $ratio_2$  and  $ratio_3$ . For clarity,  $t < t' < t''$ . A full list of controls is available in the next section. For implementation purposes, we make use of the rational expectation assumption in order to replace  $E_t ratio_{2it'}$  and  $E_t ratio_{3it''}$  with actual information at time of the merger:  $ratio_{2it'}$  and  $ratio_{3it''}$ . We then inspect the significance of  $\beta_1, \beta_2$ .

For conjecture 2 above, we use:

$$E ratio_{3it''} = \alpha + \gamma_1 ratio_{1i} + \gamma_2 ratio_{2i} + \xi_i \quad (5)$$

$$E ratio_{2it'} = \alpha + \gamma_4 ratio_{1i} + \mu_i, \quad (6)$$

We again use rational expectations and replace the expectations as necessary. Our logic is that the variable of interest for the recursive search problem is the asset ratio. Other variables may have an impact on decisionmaking at the time of a given mergers, but we argue are secondary to the problem studied here. A full list of variables is available in the data section. We then check the significance of  $\gamma_1, \gamma_2$ .

## 4.1 Comparison to Single Stage Model

A central claim of this paper is that accurate modeling of merger patterns requires the use of a multi-stage matching model. Essentially, our argument is that models that including all mergers as observations in a regression assume exchangeability of errors.<sup>10</sup> In the context of Cohen-Cole (2006), exchangeability can only be achieved by ordering mergers and conditioning merger decisions on the history and expectation of future ones. To evaluate this claim, we present empirical evidence of this feature by looking again at the size ratio of mergers as a central metric. A single-stage model, essentially one that considers each merger an independent event, would suggest that the size-ratio of mergers can be predicted according to some function:

$$ratio_i = \alpha + \eta_1 X_i + \zeta_i,$$

where  $X_i$  is as appropriately defined set of independent variables as above.

Thus a simple test of the importance of the multi-stage model is an evaluation of the same regression on two datasets. If a single stage model is sufficient, one should obtain similar results for  $\eta_1$  using data from banks that merge only once and using data from banks that merge more than once. Similarly, one should see similar results from the subset of second (or third) mergers only as found in the sample of first mergers only. Consider the following set regressions:

$$ratio_{1i} = \alpha + \eta_1 X_{it} + \zeta_i \tag{7}$$

$$ratio_{2i} = \alpha + \eta_2 X_{it} + \zeta_i \tag{8}$$

$$ratio_{3i} = \alpha + \eta_3 X_{it} + \zeta_i \tag{9}$$

$$ratio_{1'i} = \alpha + \eta_4 X_{it} + \zeta_i. \tag{10}$$

Our null hypothesis is that the single-stage model is equivalent to the multi-stage one. To reject this in favor of the multi-stage version, one must find that for each pairwise combination of  $\eta_j, j = 1...4, \eta_j \neq \eta_k$ . For clarity, let  $\eta_1, \eta_2, \eta_3$  be defined as the coefficients for  $X_i$  corresponding to the  $k$ 'th merger in a series. The coefficient  $\eta_4$  applies to  $ratio_{1'}$ , the ratio for all mergers considered as a single step (the whole sample of mergers in the dataset). Note here that the time index is  $t$  for all four specifications. In each case, the relevant time period is the time of the merger itself; there is no need to worry about sequencing or multiple time periods in a given regression.

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<sup>10</sup>Essentially, exchangeability argues that the errors from any observation of a model can be "exchanged" with one of the others without changing the content of the mode. See Bernardo and Smith (1994) for information on deFinetti's representation theorem.

## 5 Data

We use merger data for this analysis compiled by the SNL Financial. The time period examined includes the years 1986-present. In total, 3304 completed merger events involving 1344 distinct acquiring banks comprised the final dataset. Of these, there were 481 banks that had two or more mergers during the time period and 266 banks that had three or more. These will constitute the basic building blocks of our study.

Additional information on bank characteristics was included by linking this set with data based on FDIC call reports. Where appropriate, the characteristics of the top holder were used in lieu of the subsidiary. The various control variables, when used, were drawn from the quarter prior to each acquisition. Mergers where the assets of the nonsurviving entity were less than 1 percent of the surviving entity were dropped to exclude outliers. Cases in which the acquiring bank was several hundred times the size of the target are unlikely to have a significant effect on the future merger trajectory of the acquirer and can be viewed as tangential to our discussion here. Previous papers similarly drop small acquisitions.<sup>11</sup>

Though our structural interpretation of the model implies relationships that should exist independent of controls, we include an appendix with a set of ad-hoc regressions to answer potential questions of omitted variable bias.<sup>12</sup> As will be shown, these do little to impact the key results. Briefly, those we consider for straw-man purposes are modeled primarily after Hannan and Pilloff (2006). These include return-on-assets, capital-asset ratio, inefficiency, and the age of the bank. Return-on-assets (roa) is net income over total assets; capital-over-assets (ka) is total equity capital divided by total assets; inefficiency (ineff) is defined as non-interest expenses over the difference of total income minus interest expenses; finally, age is the number of days since the bank's opening.

We also include a time trend (simple time variable) and/or time fixed effects (year dummies for 1986 through 2007 with 1986 as the excluded dummy). See Table 1 below for descriptive statistics for the data. This includes information for all merging institutions, as well as breakdown by acquirer and target institutions.

## 6 Results

Various empirical exercises support the proposed theoretical matching model. First and foremost it supports the conclusion that banks exhibit clear foresight in merger activity. As evidence of this

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<sup>11</sup>Rosen (2004) drops observations where the target firm's assets are less than 5 percent of the acquirer's.

<sup>12</sup>To be clear, a finding that the controls impact our regressors of interest implies only that there are strong correlates of our key variable in the controls. It does not necessarily imply a confounding of the theory or the empirics that exclude the controls.

finding, we show results to address the main two conjectures raised above: the role of anticipated future merger size ratios on current mergers and the role of current mergers on future decisions.

Table 3 shows the results of various combinations of specifications related to conjecture 1. The column headers describe the dependent variable of the regression and the row descriptors describe which independent variables are used in each case. For each table, column 1 addresses the first merger for all banks. In deciding on the relative size of this merger, the size of its subsequent (the future planned one) merger impacts the current decision on the order of .4 for each 1 unit of the present merger. This confirms the first component of the first conjecture. Column 2 of this table confirms part 2 of the first conjecture - it finds a positive coefficient on the third merger in impacting the initial one. Columns 4-7 address exchangeability along a different dimension. Perhaps firms that have only two mergers in a sequence solve a slightly different problem than those that merge three times; notice that the model cannot distinguish between firms that plan to merge twice and those that intend to merge three times but have not yet carried out the third merger due to search frictions. Column 4 addresses the first merger ratio for firms that only merge twice in our dataset (thus the notation  $1/2$ ). The other columns follow similarly. These four columns show similar results as the initial three, albeit with much reduced sample sizes, lending support to the findings.

We anticipated that the second and third merger ratios may not be separately significant in all specifications due to data limitations on banks with three or more mergers; however, an F-test of joint significance was performed for regressions including both those regressors. These joint tests had p-values less than .05 in all cases.

Table 4 has results pertaining to conjecture 2. Notation follows similarly in this table; the principal distinction is that the independent variables are now prior mergers instead of future ones. Column 1 confirms the first component of conjecture 2, and column 3 confirms part 2. The second-ratio and first-ratio coefficients in Table 4 were not always separately significant but were highly significant jointly, as was the case in Table 3.

Table 2 summarizes the results from 3 and 4. This simplified table shows the coefficient on the ratio variable in a number of contexts. Each reported coefficient is taken from a full regression model in the form of Equations 3 or 4 above. The upper panel (A) shows the results from conjecture 1 above: what is the impact of future merger decisions on current actions. Beginning with the upper left cell, we observe the coefficient on the effect on a current merger of a change in the ratio of the subsequent merger. The upper right cell shows the impact of the third merger on the first and the lower right cell that of the third merger on the second. The lower panel (B) shows the inverse, corresponding to conjecture 2 above. This time we observe the coefficient on the subsequent merger of a change in the size of a current merger.

## 6.1 Dealing with Endogeneity

As mentioned, our principal goal in this paper is to elucidate the existence of foresight in merger planning. The baseline results confirms this; it finds a dual link between the future plans conditional on present actions and present actions based on future plans. Though this is in principle sufficient for the aims of the paper, it is useful to provide additional information on the relevance importance of each merger in the joint decision.

As should be apparent, the model proposed here involves the joint determination of two variables ( $ratio_k$  and  $ratio_{k+1}$ ). This produces a simultaneous system:

$$ratio_{1it} = \alpha + \beta_1 ratio_{2it'} + \varepsilon_i \quad (11)$$

$$ratio_{2it'} = \alpha + \gamma_1 ratio_{1i} + \eta_i, \quad (12)$$

We evaluate the system by selecting a set of appropriate instruments. In particular, to identify  $\beta_1$  we will need an instrument that is uncorrelated with  $\varepsilon_{1i}$  but correlated with  $ratio_{2}$ . Effectively, we need an instrument that can be used to predict the ratio of assets at the time of the second of a series of mergers, but is unrelated with the first. Of course, this is particularly difficult to do since any set of firm characteristics that impact either of the merged entities in the first step will likely be determinants in the second.

The instruments we will use will be deviations from expected industry characteristics. While firms could potentially plan for a target future asset ratio at the time of an initial merger, as the model implies, we hold that deviations from some set of plans and market predictions cannot be part of the current of the current decision process. Recall from the model that agents define an acceptable future matching set; however, this simply defines a subset of the range of possible asset values that match with the expected future distribution of asset values.

To be explicit, we imagine that firms anticipate the future distribution of asset values and base their matching set on this expectation. Any deviations from this expectation cannot have been used at the time of the initial planning. We thus use these deviations as our instruments. To calculate the deviations, we define the expected industry characteristics as the expected values from four independent ARMA processes. We calculate the best fitting ARMA process for the first four moments of the industry asset distribution and then take the difference between the observed industry distribution and the estimated one. These 'residuals' form our four instruments of interest.

Results of the first stage regressions are available in Table 5. This illustrates a relatively low degree of correlation between the instruments and the corresponding merger ratios. We interpret this low correlation as evidence that once a firm has chosen a merger strategy (based on expectations of the future), it is optimal to maintain that strategy even if the expectations on which the plan was

based turn out to be far from the mark. Our best guess as to why this occurs is due to some form of institutional inertia in planning or an unmodeled cost factor that makes changing plans slower than the quarterly information basis that we are using. Table 6 shows second stage results. As the test statistics confirm, the instruments are borderline weak, suggesting a bias toward OLS. It appears that the magnitude of the planning effect is large, though given the imprecision of the estimates, we would be reluctant to rely on the point estimates.

Broadly, the result confirm the OLS story that future plans vis-a-vis the size of merger partners impacts current decisions in a way that has not been captured by other studies.

## **6.2 Controls**

While the control variables have been shown to be effective at predicting the probability of merger activity, they were not statistically validated in the analysis of merger ratios. When adding controls to the regressions from Table 3 and Table 4, the coefficients on past and future ratios were largely unchanged. See tables 7, 8, and 9 at the end of the paper. This could be interpreted as evidence that the plans and foresight of bank management swamp the importance of control variables during merger programs.

## **7 Conclusions**

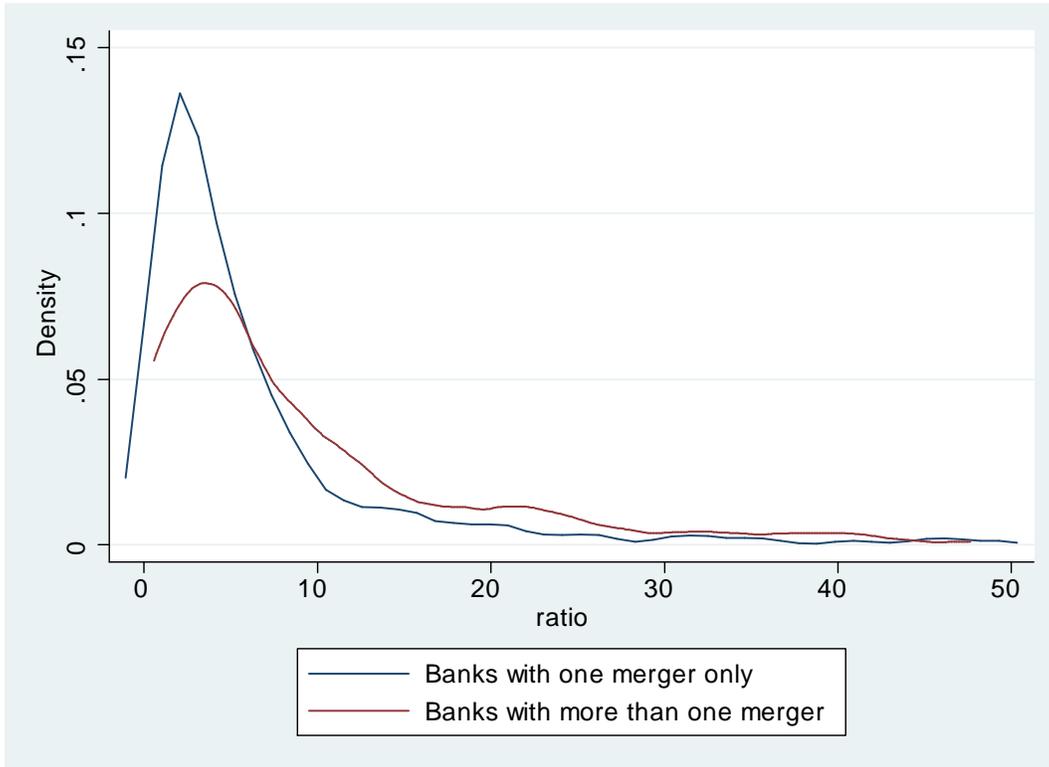
This paper has shown the perhaps unsurprising result that banks are rational in their long term merger planning. When making a merger decision, institutions consider not only the impact of the merger itself, but also how that merger will position the institution to merge again in the future. We have found that the multi-stage search model is valid on the dataset we explore, and it can enrich the framework for future evaluation of mergers. The tacit assumption that all mergers can enter regressions equivalently warrants additional scrutiny.

Though it is of clear research interest, we leave unexplored in this paper the consequences of merger foresight on specific valuation decisions of individual institutions. However, the model implies that institutions with long-term merger programs will pay a larger acquisition premium than those with no future plans.

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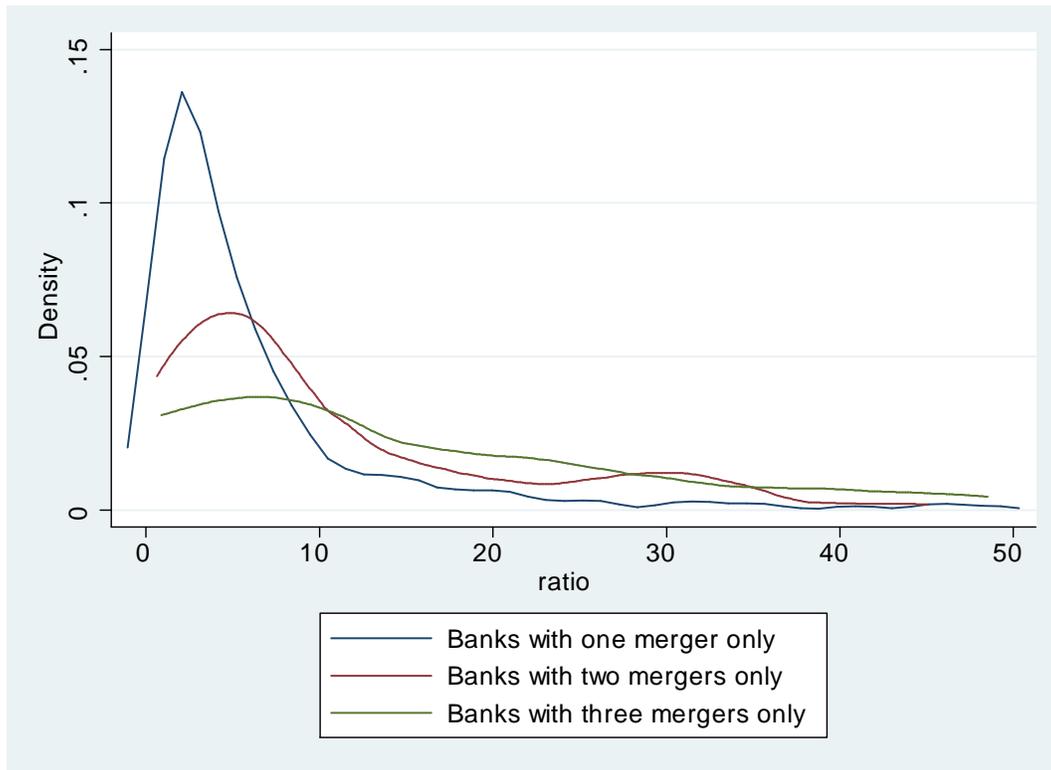
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Figure 1 : Kernel densities of first merger ratio.



Note: This figure shows that banks which engage in additional mergers in the future behave differently in the present than those banks which only merge once. Banks which only merge once tend to have smaller first-ratios than banks which merge multiple times. The blue distribution represents 477 banks which only participated in one merger over the span of the data; the red distribution comprises 161 banks which engaged in more than one merger.

Figure 2 : Kernel densities of successive merger ratios.



Note: This figure shows the evolution of the banking market structure toward consolidation over time. The blue distribution represents the asset ratio of the first/last merger of the 477 banks which only merged once; the red distribution comprises the final merger ratio of the 97 banks which merged exactly twice; the green distribution reflects the final merger ratio of the 38 banks which merged exactly three times.

Table 1 : Explanatory variables and descriptive statistics.

Variable	Description	Min	Max	Mean	Std. Dev.	Median
ka	capital-to-assets ratio	-.0033174	.5544766	.0969686	.0365811	.0890661
	stats for acquirers only	.0442510	.3199723	.0958873	.0302925	.0882580
	stats for targets only	-.0033174	.5544766	.1010839	.0460722	.0920848
roa	return-on-assets ratio	-.1074567	.2410101	.0059425	.0114556	.0059688
	stats for acquirers only	-.0170804	.0586211	.0076807	.0056392	.0068893
	stats for targets only	-.1074567	.2410101	.0038017	.0176006	.0045068
ineff	non-interest expenses over the difference of total income minus interest expenses	.2121588	10.15385	.6763915	.2941916	.6358747
	stats for acquirers only	.2345913	10.15385	.6335473	.3996892	.6045817
	stats for targets only	.2121588	2.575786	.7403582	.2454603	.6934575
age	number of days the bank had been open prior to first merger in dataset	394	72920	22141.29	15252.03	23483.5
	stats for acquirers only	394	72920	25332.52	15610.21	27715
	stats for targets only	492	67290	20985.03	14593.36	23041
assets	total assets one quarter prior to merger (in thousands of dollars)	4.222	392181	1857.895	11873.06	181.012
	stats for acquirers only	5.035	392181	2242.907	16714.99	275.817
	stats for targets only	4.222	49190.23	538.0915	2973.852	64.85
first-ratio	ratio of acquirer's assets to target's assets for first merger in dataset	.020506	49.26055	7.073556	8.437436	4.105426
second-ratio	ratio of acquirer's assets to target's assets for second merger in dataset	.3284844	47.69215	12.19762	11.95277	7.402367
third-ratio	ratio of acquirer's assets to target's assets for third merger in dataset	.8005503	48.53867	13.83658	13.11138	8.789464
first-gap	time between first and second merger (in days)	2	2065	574.0435	476.0981	426
second-gap	time between second and third merger (in days)	3	1681	377.3115	385.599	230
time	number of days in dataset elapsed prior to merger	0	2445	1065.902	703.8127	985
primerate	bank prime loan rate for the month of the merger	4.75	9.5	7.936398	1.208057	8.25

Note: Year dummies for 1986-2007 were also used in the control regressions, but are not displayed here.

Table 2 : Summary of effects of previous and subsequent mergers in a merger program.

Panel A	
<b>first-ratio on second-ratio</b> $ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 X_{it} + \varepsilon_i$	<b>first-ratio on third-ratio</b> $ratio_{1it} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it} + \varepsilon_i$
$\beta_1 = 0.419$	$\beta_1 = 0.293$
	<b>second-ratio on third-ratio</b> $ratio_{2it'} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it'} + \varepsilon_i$
	$\beta_1 = 0.418$
Panel B	
<b>second-ratio on first-ratio</b> $ratio_{2it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it'} + \varepsilon_i$	<b>third-ratio on first-ratio</b> $ratio_{3it''} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it''} + \varepsilon_i$
$\beta_1 = 0.606$	$\beta_1 = 0.333$
	<b>third-ratio on second-ratio</b> $ratio_{3it''} = \alpha + \beta_1 ratio_{2it'} + \beta_2 EX_{it''} + \varepsilon_i$
	$\beta_1 = 0.357$

Note: These values correspond to the regression coefficients for the independent merger ratio on the dependent merger ratio. Panel A relates to Table 4 while Panel B relates to Table 3. The regressions correspond (but are not identical) to equations 3-6.

Table 3 : Current merger asset ratio on future ratios.

ratio	1st merger		2nd merger	merger 1/2	merger 1/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.419 (.059)***	.391 (.079)***		.230 (.118)*	.399 (.135)***	.326 (.152)**	
3rd ratio		.130 (.081)	.418 (.084)***			.255 (.105)**	.379 (.188)**
cons	6.228 (.775)***	6.492 (1.378)***	11.643 (1.595)***	5.466 (1.037)***	6.298 (1.965)***	3.534 (1.774)**	9.826 (2.775)***
e(N)	480	264	266	214	78	76	77
e(r2)	.254	.274	.149	.104	.262	.31	.099
e(F)	51.376	22.226	24.493	3.832	8.675	8.283	4.053

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the subsequent ratios included. The first-ratio regression model is  $ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 E_t ratio_{3it''} + \beta_3 X_{it} + \varepsilon_i$ , which corresponds to equation 3. The second-ratio regression model is  $ratio_{2it'} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it'} + \varepsilon_i$ , which corresponds to equation 4. The sample includes all banks which engaged in at least three merger transactions. The symbols \*, \*\*, and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively.

Table 4 : Current merger asset ratio on past ratios.

ratio	3rd merger		2nd merger	merger 2/2	merger 3/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.357 (.064)***	.282 (.085)***			.267 (.123)**	.119 (.141)	
1st ratio		.169 (.109)	.606 (.069)***	.454 (.159)***		.374 (.200)*	.620 (.198)***
cons	12.359 (1.397)***	11.005 (1.444)***	7.871 (.884)***	6.925 (1.378)***	11.374 (2.284)***	8.932 (2.323)***	7.665 (2.098)***
e(N)	266	266	481	215	78	78	78
e(r2)	.153	.172	.257	.105	.097	.189	.245
e(F)	31.047	15.242	76.267	8.178	4.72	3.344	9.84

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the prior ratios included. The third-ratio regression model is  $ratio_{3it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 ratio_{2it'} + \beta_3 EX_{it'} + \epsilon_i$ , which corresponds to equation 5. The second-ratio regression model is  $ratio_{2it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it} + \epsilon_i$ , which corresponds to equation 6. The sample includes all banks which engaged in at least three merger transactions. The symbols \*, \*\*, and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively.

Table 5 : First-stage IV regressions.

ratio	(1)	(2)	(3)	(4)
	mean-resid	-7.02e-06 (1.00e-05)	5.51e-06 (.00002)	-2.50e-06 (.00002)
var-resid		-1.71e-14 (2.16e-14)	-9.05e-15 (2.37e-14)	-9.06e-15 (2.37e-14)
skew-resid			-.416 (.536)	-.568 (1.695)
kurt-resid				.002 (.023)
cons	17.340 (.927)***	17.226 (.887)***	17.285 (.904)***	17.290 (.903)***
e(N)	3033	3033	3033	3033
e(r2)	.0001	.0004	.0007	.0007
e(F)	.339	.	.	.

Note: This table displays the first stage regressions that correspond to the IV results in Table 6.

Table 6 : Second-stage IV regression for current merger asset ratio on predicted next ratio.

ratio	all mergers	1st merger	2nd merger	3rd merger
	(1)	(2)	(3)	(4)
next merger ratio	1.470 (.512)***	.844 (.247)***	.881 (.222)***	.281 (.273)
cons	-12.282 (12.274)	-463 (3.760)	2.916 (3.906)	14.876 (6.034)**
e(N)	1690	481	266	188
e(r2)	-1.14	-0.02	-0.035	.101
e(F)	8.234	11.655	15.57	1.043
e(Hansen J-stat)	.928	1.577	5.546	15.03
e(p-value)	.819	.665	.136	.002
e(Andersen LR-stat)	6.528	7.758	16.001	8.058
e(p-value)	.163	.101	.003	.089
e(Cragg-Donald F-stat)	1.63	1.935	4.046	2.004

Note: The excluded instruments are the distribution characteristics (mean, variance, skewness, kurtosis) of banking industry assets at the time of the subsequent merger.

Table 7 : Merger asset ratio on controls.

ratio	1st merger	2nd merger	merger 1/2	merger 1/3	merger 2/3
	(1)	(2)	(3)	(4)	(5)
surv-ka	-53.145 (9.027)***	-1.482 (38.555)	-20.841 (19.491)	-98.934 (123.798)	43.155 (168.108)
surv-roa	247.844 (117.918)**	-520.376 (328.147)	-72.983 (194.296)	-2685.854 (2481.995)	2021.699 (2986.131)
surv-ineff	-.031 (.115)	.086 (.175)	-.064 (.080)	-2.720 (1.253)**	1.200 (1.864)
surv-age	-.00008 (.00002)***	.0002 (.0001)*	-.00007 (.00005)	.0003 (.0003)	.0003 (.0005)
non-ka	26.785 (9.577)***	25.418 (35.806)	21.955 (22.448)	-91.052 (106.094)	59.223 (84.705)
non-roa	-87.876 (35.153)**	-25.090 (131.599)	-74.685 (103.630)	2802.937 (2842.601)	-683.561 (1672.803)
non-ineff	-.037 (.051)	.260 (.127)**	-.005 (.062)	6.763 (3.200)**	.237 (.169)
non-age	-.00004 (.00002)*	-.0002 (.00008)**	7.55e-06 (.00004)	-.0004 (.0002)*	-.00009 (.0002)
year dummies	included	included	included	included	included
cons	45.856 (1.700)***	12.189 (4.368)***	4.418 (2.396)*	18.253 (13.080)	-12.051 (21.871)
e(N)	1160	377	179	58	62
e(r2)	.137	.177	.165	.487	.387
e(F)	.	.	1.48	.	.

Note: Various regression specifications for the relationship between the control variables and the first merger in a merger program. The first-ratio regression model is  $ratio_{1it} = \alpha + \beta_1 X_{it} + \varepsilon_i$ . The second-ratio regression model is  $ratio_{2it'} = \alpha + \beta_1 X_{it'} + \varepsilon_i$ . The third-ratio regression model is  $ratio_{3it''} = \alpha + \beta_1 X_{it''} + \varepsilon_i$ . The sample includes all banks which engaged in at least one merger transaction. The symbols \*, \*\*, and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively.

Table 8 : Current merger asset ratio on future ratios with controls.

	1st merger		2nd merger	merger 1/2	merger 1/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.460 (.090)***	.405 (.114)***		.177 (.105)*	.469 (.389)	.469 (.396)	
3rd ratio		.161 (.094)*	.426 (.133)***			.176 (.230)	.477 (.176)***
surv-ka	-42.997 (21.442)**	-83.860 (50.425)*	107.679 (86.216)	-15.885 (19.447)	-50.919 (89.118)	-70.834 (86.784)	105.426 (175.626)
surv-roa	-149.979 (262.996)	-555.545 (882.582)	-64.830 (1476.398)	-91.866 (192.249)	-865.251 (2694.466)	-1608.147 (2315.166)	2577.924 (3000.590)
surv-ineff	-.187 (.121)	-.848 (.589)	.629 (.487)	-.094 (.090)	-2.444 (1.090)**	-1.592 (1.148)	1.196 (1.439)
surv-age	.00002 (.00008)	.0003 (.0003)	.0008 (.0004)*	-.00006 (.00004)	.0005 (.0003)	.0003 (.0004)	.0003 (.0005)
non-ka	18.657 (20.913)	17.431 (40.412)	40.826 (56.420)	19.467 (21.948)	-35.226 (86.500)	-48.785 (89.859)	59.370 (77.985)
non-roa	-207.493 (101.051)**	-256.104 (336.519)	25.101 (147.754)	-92.923 (98.917)	1277.346 (1936.245)	2007.776 (2012.400)	-239.860 (1571.001)
non-ineff	.063 (.082)	1.751 (1.857)	.539 (.199)***	.012 (.068)	6.204 (2.886)**	3.371 (3.345)	.403 (.161)**
non-age	-.0001 (.00005)***	-.0002 (.00008)***	-.0002 (.0001)*	-3.74e-06 (.00004)	-.0004 (.0002)*	-.0003 (.0002)	-.0002 (.0002)
year dummies	included	included	included	included	included	included	included
cons	35.450 (4.419)***	38.273 (8.138)***	-24.039 (11.426)**	3.600 (2.506)	5.628 (12.291)	8.985 (10.241)	-34.174 (22.420)
e(N)	373	194	199	179	58	58	62
e(r2)	.379	.465	.345	.195	.556	.596	.483
e(F)	.	.	.	1.451	.	.	.

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the subsequent ratios and controls included. The first-ratio regression model is  $ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 E_t ratio_{3it''} + \beta_3 X_{it} + \epsilon_i$ , which corresponds to equation 3. The second-ratio regression model is  $ratio_{2it'} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it'} + \epsilon_i$ , which corresponds to equation 4. The sample includes all banks which engaged in at least three merger transactions. The symbols \*, \*\*, and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively.

Table 9 : Current merger asset ratio on past ratios with controls.

ratio	3rd merger		2nd merger		merger 2/2		merger 3/3		merger 2/3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)			
2nd ratio	.329 (.098)***	.289 (.095)***			.318 (.217)	.357 (.222)				
1st ratio		.152 (.131)	.547 (.080)***	.376 (.174)**		.269 (.144)*	.479 (.175)***			
surv-ka	-197.858 (58.654)***	-187.474 (57.519)***	13.447 (31.431)	-29.966 (25.917)	-257.673 (57.983)***	-253.378 (56.805)***	33.744 (143.771)			
surv-roa	508.106 (1347.544)	408.549 (1368.319)	-163.806 (261.444)	-486.930 (303.852)	1005.120 (1922.747)	1240.166 (1745.945)	3942.209 (3283.979)			
surv-ineff	-.017 (.010)*	-.018 (.011)*	.053 (.102)	-.027 (.040)	-.013 (.012)	-.016 (.013)	.922 (1.967)			
surv-age	.0003 (.0003)	.0002 (.0003)	.0001 (.00008)*	9.14e-06 (.00005)	.0001 (.0004)	1.00e-05 (.0003)	.0003 (.0004)			
non-ka	98.163 (54.385)*	106.287 (55.319)*	37.788 (31.218)	52.895 (26.664)**	181.192 (86.661)**	193.902 (80.445)**	78.172 (69.566)			
non-roa	58.805 (116.437)	39.604 (118.535)	-42.207 (127.686)	13.362 (135.399)	-253.256 (129.344)*	-266.862 (117.510)**	-934.495 (1381.286)			
non-ineff	.525 (.457)	.525 (.462)	.253 (.143)*	.870 (.457)*	1.603 (.682)**	1.711 (.710)**	.400 (.206)*			
non-age	.00007 (.0001)	.00006 (.0001)	-.0002 (.00007)**	-.0001 (.00006)*	-.0002 (.0001)	-.0003 (.0001)**	-.0003 (.0002)			
year dummies	included	included	included	included	included	included	included			
cons	23.208 (8.230)***	21.942 (8.097)***	6.570 (3.722)*	40.107 (3.259)***	-5.283 (7.816)	-7.314 (7.284)	-20.362 (18.884)			
e(N)	198	198	377	178	62	62	62			
e(r2)	.326	.338	.369	.343	.511	.55	.519			
e(F)	.	.	.	.	.	.	.			

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the prior ratios and controls included. The third-ratio regression model is  $ratio_{3it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 ratio_{2it'} + \beta_3 EX_{it'} + \varepsilon_i$ , which corresponds to equation 5. The second-ratio regression model is  $ratio_{2it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it} + \varepsilon_i$ , which corresponds to equation 6. The sample includes all banks which engaged in at least three merger transactions. The symbols \*, \*\*, and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively.