Understanding Merger Incentives and Outcomes in the
US Mutual Fund Industry

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Abstract

This paper examines the incentives of acquirers and targets in the merger market. Using data on acquisitions among mutual fund management companies from 1991 through 2004, I estimate a two-sided matching model of the merger market jointly with equations representing merger outcomes. According to the empirical investigation, although the desire to achieve a sufficient scale to attract investors is a key driver for mergers, some mergers seem to be driven by objectives other than shareholder value maximization. I find that companies that are potentially prone to misaligned incentives between owners and managers are more acquisitive than others, yet have significantly

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worse post-merger operating performance. I also find that these acquirers, despite their higher willingness to pay for targets, are not any more likely to match with high-quality targets, potentially due to targets’ incentive to avoid bad organizations.

**JEL classification:** G20; G30; G34

**Keywords:** M&A; Two-sided matching; Non-value-maximizing behavior
1. Introduction

A variety of motives may impel firms to pursue an acquisition. Companies may acquire to increase shareholder value or to obtain private benefits for managers. The idea that managerial incentives might diverge from shareholder value maximization is an old and influential one, and there has been a significant line of research examining how such divergent objectives may impact acquisition decisions (Baumol, 1959; Jensen, 1986; Roll, 1986; Shleifer and Vishny, 1988; Morck, Shleifer and Vishny, 1990; Malmendier and Tate, 2008). Following on the literature, this paper studies how merger behavior and merger outcomes differ between the two types of acquirers, as well as how they may be differentially evaluated by targets in the merger market. I address these questions in the context of acquisitions among mutual fund management companies in the US from 1991 to 2004.

The key departure of this paper compared to the existing literature is that I examine how acquirers’ incentives and targets’ incentives interact in determining the equilibrium of the merger market, instead of focusing on only one side. In the merger market, companies that are at least partly driven by managerial private benefits, such as empire-building motives, might be more eager to pursue an acquisition than value-maximizing companies all else equal, because of the additional private benefits their managers get. However, if acquirers with managerial motivations are worse at managing the combined companies, targets might prefer value-maximizing acquirers, as targets’ managers might share the success or failure of the merged firm through earn-out contracts or employment contracts that link pay to firm performance. One goal of this paper is to understand how these incentives of the two sides
influence who matches with whom in the merger market.

To investigate these issues, this paper estimates a model of takeover market together with equations representing the outcomes of mergers (Shim and Okamuro (2011) similarly look at both merger behavior and merger outcome). I model the takeover market as a two-sided matching game in which pairings between acquirers and targets arise as a stable assignment. Since I want to study how the equilibrium matching in the takeover market is influenced by both acquirers’ and targets’ preferences, a single agent model such as probit or logit would not be sufficient and an equilibrium model such as matching game is called for. The existing literature that uses conventional regression methods to examine mergers largely ignores the fact that M&As are the results of joint selection of both the acquirer and the target, and consequently does not fully capture the endogenous nature of mergers in their analysis. The matching model of this paper offers a more rigorous and integrated way to investigate mergers and their outcomes by allowing both acquirers’ and targets’ incentives to influence the equilibrium matching.

Moreover, a matching model allows me to account for interaction among the choices made by different firms: Since a target cannot be sold to more than one firm, and a firm cannot acquire more than a certain number of targets in a given period, the feasible choice set for a given firm depends on other firms’ choices. This interaction among the choices made by different firms makes a matching game a more suitable modeling framework for the merger market than a standard single-agent discrete choice model, because only the former accounts for the possibility that firm A chose target X instead of target Y not because firm A prefers X to Y, but rather because target Y was not available to firm A since Y
had a better merger partner. Failing to account for such interaction among players is likely to lead to biased estimates of acquirers’ preferences over target characteristics and targets’ preferences over acquirer characteristics, as Gordon and Knight (2009) demonstrated in the context of school district mergers. This problem is analogous to the problems that arise when one uses a single-agent model for a game, and the literature has long shown pitfalls of such an approach (e.g., Berry, 1992).

Since a company’s acquisition motive is never directly observed, I employ a proxy that might indicate acquirers with managerial motivations and empirically test whether the proxy captures any systematic behavioral patterns. The proxy is based on the following ideas: (1) public firms are more prone to incentive problems due to the separation of ownership and control, and (2) companies that have performed poorly might be more vulnerable to incentive problems (Morck, Shleifer and Vishny, 1990). Based on the proxy, I identify a set of companies that could potentially have managerial motives for acquisitions, and empirically test whether their behavior systematically differs from others’ in three key dimensions: tendency to pursue an acquisition, merger outcomes, and targets’ evaluation of them in the merger market.

As a merger outcome variable, I study post-merger asset growth. Economies of scale in marketing and distributing funds are important in this industry due to consumers’ desire for the convenience of one-stop shopping, and post-merger asset growth is a good measure

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1In contrast, a version of Roll (1986)’s hubris hypothesis could predict that well performing firms are more likely to acquire out of managerial motivations. Thus, it is an empirical question whether the proxy is associated with behavior that is indicative of non-value-maximizing acquisitions.

2My estimation allows the proxy to be irrelevant in explaining these three dimensions. Thus, if the proxy does not represent any meaningful distinction of the type of acquirer, empirical results would show it.
of the degree to which the newly merged firm captures such scale economies. I then jointly estimate the matching model and the outcome equations, allowing correlation between the errors of the matching model and the outcome equations (similar to Sorensen (2007)). The interdependence among players in the matching model presents numerical difficulties for estimation. Bayesian methods using Gibbs sampling and data augmentation provide an elegant solution to this numerical problem.

My estimation results provide an interesting picture about the merger market in the mutual fund industry. First, I find that value-maximization is a key motive for many acquisitions in this industry. The results indicate that firms are more likely to merge with other companies that use the same channel of distribution (selling funds directly to investors or indirectly through intermediaries), suggesting that many firms engage in an acquisition in order to benefit from economies of scale in marketing and distributing funds. And they do benefit from such scale economies post-merger, as the outcome equations show that the merged firm attracts larger asset inflows when the two merging firms use the same distribution channel.3

However, the results also suggest that some acquisitions in this industry seem to be driven by objectives other than shareholder value maximization. In particular, I find that the proxy — public companies with poor recent performance — predicts the following three, distinctive things. First, all else equal, i.e., holding fixed the amount of efficiency gains from mergers, companies identified by the proxy are more acquisitive. This is consistent with the idea that because of the additional private benefits their managers get, these companies are more eager

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3Since cost-cutting is another important source of synergies but could not be included in the empirical analysis due to lack of data on costs, this paper does not claim that it captures the full extent of synergy-driven mergers. Rather, the claim is that its empirical finding on the distribution channels indicates that at least some aspects of synergies are considered in merger decisions.
to pursue an acquisition than value-maximizing companies. Second, although they are more acquisitive, acquirers identified by the proxy are much worse at achieving asset growth post-merger when they make an acquisition. This finding is in line with much of the literature that finds worse outcomes for managerially motivated acquirers (Morck, Shleifer and Vishny, 1990; Masulis, Wang and Xie, 2007; Carline, Linn and Kadav, 2009). Third, despite their greater willingness to acquire, which under reasonable assumptions translates into higher willingness to pay for targets, acquirers identified by the proxy are not any more likely to match with high-quality targets. I interpret this finding to be consistent with the idea that targets would like to avoid bad organizations as their merger partners. In this industry where human capital is crucial, one of the assets that an acquirer tries to buy is often the people from the target company. As a result, a high proportion of targets’ managers stay with the company after the merger instead of “cashing out,” and this could explain why targets care about post-merger performance of merged organizations. These three behavioral patterns associated with the proxy portrait a unified picture of companies pursuing acquisitions for objectives other than value maximization.⁴

Using the model’s estimates, I perform counterfactual analysis to examine the role of targets’ incentive in resource allocation in the merger market. According to the analysis, targets’ dislike of badly run organizations is a powerful mechanism to discourage inefficient

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⁴Even if we are reluctant to interpret the proxy as representing managerial motivations, the key empirical facts of the paper — underperforming public companies are much more acquisitive, have much worse outcomes when they do make an acquisition, and do not seem to be liked by targets as merger partners — still remain. I decided to interpret the proxy as reflecting managerial motives because these behaviors seem inconsistent with value maximization and also because the existing literature suggests that the proxy can be reasonably expected to capture managerial motives. However, since I do not provide any direct evidence that these firms have managerial rent-seeking motives, there could be alternative interpretations for the findings. Furthermore, there could be other proxies that reflect managerial motives. The particular one I use is simply one of those.
takeovers: Without it, non-value-maximizing acquirers would buy many more firms.

This paper makes two contributions. First, unlike most prior work in the merger literature which examines either acquirers’ incentives or targets’ incentives but not both simultaneously, my paper explicitly addresses the fact that both acquirers’ and targets’ incentives are important in the merger market by employing a matching model. Second, researchers have studied various mechanisms that could discourage the non-value-maximizing behavior of managers, such as product market competition, labor market competition, compensation schemes, and monitoring by the board of directors (see, for instance, Jensen and Murphy (1990) and Holmstrom and Kaplan (2001)). I show that targets’ dislike of badly managed organizations can provide partial discipline for inefficient acquirers. In that regard, this paper is related to the paper of Mitchell and Lehn (1990), which shows that bad acquirers later become takeover targets. The main difference between this paper and theirs is that I study targets’ preference for efficient acquirers as a possible discipline mechanism whereas they focus on efficient acquirers taking over firms who previously made inefficient acquisitions.

A brief overview of the rest of the paper follows. Section 2 provides backgrounds on the mutual fund industry and describes the data. I discuss my model of the merger market in Section 3. Section 4 then presents an econometric model of the merger market and discusses strategies for estimation. Section 5 provides empirical findings from the model and discusses counterfactual exercises I performed. Section 6 concludes the paper.

2. Industry and data

2.1. Mutual fund industry
Mutual fund management companies such as Fidelity and T. Rowe Price offer wide ranges of mutual funds and retain professional portfolio managers to manage the funds. The set of mutual funds offered by a fund management company is called a fund family. This paper focuses on mergers between fund management companies, not mergers between individual mutual funds. Individual mutual funds are considered as products produced by management companies and sold to consumers (fund investors) in this paper. For the purpose of this study, I use the term “shareholders” to refer to the shareholders of fund management companies. Furthermore, I use the term “managers” to refer to senior executives such as the CEO of a fund management company and “fund managers” to refer to the people who choose investments for individual funds. Of course, some managers are also fund managers.

The mutual fund industry merits attention due to the sheer size of assets managed by mutual fund companies in the US ($13 trillion at the end of 2012). Furthermore, the mutual fund industry provides a very nice setting for application of this paper’s methodology for multiple reasons. First of all, legal precedents favorable to poison pills and other anti-takeover tactics made hostile takeovers rare in the period I study, 1991 through 2004. Hostile takeovers are especially rare in this industry because of the importance of human capital. In the words of Todd Ruppert, former president and CEO of T. Rowe Price Global Investment Services, “You just can’t do a hostile takeover in this industry. The asset you are really buying is the people, and they can choose to walk out. So, you can only realistically deal with a motivated seller.”

This feature ensures that mergers in this industry are likely to be two-way selections. Thus, the matching model which explicitly accounts for joint selection is a

\footnote{Funds Europe report, http://www.funds-europe.com}
suitable framework for mergers in this industry.

Second, since firms in the matching model interact with each other (in other words, it is a game, not a single-agent model), it is crucial to have information on all players in the industry in order to solve for equilibrium matching. In typical industries, this is not feasible due to lack of data on private companies. In the mutual fund industry, however, data on both public and private fund management firms are available to researchers due to mandatory disclosure requirements of the Securities and Exchange Commission. Thus, the mutual fund industry provides an excellent setting for application of the matching model to study merger behavior. The availability of data on private companies also makes the identification strategy of this paper differ from that of the previous corporate governance literature. Although the research questions are similar in this paper and the prior literature on corporate governance — whether corporate governance is an important factor in determining the likelihood and outcome of mergers — one of the key differences is that this paper examines a mix of private and public companies, while the existing literature on corporate governance mainly examines public companies due to lack of data on private companies. The prior literature examines how merger behavior or merger outcomes differ among public companies with different degrees of corporate governance (Morck, Shleifer and Vishny, 1990; Gompers, Ishii and Metrick, 2003; Masulis, Wang, Xie, 2007). In contrast, I have private companies as well as public companies in the data set, and thus rely on a different source of identification by exploiting the fact that it is mainly public companies that are potentially subject to misaligned incentives due to separation of ownership and management. In other words, the identifying power of this paper comes from using a mix of private and public companies. As a result, this paper’s
identification strategy is complementary to that of the existing literature, and it makes the mutual fund industry a very interesting setting for merger analysis.

Finally, as the summary statistics in Table 1 below show, the average size of acquirers is more than 10 times larger than that of targets. This justifies the decision to conceptualize merger cases in the mutual fund industry as “acquisitions” rather than “mergers of equals,” making the matching model an appropriate framework for this paper’s analysis.

2.2. Data

I study data on US mutual funds from the Center for Research in Security Prices (CRSP). The CRSP data set includes data on all open-end mutual funds that have ever existed including: the amount of assets invested by the fund, the identity of the management company running the fund, the fund’s investment objective, the fund’s monthly returns, and the structure of the fund’s fees. CRSP assigns each fund a unique identifier that stays the same even when the fund’s management company changes.

CRSP also assigns each management company an identifier but reuses the identifiers of extinct management companies so that identifiers are not necessarily unique. I constructed a unique management company identifier by checking the names and years of operation of management companies with the same identifier to determine whether they are the same companies. I also identified management companies as public or private using Thomson Financial’s SDC Platinum and the web sites of management companies. Hereafter, I label publicly traded companies and subsidiaries of publicly traded companies as “public.” I label all other management companies in the sample, including the small numbers of non-profit
companies and companies owned by fund investors such as Vanguard, as private companies.

I identified mergers and acquisitions using the CRSP data rather than press releases. Identifying mergers using press releases would be excessively time-consuming and risk omitting many unreported mergers of small or private companies. Using the CRSP data presents some problems, but enables me to identify all mergers between fund management companies, big or small. I say that company $A$ acquires company $B$ in year $t$ if (1) during year $t$ company $A$ acquires more than 90% of funds that belonged to company $B$ in year $t - 1$ and survived into year $t$, and (2) company $B$ dies during year $t$. By this definition, a total of 266 mergers occurred during the period from 1991 through 2004, an average of 19 per year. For each merger case, I have information on the acquiring firm and target firm prior to the merger, and also how the merged company performs after the merger. Designation as acquirer or target is solely based on the data: The surviving firm is the acquirer and the disappearing firm is the target.

My main interest lies in how merger behavior and merger outcomes differ between efficient acquirers and inefficient acquirers, but a company’s acquisition motive is not observed. Therefore, I employ a proxy for acquirers with managerial motivations. My proxy is based on the following two ideas: (1) public firms are more prone to incentive problems due to the separation of ownership and control, and (2) companies that have performed poorly might be more vulnerable to incentive problems. The idea that public companies are vulnerable to incentive problems is an old one, going back to Berle and Means (1932). There are theories and empirical works that support idea (2) as well (Morck, Shleifer and Vishny, 1990; Edlin

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6It is hard to identify the exact month a merger occurs, and an actual integration could happen with some time lag after a merger announcement.
and Stiglitz, 1995; Chevalier and Ellison, 1999; Huson, Parrino, and Starks, 2001; Kaplan and Minton, 2012). In the context of the mutual fund industry, Chevalier and Ellison (1997) show that funds that trail the market have an incentive to gamble and try to catch the market. In addition, managers with empire-building motives would be more inclined to make an acquisition when the internal growth of their firms slows down.

Therefore, I designate public companies with poor recent performance as a group that potentially has non-value-maximizing motivations for acquisitions, and empirically test whether their behavior differs from others’. In doing so, I separately control for public ownership and poor recent performance to ensure that the interaction between these two variables, which is my proxy, does not represent a systematic difference between public and private companies or between companies with good and poor recent performance.

To construct the empirical proxy, I need a measure of firm performance, and I follow the mutual fund literature to do so. First, I measure the return of fund $f$ during year $t$ using objective-adjusted-returns ($OAR_{f,t}$). $OAR_{f,t}$ of fund $f$ is defined as

$$
OAR_{f,t} = \prod_{m=1}^{12} \left( 1 + R_{f,m} \right) - \prod_{m=1}^{12} \left( 1 + R_{o,m} \right) - 1,
$$

where $R_{f,m}$ is the return of fund $f$ in month $m$, and $R_{o,m}$ is the average return of all funds in the market with the same investment objective as fund $f$ in month $m$. This measure of returns “implicitly adjusts for sector, industry, and style-specific factors that may exogenously affect all funds in the same investment objective category” (Jayaraman, Khorana, and Nelling, 2002). Beginning in 1992, CRSP assigns each fund to one of 192 categories on the basis of its investment objective,\textsuperscript{7} enough categories to capture systematic differences among different types of funds.

\textsuperscript{7}There are 27 categories of investment objectives prior to 1992.
To assess whether a company performed well or poorly prior to a merger, I calculate the weighted $OAR$ of all funds offered by the company in the year immediately preceding the merger ($WOAR$), using as weights the amount of assets each fund manages. A negative $WOAR$ means the company’s performance is below average. Then, my proxy for acquirers with managerial motivations is public companies whose $WOAR$ is negative in the year prior to the merger. To minimize lost observations, I use all funds that have at least 3 months of return information in calculating $WOAR$. I calculate $OAR$ for each fund assuming that a fund earns the average return of its investment objective category in each month for which the fund lacks return data. The results do not change when I exclude funds that have less than 6 months or less than 9 months of return data. Table 1 presents summary statistics for the mergers in my sample and compares various attributes of acquirers and targets. One interesting fact to note is that on average acquirers have higher $WOAR$ than targets in many years, which suggests that many of the acquisitions could be efficiency-driven. Our focus would be then on whether there is a subset of companies whose acquisitions do not seem value maximizing.

[Table 1 about here]

3. Model

This section develops a model of the takeover market as a two-sided matching game (Roth and Sotomayor, 1990; Sorensen, 2007; Fox, 2010; Akkus, Cookson and Hortaçsu, 2012; Chen and Song, 2012) wherein potential acquirers and potential targets decide whether they want and with whom to merge. The primitives of the model are acquirers’ and targets’ preferences,
which, together with the rules of the matching game, determine the equilibrium matching.

Before I start to present the matching model, it is worthwhile to discuss why simpler models such as probit or logit are not appropriate. The first key conceptual issue that single-agent discrete choice models such as probit or logit cannot adequately handle but a matching model can is the two-way selection nature of mergers. Since both acquirers’ and targets’ preferences play a role in determining who merges with whom, we need a model that can account for such joint selection of the merger market. The second conceptual issue that single-agent models cannot address while a matching model can is interaction among the choices by different firms. In practice, a target cannot be sold to more than one firm, and a firm cannot acquire more than a certain number of targets in a given period. Therefore, what a firm can do in the merger market depends on what matchings other firms form. The matching model was developed to exactly account for such interaction by explicitly modeling the dependence of the “effective” choice set of a firm on other players in the market.

A counterexample would be choice of a car. When consumer A decides on which car to buy, it is a one-way selection since cars don’t have preferences over buyers, and the choice of car by other consumers does not limit the set of available cars consumer A can choose from. In this case, a probit or logit model would be an appropriate modeling choice. In the merger market, however, each firm, whether an acquirer or a target, has preferences over its merger partner, and each firm is unique so that once a firm is sold there are no identical copies of the same firm available for other merger opportunities. Due to these inherent features of the merger market, I employ the matching model in this paper.
3.1. Agents

Market $t$ has two non-overlapping sets of agents. The set of potential acquirers is $I_t$ and the set of potential targets is $J_t$. The numbers of potential acquirers and potential targets in market $t$ are $|I_t|$ and $|J_t|$, respectively. Each potential acquirer can buy up to one target, and each potential target can be sold to only one acquirer. Hence, the model is a one-to-one, two-sided matching model in which one side of the market consists of potential acquirers and the other of potential targets. I assume a complete information game to make the model tractable. Searching for matches is costless.

As discussed in Section 2, I conceptualize mergers in my data set as “acquisitions” rather than “mergers of equals,” because the large size difference between acquirers and targets suggests that there is more than a nominal distinction between the two. Hence, a two-sided matching model, which divides firms into either the acquirer side or the target side, seems to be a better representation of the merger market than an alternative modeling choice such as a roommate model, which treats all firms symmetrically.

Managers of potential acquirers and targets are the decision makers. Each manager maximizes his own expected utility. If a manager’s interests align perfectly with shareholders’ interests, maximizing the manager’s utility is equivalent to maximizing shareholders’ utility. If these interests diverge, the manager maximizes his expected utility subject to constraints.

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8This assumption is relaxed during estimation. All results I obtain in this section hold for a many-to-one matching model if I assume responsive preferences. Preferences are responsive if for any two matchings that differ in only one target, an acquirer prefers the matching that contains the more preferred target.

9However, the merger market is not like a marriage market or pairings between venture capitalists and entrepreneurs where a division between the two sides is clearly defined. Therefore, I examine robustness of the results to a few alternative assumptions on who belongs to the set of potential acquirers vs. the set of potential targets.
imposed by the shareholders, such as employment contracts or oversight by independent
directors. I further assume that targets do not have a problem of misaligned incentives.
This assumption allows me to focus on conflicts of interest at potential acquiring companies,
and is partly justified by the following reason. Since hostile takeovers are rare in the mutual
fund industry, management resistance to takeovers, such as poison pills or greenmail which
is intended to resist the sale of the firm, is not relevant for my analysis. Shareholders and
managers may disagree regarding by whom they should be acquired, but it seems to be of
second order importance compared to the potential agency problems at acquiring companies.

3.2. Preferences

Let $S_{i,j,t}$ be potential acquirer $i$’s valuation of a merger with target $j$ in market $t$. The
valuation measures the benefit of the merger to the potential acquirer’s manager. $S_{i,j,t}$ is
modeled as the sum of the efficiency gains from the acquisition and the private gains the
manager obtains from the deal. This reflects managers’ need to pay some attention to
shareholders’ interests even if they also pursue their own private interests. If a company
pursues an acquisition purely for the sake of shareholder value maximization, managers’
private benefits do not enter the company’s valuation $S$.

Both private benefits and efficiencies resulting from mergers depend upon companies’
characteristics. A dummy variable, $M$, indicates whether managers’ private benefits enter
the acquirer’s valuation. If I include in $S$ just the variable $M$ but no interactions between
$M$ and other characteristics of the acquirer or target, the coefficient on $M$ represents the
value of private benefits received by an inefficient acquirer from any merger, independent of
the merging parties’ characteristics. Interactions between \( M \) and other characteristics of the acquirer allow the value of private benefits from a merger to vary with these characteristics, helping us identify attributes of inefficient acquirers that particularly encourage them to make acquisitions. Interactions between \( M \) and targets’ characteristics allow inefficient acquirers and efficient acquirers to assign different values to characteristics of merger partners. Increases in efficiency from acquiring target company \( j \) are modeled as a function of various characteristics of the target and acquirer, and interactions between these characteristics reflecting match-specific synergies. In the empirical analysis, the interactions will include, among other things, whether the acquirer and target have the same channel of distribution and whether they serve similar market segments. These are intended to capture match-specific economies of scale in marketing and distribution. In sum, the variables that affect the players’ utility from a match between potential acquirer \( i \) and target \( j \) in year \( t \) fall in three categories: those that reflect efficiency gains from the match \( (X_{i,j,t}) \), one that reflects whether the acquirer has managerial motivations \( (M_{i,t}) \), and interactions between some of \( X_{i,j,t} \) and \( M_{i,t} \) \( (X_{i,j,t}M_{i,t}) \).

A target and an acquirer split the acquirer’s valuation of the match: Acquirer \( i \) keeps a portion \( \lambda_{i,j,t} \) of the valuation for himself and gives target \( j \) a portion \( (1 - \lambda_{i,j,t}) \) of the valuation as an acquisition price. Hence, potential acquirer \( i \)’s utility from buying potential target company \( j \) is as follows.

\[
U_{i,j,t} = \lambda_{i,j,t} S_{i,j,t} = \lambda_{t} \left[ X_{i,j,t}' \alpha_{X} + \alpha_{M} M_{i,t} + X_{i,j,t}' M_{i,t} \alpha_{XM} \right].
\] (1)
Potential target $j$’s utility from being acquired by company $i$ would be $(1 - \lambda_{i,j,t}) S_{i,j,t}$ if targets do not have any additional preferences about merger partners beyond the acquisition price. However, there could be factors that targets care about but are not adequately priced in the merger market. For instance, even if participants of the takeover market expect inefficient acquirers to have worse merger outcomes, the acquisition prices offered by these acquirers are unlikely to fully reflect their expected poor post-merger performance, because they pursue acquisitions out of inefficient motives in the first place. Acquirers that are managerially motivated, precisely because they are managerially motivated, would offer prices that are not fully consistent with targets’ valuation of a merger with them. Therefore, targets’ utility from being acquired by an inefficient acquirer might depend on not just the acquisition price, but also the fact that the acquirer will likely mismanage post-merger. This is particularly relevant in this market where human capital is crucial and consequently the post-merger retention rate of targets’ management is relatively high. Therefore, I model potential target $j$’s utility from being acquired by company $i$ as

$$V_{i,j,t} = (1 - \lambda_{i,j,t}) S_{i,j,t} + \beta_M M_{i,t} = (1 - \lambda_t) \left[ X_{i,j,t} X + \alpha_M M_{i,t} + X_{i,j,t} M_{i,t} \alpha_{XM} \right] + \beta_M M_{i,t}. \quad (2)$$

The second term $\beta_M M_{i,t}$ allows the possibility that the target cares about whether the acquiring firm is managerially motivated, since it is a strong predictor of how well the firm will manage post-merger.

Note that $\alpha_M$, which reflects inefficient acquirers’ urge to merge, enters both $U_{i,j,t}$ and $V_{i,j,t}$ via $S_{i,j,t}$. $\alpha_M$ enters targets’ utility function $V_{i,j,t}$ because I assume that inefficient
acquirers’ greater willingness to make an acquisition will translate into a higher acquisition price offered to targets, as any plausible bargaining model would predict. Previous research found that acquirers seeking private benefits for managers indeed tend to pay more (Morck, Shleifer, and Vishny, 1990; Slusky and Caves, 1991).

Potential acquirer $i$ prefers a match that confers higher utility $U_{i,j,t}$, and potential target $j$ prefers a match that confers higher utility $V_{i,j,t}$. The set of utilities of potential acquirers in market $t$ is $U_t = \{U_{i,j,t} | i \in I_t \& j \in J_t \cup 0\}$ and the set of utilities of potential targets in market $t$ is $V_t = \{V_{i,j,t} | i \in I_t \cup 0 \& j \in J_t\}$. In the expression for $U_t$, 0 represents the option of not buying any target and in the expression for $V_t$, 0 represents the option of not being sold to any acquirer. I assume that $U_t$ and $V_t$ are such that no acquirer is indifferent between two targets, and no target is indifferent between two acquirers (necessary for uniqueness of equilibrium).

The signs and magnitudes of $\alpha_M$ and $\beta_M$ are of key interest in this paper. If managers obtain private benefits from making an acquisition, $\alpha_M$ will be positive. If targets have an incentive to avoid inefficient acquirers because of the expectation that these acquirers will do a bad job of managing the merged organization, $\beta_M$ will be negative and the targets’ utility from matching with an inefficient acquirer decreases by the magnitude of $\beta_M$. The signs and magnitudes of $\alpha_M$ and $\beta_M$ affect the set of merger partners available to each acquirer. A positive $\alpha_M$ (thus higher willingness to pay) expands the set of targets willing to match with the inefficient acquirers, while a negative $\beta_M$ shrinks the set of targets willing to match with the inefficient acquirers.

I assume that acquirers and targets share the valuation of mergers uniformly for all
possible matches within a market, so that $\lambda_{i,j,t} = \lambda_t$. I assume this fixed sharing to generate a feasible econometric model. An ideal model would allow some transfers, but the matching literature has not yet generally characterized equilibrium in matching models with partially transferable utility.\footnote{See Legros and Newman (2007) for progress on this topic. An alternative model I could have used is a two-sided matching game with fully transferable utility as in Fox (2010). I decided to use a fixed sharing rule instead of a fully transferable utility model, since the former permits the two sides of the market to have conflicting valuation of the same transaction, which is one of the key features I want to model. See Fox (2010) for a discussion of matching models with transfers.} The fixed sharing rule, though restrictive, allows the key elements I want to model. Because acquirers’ characteristics enter the valuation $S$ (and therefore $U$ and $V$), some acquirers can pay systematically more than other acquirers for a given target. Similarly, some targets can obtain higher utility than others from matching with a given acquirer, depending on their characteristics. A fixed sharing rule does not, however, allow some acquirers to pay a higher or lower proportion of a deal’s valuation, $S$, to targets. Thus, the model does not allow an unattractive acquirer to buy an attractive target by offering the target a higher proportion of the deal’s valuation than other acquirers would offer. I try to test the sensitivity of my results to the assumption of the fixed sharing rule in Section 5, but I can do so only to a limited degree.

3.3. Stable matchings

An equilibrium concept used for two-sided matching games is stability. A matching is stable if no pair of an acquirer and a target can break off the current matching and be strictly better off under the new matching. The structure of my model means there will be a unique stable matching for each set of utilities. Online Appendix 1 provides a proof. The intuition behind the uniqueness of equilibrium is as follows. If $\beta_M$ is zero, equilibrium is
unique because preferences of targets are aligned with those of acquirers (Sorensen, 2007).

A non-zero $\beta_M$ does not introduce any cycles into preferences because it shifts the utility of every target by the same amount. Therefore, a non-zero $\beta_M$ in targets’ utility function does not destroy the uniqueness of equilibrium. Maintaining uniqueness requires that the second term of $V_{i,j,t}$ not be match-specific, and my model satisfies this condition because $\beta_M M_{i,t}$ does not depend on $j$.

The unique stable matching of the model is characterized by a set of inequalities. Let $i \in I_t$ denote a potential acquirer and $j \in J_t$ a potential target. $j = \mu(i)$ and $i = \mu(j)$ if acquirer $i$ and target $j$ are partners in matching $\mu$. Then, matching $\mu$ is stable if and only if the following inequalities hold.

$$\forall i \ U_{i,\mu(i),t} \geq U_{i,j,t} \text{ for } \forall j \in \{ j | V_{i,j,t} \geq V_{\mu(j),j,t} \} \cup \{0\} \text{ and}$$

$$\forall j \ V_{\mu(j),j,t} \geq V_{i,j,t} \text{ for } \forall i \in \{ i | U_{i,j,t} \geq U_{i,\mu(i),t} \} \cup \{0\}. \tag{3}$$

In words, stability requires that each acquirer match with the best target among those willing to match with the acquirer, and that each target match with the best acquirer among those willing to buy it. Thus, a firm’s merger partner in equilibrium depends on the firm’s relative ranking compared to other firms on the same side of the market. The equilibrium condition in (3) shows why it is misleading to use a standard discrete choice framework, such as probit or logit, for estimation of this game. The interaction among choices made by different firms restricts the “effective” choice set of each firm to be a subset of all potential merger partners existent in the market. Hence, if we run a probit for the choice of a target
from acquirers’ perspective, the probit model does not allow the possibility that firm A chose
target X instead of target Y not because firm A prefers X to Y, but because Y had a better
merger partner available and thus was not in A’s “effective” choice set. The matching model
correctly accounts for such interaction.

4. The econometric model

My econometric model consists of a matching model and outcome equations. This section
discusses their empirical specifications, identification of the model and estimation strategies.

4.1. Model specification

Since mutual funds are sold nationwide, there is only one geographic market. Accordingly,
each period of time defines a market. I choose periods of a year rather than a shorter period
because I do not observe from the data the exact month in which a merger occurs.

The set of potential targets $J_t$ consists of all fund management companies actually ac-
quired in year $t$, and the set of potential acquirers $I_t$ consists of all other companies that are
not acquired or liquidated in year $t$. These definitions make the econometric model more
tractable. The lack of hostile takeovers partially justifies this modeling choice for the set
of potential targets. When I estimate the model, I try a few alternative specifications that
relax this assumption.

4.1.1. Utility functions in the matching model

The primitives of my econometric model are the utility functions of potential acquirers
and targets in the matching market. Table 2 lists the variables that enter the utility functions,
$X_{i,j,t}$, $M_{i,t}$, and $X_{i,j,t}M_{i,t}$. Acquirers’ utility function ($U_{i,j,t}$) and targets’ utility function ($V_{i,j,t}$) are then as follows.

\[
U_{i,j,t} = \lambda_t S_{i,j,t} = \lambda_t \left[ X'_{i,j,t} \alpha_X + \alpha_M M_{i,t} + X'_{i,j,t} M_{i,t} \alpha_X M + \omega_{i,j,t} \right],
\]

\[
V_{i,j,t} = (1 - \lambda_t) S_{i,j,t} + \beta_M M_{i,t} + \epsilon_{i,j,t}
\]

\[
= (1 - \lambda_t) \left[ X'_{i,j,t} \alpha_X + \alpha_M M_{i,t} + X'_{i,j,t} M_{i,t} \alpha_X M + \omega_{i,j,t} \right] + \beta_M M_{i,t} + \epsilon_{i,j,t}.
\]

(4)

[Table 2 about here]

Two error terms appear in the utility functions, $\omega_{i,j,t}$ and $\epsilon_{i,j,t}$. They represent factors unobservable to a researcher that players consider when deciding to match. $\omega_{i,j,t}$ represents match-specific unobserved factors and enters both $U_{i,j,t}$ and $V_{i,j,t}$. $\epsilon_{i,j,t}$ is an additional error term in $V_{i,j,t}$ that allows imperfect correlation between the errors in $U_{i,j,t}$ and $V_{i,j,t}$. To preserve the uniqueness of equilibrium, I require $\epsilon_{i,j,t} = \epsilon_{i,t}$. We can interpret $\epsilon_{i,t}$ as representing characteristics of acquirers unobservable by the econometrician that all targets value similarly. Distributional assumptions on the error terms are provided in Online Appendix 2 where I discuss my estimation strategy in detail.

An important feature of my model is that the variable $M$ plays a dual role: It simultaneously represents conflicts of interest between owners and managers at inefficient acquirers ($\alpha_M$) and targets’ preference about inefficient acquirers beyond the acquisition price ($\beta_M$). Thus, targets’ overall preference regarding $M$ is given by $[(1 - \lambda_t) \alpha_M + \beta_M] M_{i,t}$.\(^{11}\)

\(^{11}\)To simplify the argument for identification, I ignore the interactions of $M$ with other acquirer and target characteristics. The argument remains valid when I include additional interaction terms. Also, I treat $\lambda_t$ as a known constant in the identification argument. I can normalize $\lambda_t$ without loss of generality, as discussed below.
allows me to identify the incentive of the targets not to participate in a particular merger separately from the incentives of the acquiring firms to undertake the merger? I can separately identify these two effects because I use two related but distinct pieces of information: which potential acquirers actually make an acquisition and who matches with whom conditional on making an acquisition or being acquired. A key requirement for identification is that not all potential acquirers prefer acquiring to not acquiring. If this assumption is valid, potential acquirers’ decisions to acquire convey information regarding which characteristics increase the utility of a match, helping to identify $\alpha_M$. Then $\beta_M$ can be separately identified from the pattern of matching conditional on participating in a merger. If inefficient acquirers tend to match with their less preferred targets although their participation in the merger market is disproportionately more likely, we can infer that targets do not like them.

As a heuristic identification argument, suppose that we have 8 potential acquirers and 4 targets. Potential acquirers are $A, a, B, b, C, c, D, d$, and targets are 1, 2, 3, 4. A capital letter represents a potential acquirer with $M = 0$ ($A, B, C, D$) and a lower case letter represents a potential acquirer with $M = 1$ ($a, b, c, d$). Other than that, company $A$ is identical to $a$, $B$ is identical to $b$, $C$ to $c$ and $D$ to $d$. Suppose that targets’ preference ranking over acquirers is $A > B > C > D$ (thus $a > b > c > d$) and acquirers’ preference ranking over targets is $1 > 2 > 3 > 4$. We will consider three scenarios to illustrate inference of $\alpha_M$ and $\beta_M$.

Scenario 1: $A$ merges with 1, $a$ merges with 2, $b$ merges with 3, and $c$ merges with 4. Firms with lower case letters are disproportionately more likely to participate in any merger than firms with capital letters (3 out of 4 vs. 1 out of 4), but $A$ matched with a better target than $a$ did. From these patterns, I would infer that $\alpha_M > 0$ and $(1 - \lambda_t)\alpha_M + \beta_M < 0$. Scenario
2: A merges with 1, a merges with 2, B merges with 3 and b merges with 4. Firms with lower case letters are equally likely to participate in a merger as firms with capital letters, but tend to merge with worse targets. From these patterns, I would infer that $\alpha_M = 0$ and $(1 - \lambda_t)\alpha_M + \beta_M < 0$. Scenario 3: a merges with 1, b merges with 2, A merges with 3 and c merges with 4. Firms with lower case letters are disproportionately more likely to participate in a merger than firms with capital letters, and a matched with a better target than A did. From these patterns, I would infer that $\alpha_M > 0$ and $(1 - \lambda_t)\alpha_M + \beta_M > 0$.

As is clear from this identification argument, the identification of $\alpha_M$ and $\beta_M$ crucially depends on the assumption that some potential acquirers actively choose not to participate in a merger. This seems reasonable given that some firms would simply expect low returns from a merger due to their characteristics. Another key assumption is the fixed sharing rule, because the acquisition price is predicted based on that assumption. Particularly, the assumption implies that inefficient acquirers’ greater willingness to acquire will translate into a higher willingness to pay for targets.

As in a standard discrete choice model, the parameters of the utility functions are identified up to scale and level. I normalize the scale of the coefficients by fixing the variances of the disturbance terms $\omega_{i,j,t}$ and $\epsilon_{i,t}$ at 1 and $(1 - \lambda_t)^2$, respectively.\(^\text{12}\) I normalize the level of the coefficients by setting the mean utility of no acquisition to 3. I also fix the constant term in $U_{i,j,t}$ for $j \neq 0$ to ensure that both the acquisition decision of potential acquirers and actual matching pattern are used in the identification of $\alpha_M$ and $\beta_M$.\(^\text{13}\) Finally, I normalize

\(^{12}\)I fix the variance of $\epsilon_{i,t}$ at $(1 - \lambda_t)^2$ to make $(1 - \lambda_t)\omega_{i,j,t}$ and $\epsilon_{i,t}$ have the same scale in $V_{i,j,t}$.

\(^{13}\)If I entirely free up the constant term in $U_{i,j,t}$, the constant could become large enough to make every potential acquirer want to buy any target. In this case, the acquisition decision of potential acquirers does not have any bite, and $\alpha_M$ and $\beta_M$ are not separately identified. Since my identification argument relies on
\( \lambda_t \) to 0.5, which is an innocuous normalization as only the relative magnitudes of utility influence the equilibrium matching.

Since the number of potential acquirers exceeds 600 in some years, it is computationally burdensome to use all potential acquirers in estimation. I therefore reduce the set of potential acquirers in two ways. First, I eliminate companies that have nearly zero probability of making an acquisition. I check the minimum age and size of all actual acquirers and delete from the set of potential acquirers companies that do not surpass these thresholds. Second, I randomly choose 20\% of the inactive potential acquirers that survived the first round of deletion, and include only these random selections and the actual acquirers in the set of potential acquirers. The resulting number of potential acquirers ranges from 5 to 8 times the number of potential targets. The signs of key coefficients are robust to the random selections. The magnitudes of the coefficients on the variables that capture match-specific efficiency gains are robust as well. The magnitudes of \( \alpha_M \) and \( \beta_M \) change depending on the random selections, which is not surprising given that the identification of \( \alpha_M \) and \( \beta_M \) depends on who the potential acquirers are. Crucially, however, the signs and the relative magnitudes of \( \alpha_M \) and \( \beta_M \) remain stable regardless of the random selections, suggesting that the main conclusions of this paper are not sensitive to them.

### 4.1.2. Merger outcome equations

To measure mergers’ impact, I use post-merger asset growth. This measure captures using both the acquisition decision of potential acquirers and the matching pattern between actual acquirers and targets, I need to avoid such a situation. Hence, I fix the level of constant at 3. Which specific number I choose for the constant does not affect the estimation results, as long as the number is such that some potential acquirers prefer the outside option of no acquisition to making an acquisition.
acquirers’ ability to exploit demand-side economies of scale in marketing and distribution, an important rationale for mergers in this industry.\textsuperscript{14} Let $TNA_{i,t}$ be the total net value of assets managed by company $i$ at the end of year $t$. $100 \times \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}}$ is then the net asset inflow into company $i$ during year $t$ as a percentage of the value of existing assets.

Please note that the net asset growth rate used in the paper differs from that used in most papers on mutual funds (e.g., Sirri and Tufano, 1998), since the measure does not net out reinvestments of dividends and capital gains distributions. I decided to use this unconventional measure because I view high reinvestments due to superior post-merger fund performance as part of merger outcomes.\textsuperscript{15} I use the annual net asset growth rate for three years after the merger. If acquirer $i$ and target $j$ merge in year $t$, then $\Delta F_{i,j,t+1}, \Delta F_{i,j,t+2},$ and $\Delta F_{i,j,t+3}$ represent the net asset growth rate for the combined company during years $t + 1$, $t + 2$, and $t + 3$, respectively. For instance, if the sum of the assets of the acquirer and target in year $t$, year of merger, is 1 billion dollars, and the asset size of the merged company in year $t + 1$ is 1.5 billion dollars, $\Delta F_{t+1}$ for that merger would be 50%. As such, the outcome equations essentially reflect the profitability of the merger from shareholders’ perspective (fund companies’ revenue is a fraction of the assets).\textsuperscript{16} For each potential match between $i \in I_t$ and $j \in J_t$, the net asset growth rates are functions of the characteristics of the acquirer and target, interactions between the two companies’ characteristics, and some

\textsuperscript{14}Acquirers might decide to combine certain mutual funds after a merger to streamline their portfolios. Since assets of the closed funds are transferred to the absorbing funds, fund exits should not have any direct effect on this outcome measure.

\textsuperscript{15}In an earlier version of this paper, I found some empirical support for better post-merger returns of funds acquired by value-maximizing acquirers compared to post-merger returns of funds acquired by non-value-maximizing acquirers.

\textsuperscript{16}While the outcome measure captures the revenue consequences of a merger very well, it doesn’t capture the cost consequences of a merger. As such, cost-cutting, which could be another important rationale for mergers, is not studied in this paper.
control variables such as year dummies.

\[ \Delta F_{i,j,t+1} = Z'_{i,j,t+1} \theta, \quad \Delta F_{i,j,t+2} = Z'_{i,j,t+2} \theta, \quad \Delta F_{i,j,t+3} = Z'_{i,j,t+3} \theta. \]  

(5)

\[ Z_{i,j,t+1}, Z_{i,j,t+2}, \text{ and } Z_{i,j,t+3} \] are identical except that the year dummies and some control variables change with the year the dependent variable is measured. The impact of overall industry growth on asset flows is captured by the year dummies. Just as the utility functions in the matching model are functions of both efficiency gains and private benefits to managers, the outcome equations are also functions of efficiency gains and private benefits. Interactions between the characteristics of the acquirer and target reflect match-specific synergies. The variable \( M \) reflects private benefits to managers. I separately include a dummy variable to indicate a public acquirer and a dummy variable to indicate an acquirer with a negative pre-merger \( WOAR \) in order to ensure that the variable \( M \) does not represent a systematic difference between public and private companies or between companies with good and poor recent performance.

We can see the list of variables that enter the outcome equations from Table 4, and the definition of those variables can be found in Table 2. To simplify notation, I summarize these outcome equations as \( \Delta F_{i,j,t} = Z'_{i,j,t} \theta. \)

Since unobserved factors that predict merger outcomes are also likely to affect matching

\[ \text{Some acquirers make multiple acquisitions in a year. Rather than double count observations corresponding to multiple acquisitions by the same acquirer, I treat the target as having the average characteristics of all targets acquired by the acquirer during the year in estimation of the outcome equation. To ensure that a few outliers do not distort the results from the outcome equation, I cap the maximum and minimum net asset growth rate at 100% and -50%. The sample includes 12 observations with net asset growth rate exceeding 100% and 6 observations with net asset growth rate below -50%}. \]
decisions, I allow correlation between the errors in the utility functions of the matching model and the outcome equations. The errors in the outcome equations are as follows.

\[ \Delta F_{i,j,t} = Z'_{i,j,t} \theta + \rho \omega_{i,j,t} + \nu_{i,j,t}. \]  

(6)

\( \omega_{i,j,t} \) is the disturbance term included in \( U_{i,j,t} \) and \( V_{i,j,t} \) of the matching model. Hence, the unobserved factors that affect the utility functions in the matching model are allowed to affect the outcome equations through \( \rho \). For the distributional assumption on \( \nu_{i,j,t} \), see Online Appendix 2. Similarly, we might expect observed match-specific factors that predict higher matching utility to predict better merger outcomes. However, I do not impose any cross-equation restrictions between the matching utility functions and the outcome equations, because I want to test, not impose, whether efficiency gains that influence matching decisions also affect merger outcomes in the expected manner.

4.2. Estimation methods

The likelihood function to be used in estimation has a complicated region of integration because a player’s choice set depends on other players in the market. Due to this complex interdependence among players, one cannot write the likelihood function in closed form, so I rely on simulation to estimate my model. Bayesian methods using Gibbs sampling and data augmentation provide an elegant solution to deal with the problem, so I use Bayesian techniques developed and employed by Albert and Chib (1993), Geweke, Gowrisankaran, and Town (2003), and Sorensen (2007), among others. Online Appendix 2 presents the likelihood
function and posterior distribution to be used in my estimation.

5. Findings

In this section, I discuss the estimates of the model. I also discuss alternative specifications I estimated as to check robustness. Finally, I describe my counterfactual analysis.

5.1. Estimation results

Tables 3 and 4 report the estimates of the model. The first column of Table 3 reports the estimated coefficients of the utility functions in the matching model. The second column of Table 3 reports marginal probabilities associated with the estimated coefficients. Table 4 reports the estimated coefficients of the outcome equations. The bottom of Table 4 notes the estimated correlation between the errors in the matching model and the outcome equations. The estimation is based on a many-to-one matching model to account for multiple acquisitions by some acquirers in a year. In the data, about 15% of all actual acquirers make multiple (mostly two) acquisitions in a year.

I start with the results from the matching model in Table 3. First, the estimated coefficients on the interaction terms provide evidence that efficiency gains are important in determining players’ utility from mergers. The coefficient on “similarity in the proportion of money market funds between the acquirer and target” is positive and significant. Given that institutional investors such as pension plans hold more than half of all money market fund assets, this positive coefficient suggests that companies prefer as merger partners those

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18I get similar results from estimating a one-to-one matching model wherein I treat an acquirer who makes multiple acquisitions in a year as a separate acquirer for each of the transactions.
that serve a similar market segment and investor clientele. Institutional investors and retail investors have different needs and require different styles of marketing and distribution, so two merging companies achieve greater economies of scale when they serve similar market segments. The associated marginal probability indicates that when an acquirer who offers no money market fund chooses between two targets, one of which offers no money market fund and the other of which offers only money market funds but is otherwise identical, the probability that the acquirer will prefer the former is 72.6%, a marginal increase of 22.6 percentage points from a 50-50 random chance.

[Table 3 about here]

In addition, the coefficient on “same distribution channel” is positive and significant, indicating that companies that mainly sell funds through intermediaries such as brokers (load funds) prefer to match with companies that also sell through brokers rather than with companies that sell funds directly to investors (no-load funds), and vice versa. This suggests that economies of scale in marketing and distributing funds are an important rationale for mergers in this industry. The probability that acquirer $i$ will prefer target $j$ to target $j'$, when only $j$ has the same distribution channel as the acquirer and otherwise $j$ and $j'$ are identical, is 56.6%, a marginal increase of 6.6 percentage points from a 50-50 random chance.

Second, the estimated coefficients on the variable $M$ suggest that private benefits for managers are also prominent in some players’ matching decisions. The positive $\alpha_M$ suggests that given fixed efficiency gains, companies with $M = 1$ are more eager to make an acquisition than those with $M = 0$. This result is consistent with the idea that poorly performing
public companies, whose managers might be more likely to pursue an acquisition that is not value-maximizing for shareholders, are more acquisitive than others due to the presence of additional managerial gains. $\beta_M$ is negative and significant, suggesting that targets dislike acquirers with $M = 1$, all else (including acquisition price) equal. As we will see when we discuss the outcome equations below, acquirers with $M = 1$ attract significantly less money from fund investors post-merger than do acquirers with $M = 0$. Hence, the negative $\beta_M$ is consistent with targets’ reluctance to allow an unskillful acquirer to manage the merged company. This incentive almost entirely offsets the effect of the $M$ acquirers’ greater willingness to pay ($(1 - \lambda_t)\alpha_M$ enters the target’s utility function, and $\lambda_t$ is normalized to 0.5).\textsuperscript{19} Some coefficients for the interactions of $M$ with acquirer or target characteristics are significant. For instance, one might interpret the negative coefficient on “$M \times PastAcq$” to suggest that inefficient acquirers cannot get away with making bad acquisitions too often.

Finally, the estimated coefficients on other acquirer and target characteristics in Table 3 are reasonable. Public companies tend to obtain greater utility from making an acquisition. This could reflect the fact that public companies have the flexibility to issue stock to finance their acquisitions. Among acquirers with $M = 0$, an acquirer’s utility from an acquisition is higher if the acquirer has made other acquisitions in the past three years. Unobserved time-invariant characteristics that make some acquirers consistently value acquisitions highly may account for this result. The coefficient on targets’ pre-merger performance suggests that acquirers prefer targets that performed well pre-merger.

Table 4 reports the estimation results for the outcome equations. First, the results show

\textsuperscript{19}I get similar results if I include $M$ only as a stand-alone term without any interactions involving $M$. 

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that the sources of efficiency gains that affect utility functions in the matching model also affect post-merger asset growth. For example, the coefficient on the dummy variable for using the same distribution channel is positive and significant. The coefficient indicates that if the merging companies have the same distribution channel the combined company attracts 7.2% more money from investors annually for three years after the merger than if the two have different channels. The coefficients on “similarity in the proportion of institutional funds” and “similarity in the proportion of money market funds” are also positive, although not significant. I did not impose any cross-equation restrictions between the matching utility functions and the outcome equations, because I wanted to check whether efficiency gains that influence matching decisions also affect merger outcomes in the expected manner. My results show that broadly this is the case.

[Table 4 about here]

From the outcome equations, I find that acquirers with $M = 1$ receive less favorable post-merger asset flows, controlling for differences in the characteristics of targets. The estimated coefficient on $M$ in the outcome equations is negative and significant (-12.496), and its magnitude indicates that $M$ acquirers receive 7.2% less capital from investors annually than do other acquirers with $M = 0$ for three years after the merger.\textsuperscript{20} Since I included dummy variables for public acquirers and for acquirers with negative pre-merger WOAR, the coefficient on $M$ does not reflect investors’ response to acquirers’ poor pre-merger performance or different growth rates for public and private companies.

\textsuperscript{20}The difference is not 12.5% because of the difference-in-difference structure of the regression.
The estimated correlation (calculated using the estimated \( \rho \)) does not differ significantly from zero, indicating that the errors in the matching utility functions and the outcome equations are not closely correlated. As a result, the magnitudes of \( \theta_M \) obtained from the joint estimation and from separate estimation of the outcome equations (not reported) are very similar. I do not find evidence that a systematic difference between inefficient and efficient acquirers in the unobserved quality of their matches contributes to the difference in their post-merger asset flows.

In sum, I have two main findings. First, efficiency gains, especially match-specific scale economies in marketing and distribution, are an important determinant of both matching decisions and merger outcomes. Second, \( M \) predicts three distinct things. \( M \) acquirers are eager to acquire (positive \( \alpha_M \)), they have poor post-merger management skills (negative \( \theta_M \)), and their poor management skills render them unattractive to targets (negative \( \beta_M \)). Although each finding by itself doesn’t allow us to draw any conclusion, these three distinctive behavioral patterns associated with the proxy \( M \), when combined together, portrait a unified picture of companies pursuing acquisitions for objectives other than shareholder value maximization. According to the findings, companies that are expected to be potentially more vulnerable to agency problems according to the proxy are much more likely to acquire, but when they do acquire, they have much worse outcomes. If poorly performing public companies make acquisitions more often because they have greater efficiency gains to obtain, we would not expect to find consistently worse post-merger performance by these companies. This incongruence of merger behavior and merger outcome suggests that objectives other than shareholder value maximization might have driven their acquisitions.
5.2. *Alternative specifications and discussions*

My primary model assumes that the set of potential targets is identical to the set of actual targets. To see if a selection bias is a concern, I redefined the set of potential targets in five different ways and adjusted the set of potential acquirers accordingly (because a company cannot appear in both sets). First, I expanded the set of potential targets by pooling actual targets over a two-year period: The set of potential targets in year $t$ consists of actual targets in year $t$ or $t + 1$. This alternative definition of potential targets recognizes that a company might go up for sale, fail to find a suitable buyer in one year, decide to wait, and succeed in finding a buyer in the following year. Second, I expanded the set of potential targets by pooling actual targets over a three-year period: The set of potential targets in year $t$ consists of actual targets in year $t$, $t + 1$ or $t + 2$. In the next three robustness checks, I choose firms whose assets under management are less than $10$ million, $100$ million and $1$ billion, respectively, and include them in the set of potential targets in year $t$ along with the actual targets. These three cases are examined due to the earlier finding that targets tend to be much smaller than acquirers.

In each of these cases, I allow each potential target the outside option of not being acquired, by modeling a target’s reservation utility as a function of its characteristics, such as age, ownership, recent performance, and size. These alternative specifications generate similar results to those of my primary model, alleviating concerns over the sensitivity of estimation results to the particular assumption regarding the set of potential targets.$^{21}$

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$^{21}$I thank the anonymous reviewer for encouraging me to investigate this issue carefully. All unreported results are available from the author upon request.
Another important assumption of my primary model was the fixed sharing rule. The fixed sharing rule does not allow a less attractive acquirer to buy a better target by offering to pay a higher proportion of the acquirer’s valuation. In this section, I try to introduce a slightly more flexible sharing rule while maintaining the tractability of the main model. To this end, I allow limited transfers between acquirers and targets. Because of the computational burdens of allowing transfers, I allow transfers to vary across acquirers but not targets, an approach similar to allowing \( \lambda_{i,j,t} \) to vary with \( i \) but not with \( j \) (\( \lambda_{i,j,t} = \lambda_{i,t} \)). Think of this model as allowing acquirers to differ in their aggressiveness in pursuing a target. This model preserves the uniqueness of equilibrium.

I assume that the transfer of acquirer \( i \) is inversely related to its “attractiveness.” If targets compete to match with an attractive acquirer, the acquirer will need to pay a smaller transfer to targets than an unattractive acquirer would have to pay. Using targets’ utility function, I infer each target’s preference rankings over all acquirers, and then compute the average of the rankings for each acquirer. For example, if there are 20 acquirers, and acquirer \( i \) is the least preferred match for every target, \( i \)’s average ranking is 20. I normalize the rankings so that they sum to 0 over all acquirers and lie between -0.1 and 0.1. Then I set the transfer of acquirer \( i \) equal to its normalized ranking. Given the scale of utility, the transfers are large enough to change some targets’ rankings of acquirers. The results from this specification are similar to the results from my primary model.\(^{22}\)

\(^{22}\)This, although providing some assurance about the robustness of my results to the assumption of the fixed sharing rule, is ad-hoc because transfers are not explicitly modeled as an outcome of some bargaining process. Incorporating a bargaining process into the model and estimating a matching model with limited transfers is an interesting path to take, but is beyond the scope of this paper.
5.3. Counterfactual analysis

In this section, I use the estimated parameters reported in Table 3 to check how well the model explains the data and perform counterfactual analyses. I use the point estimates of the parameters of the matching utility functions in Table 3 to compute $U_{i,j,t}$ and $V_{i,j,t}$ for each possible match. I use the computed $U$s and $V$s to determine each player’s rankings of its possible matches. Applying the Gale-Shapley algorithm (1962) to the preference rankings yields the stable matching. The first panel in Table 5 shows the actual data and the second panel shows the model’s prediction on the frequency of acquisitions by each type of acquirer. Comparing the two panels indicates that the model does a good job of predicting who will make an acquisition.

[Table 5 about here]

One theme of this paper is that targets have an incentive to avoid an inefficient acquirer which the targets expect to struggle post-merger, and that such an incentive shrinks the set of targets willing to match with inefficient acquirers. This incentive thus acts as a mechanism to discourage non-value-maximizing takeovers. My first counterfactual analysis examines the impact of eliminating this mechanism by calculating the stable matching that would occur if $\beta_M = 0$ (under the interpretation that $M$ captures managerial motives). The third panel in Table 5 shows that under this scenario inefficient acquirers would become significantly more attractive to targets. As a result, they would make acquisitions much more often than they do in reality. This result suggests that targets’ incentive to avoid bad organizations deters a large number of inefficient mergers.
In my second counterfactual analysis, I set $\alpha_M$, $\beta_M$, and all coefficients in the matching model for the interactions of $M$ with characteristics of the merging companies equal to zero. These parameter values assume that managers’ private benefits play no role in the merger market. Companies would pursue an acquisition only based on efficiency reasons. The fourth panel of Table 5 reports the stable matching under this scenario. The results show that the companies I label as inefficient acquirers would make many fewer acquisitions if these acquirers were required to set acquisition prices only based on efficiency gains. Despite post-merger underperformance by these companies, they make some acquisitions even in this scenario because they can still achieve match-specific efficiency gains by buying particular targets. Another reason why inefficient acquirers remain active is that setting $\beta_M = 0$ eliminates targets’ reluctance to merge with organizations that will be badly managed.

My last counterfactual analysis considers what will happen if inefficient acquirers cannot raise their bids to reflect anticipated private benefits and targets still shun these acquirers because of their poor management skills. I set $\alpha_M$ and all other coefficients for the interactions of $M$ in the matching model equal to zero, but leave $\beta_M$ at its estimated value. The last panel of Table 5 reports the stable matching under this scenario. The results show that since targets have a strong incentive to avoid inefficient acquirers, these acquirers will be a lot less active in the merger market if they cannot make up for their unattractiveness by paying higher prices. Although it is true that $M$ likely captures more than just managerial motivations, these counterfactual analyses provide some suggestive evidence about the role of non-value-maximizing motives in the merger market.
6. Conclusion

In this paper, I find that there are many synergy-driven acquisitions in the mutual fund industry. Many firms engage in acquisitions to achieve economies of scale in marketing and distribution, and they do benefit from such scale economies post-merger. However, I find that not all acquisitions seem to be efficient in this industry. There is a group of companies whose acquisitions seem at least partly driven by motives other than shareholder value maximization. They are eager to acquire, but are very poor at managing merged organizations post-merger. I also find suggestive empirical evidence that targets may have an incentive to avoid takeovers by bad organizations, providing some discipline that discourages inefficient takeovers.

Given the magnitude of inefficient acquirers’ post-merger underperformance and the strong dislike of inefficient acquirers by targets, it would be fruitful to look inside the merged companies and investigate what happens in these merged firms. Do they lose key fund managers during the integration process? Are they ineffective at streamlining their product lines after the merger? Although not pursued in this paper due to time constraints of collecting data, it would be also interesting to see if we can corroborate the findings of this paper by directly examining variables that represent managerial incentives, such as the independence of boards. These questions remain as a future avenue of research.

My paper shows that an empirical matching model could provide a useful framework for merger analysis. However, there are limitations to the current model. Relaxing some of the key assumptions, such as incorporating dynamic considerations into the model and
allowing some transfers between merger partners, would be another fruitful avenue to pursue for future research.

References


Jensen, M., Murphy, K., 1990. Performance pay and top-management incentives. Journal of
Political Economy 98, 225-264.


1589-1622.


Table 1
Descriptive statistics for companies that are actual acquirers or targets.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number</th>
<th>TNA, billions</th>
<th>Number of Funds</th>
<th>Public Company</th>
<th>Load Company</th>
<th>Young Company</th>
<th>Pre-Merger WOAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>Acquirer 19</td>
<td>9.74 (26.74)</td>
<td>21.89 (39.59)</td>
<td>0.59 (0.51)</td>
<td>0.89 (0.32)</td>
<td>0.05 (0.23)</td>
<td>-0.000 (0.017)</td>
</tr>
<tr>
<td></td>
<td>Target 22</td>
<td>0.29 (0.53)</td>
<td>3.09 (3.28)</td>
<td>0.1 (0.31)</td>
<td>0.5 (0.51)</td>
<td>0.18 (0.39)</td>
<td>-0.014 (0.051)</td>
</tr>
<tr>
<td>1992</td>
<td>Acquirer 14</td>
<td>4.28 (5.99)</td>
<td>16.14 (12.06)</td>
<td>0.57 (0.51)</td>
<td>0.71 (0.47)</td>
<td>0.14 (0.36)</td>
<td>0.021 (0.067)</td>
</tr>
<tr>
<td></td>
<td>Target 19</td>
<td>0.22 (0.35)</td>
<td>3.37 (2.87)</td>
<td>0.29 (0.47)</td>
<td>0.53 (0.51)</td>
<td>0.16 (0.37)</td>
<td>-0.022 (0.112)</td>
</tr>
<tr>
<td>1993</td>
<td>Acquirer 13</td>
<td>13.92 (24.96)</td>
<td>35 (36.26)</td>
<td>0.77 (0.44)</td>
<td>0.92 (0.28)</td>
<td>0 (0.028)</td>
<td>0.003 (0.014)</td>
</tr>
<tr>
<td></td>
<td>Target 15</td>
<td>2.24 (5.18)</td>
<td>14.27 (26.45)</td>
<td>0.4 (0.51)</td>
<td>0.53 (0.52)</td>
<td>0.2 (0.41)</td>
<td>-0.013 (0.045)</td>
</tr>
<tr>
<td>1994</td>
<td>Acquirer 14</td>
<td>19.50 (25.01)</td>
<td>66.14 (68.15)</td>
<td>0.79 (0.43)</td>
<td>0.79 (0.50)</td>
<td>0 (0.0)</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>Target 15</td>
<td>2.28 (3.39)</td>
<td>16.13 (16.71)</td>
<td>0.54 (0.52)</td>
<td>0.67 (0.49)</td>
<td>0.13 (0.35)</td>
<td>-0.002 (0.032)</td>
</tr>
<tr>
<td>1995</td>
<td>Acquirer 12</td>
<td>11.06 (8.62)</td>
<td>56.67 (40.67)</td>
<td>0.58 (0.51)</td>
<td>0.83 (0.39)</td>
<td>0 (0)</td>
<td>0.003 (0.008)</td>
</tr>
<tr>
<td></td>
<td>Target 13</td>
<td>1.74 (3.10)</td>
<td>10.85 (10.84)</td>
<td>0.5 (0.52)</td>
<td>0.54 (0.52)</td>
<td>0.23 (0.44)</td>
<td>-0.011 (0.013)</td>
</tr>
<tr>
<td>1996</td>
<td>Acquirer 16</td>
<td>17.83 (28.76)</td>
<td>68.19 (90.29)</td>
<td>0.86 (0.36)</td>
<td>0.81 (0.40)</td>
<td>0.06 (0.25)</td>
<td>-0.003 (0.022)</td>
</tr>
<tr>
<td></td>
<td>Target 17</td>
<td>2.47 (3.72)</td>
<td>11.06 (12.18)</td>
<td>0.29 (0.47)</td>
<td>0.41 (0.51)</td>
<td>0.29 (0.47)</td>
<td>-0.021 (0.036)</td>
</tr>
<tr>
<td>1997</td>
<td>Acquirer 26</td>
<td>15.32 (22.04)</td>
<td>66.85 (71.71)</td>
<td>0.65 (0.49)</td>
<td>0.73 (0.45)</td>
<td>0 (0)</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>Target 31</td>
<td>3.74 (10.75)</td>
<td>19.97 (25.72)</td>
<td>0.58 (0.50)</td>
<td>0.68 (0.48)</td>
<td>0.10 (0.30)</td>
<td>0.006 (0.034)</td>
</tr>
<tr>
<td>1998</td>
<td>Acquirer 8</td>
<td>10.85 (14.17)</td>
<td>65.63 (77.89)</td>
<td>0.88 (0.35)</td>
<td>0.88 (0.35)</td>
<td>0.13 (0.35)</td>
<td>0.024 (0.034)</td>
</tr>
<tr>
<td></td>
<td>Target 9</td>
<td>1.28 (1.45)</td>
<td>12.89 (14.61)</td>
<td>0.38 (0.52)</td>
<td>0.67 (0.52)</td>
<td>0.11 (0.33)</td>
<td>-0.049 (0.163)</td>
</tr>
<tr>
<td>1999</td>
<td>Acquirer 19</td>
<td>21.20 (29.48)</td>
<td>83.37 (80.55)</td>
<td>0.74 (0.45)</td>
<td>0.79 (0.42)</td>
<td>0.16 (0.37)</td>
<td>-0.002 (0.042)</td>
</tr>
<tr>
<td></td>
<td>Target 23</td>
<td>6.80 (12.49)</td>
<td>25.30 (38.36)</td>
<td>0.48 (0.51)</td>
<td>0.57 (0.51)</td>
<td>0.13 (0.34)</td>
<td>-0.045 (0.100)</td>
</tr>
<tr>
<td>2000</td>
<td>Acquirer 21</td>
<td>18.67 (33.98)</td>
<td>71.57 (92.28)</td>
<td>0.71 (0.46)</td>
<td>0.81 (0.40)</td>
<td>0.14 (0.36)</td>
<td>0.001 (0.099)</td>
</tr>
<tr>
<td></td>
<td>Target 23</td>
<td>2.38 (3.44)</td>
<td>16.26 (16.16)</td>
<td>0.52 (0.51)</td>
<td>0.39 (0.50)</td>
<td>0.09 (0.29)</td>
<td>-0.023 (0.137)</td>
</tr>
<tr>
<td>2001</td>
<td>Acquirer 20</td>
<td>60.98 (129.92)</td>
<td>98.1 (85.64)</td>
<td>0.7 (0.47)</td>
<td>0.55 (0.51)</td>
<td>0.93 (0.22)</td>
<td>0.030 (0.062)</td>
</tr>
<tr>
<td></td>
<td>Target 26</td>
<td>4.73 (13.77)</td>
<td>19.31 (31.80)</td>
<td>0.48 (0.51)</td>
<td>0.42 (0.50)</td>
<td>0.23 (0.43)</td>
<td>-0.027 (0.139)</td>
</tr>
<tr>
<td>2002</td>
<td>Acquirer 23</td>
<td>31.71 (43.73)</td>
<td>95.74 (99.99)</td>
<td>0.74 (0.45)</td>
<td>0.65 (0.49)</td>
<td>0 (0)</td>
<td>0.015 (0.064)</td>
</tr>
<tr>
<td></td>
<td>Target 32</td>
<td>3.48 (7.15)</td>
<td>24.16 (33.26)</td>
<td>0.42 (0.50)</td>
<td>0.5 (0.51)</td>
<td>0.03 (0.18)</td>
<td>0.007 (0.076)</td>
</tr>
<tr>
<td>2003</td>
<td>Acquirer 10</td>
<td>29.88 (46.20)</td>
<td>75.7 (82.52)</td>
<td>0.5 (0.53)</td>
<td>0.8 (0.42)</td>
<td>0 (0)</td>
<td>0.020 (0.060)</td>
</tr>
<tr>
<td></td>
<td>Target 11</td>
<td>2.87 (5.30)</td>
<td>27 (42.93)</td>
<td>0.55 (0.52)</td>
<td>0.45 (0.52)</td>
<td>0 (0)</td>
<td>-0.011 (0.042)</td>
</tr>
<tr>
<td>2004</td>
<td>Acquirer 10</td>
<td>16.72 (23.64)</td>
<td>58.9 (65.34)</td>
<td>0.5 (0.53)</td>
<td>0.6 (0.53)</td>
<td>0 (0)</td>
<td>0.029 (0.116)</td>
</tr>
<tr>
<td></td>
<td>Target 10</td>
<td>1.26 (3.32)</td>
<td>6.8 (9.60)</td>
<td>0.44 (0.53)</td>
<td>0.3 (0.48)</td>
<td>0 (0)</td>
<td>0.006 (0.066)</td>
</tr>
</tbody>
</table>

Notes: The number of acquirers is often smaller than the number of targets since some acquirers make multiple acquisitions in a year. TNA (Total Net Assets) for a fund is the market value of all securities owned by the fund minus its total liabilities. TNA for a firm is the sum of TNA over all funds it owns. Public Company equals one if the company is publicly traded (or a subsidiary of a publicly traded company) and zero otherwise. Load Company equals one if the company mainly sells load funds through brokers and zero otherwise. Young Company equals one if the company is less than 3 years old and zero otherwise.
Table 2
List of variables in the matching model (all measured in the year before the merger).

1. \( X_{ijt} \)

### A. Interaction Effects

**Size Ratio** = Target’s \( TNA \) / Acquirer’s \( TNA \)

\( TNA \) = the sum of the market value of all securities owned by the firm’s funds minus their total liabilities, measured in $10 billions

**Similarity in proportion of MM Funds** = minus of the absolute difference between the acquirer and target in the proportion of money market funds. If the acquirer offers no money market fund, and the target has 100% of its fund offering in money market funds, this variable will be \(-0.1\) = \(-1\)

**Similarity in proportion of Institutional Funds** = minus of the absolute difference between the acquirer and target in the proportion of institutional funds.

**Same Public Status** equals one if the acquirer and target are both public or both private and zero otherwise.

**Same Distribution Channel** equals one if the acquirer and target are both load companies or both no-load companies and zero otherwise.

### B. Target’s Characteristics

- \( TNA \)
- \( TNA^2 \)
- Number of Funds
- Number of Money Market Funds
- Number of Institutional Funds
- Public Company equals one if the company is public and zero otherwise.
- Young Company equals one if the company is less than 3 years old and zero otherwise.
- Load Company equals one if the company mainly sells load funds through brokers and zero otherwise.
- \( WOAR \) ranking is the relative standing of the target’s pre-merger \( WOAR \) compared to other targets’ pre-merger \( WOAR \). I rank actual targets in each year based on their pre-merger \( WOAR \) levels. A higher ranking indicates better recent performance. Then I normalize the rankings by dividing them by the total number of actual targets in that year. For example, if we have 20 actual targets, the worst-performing target will be assigned \( 1/20 \), and the best-performing target will be assigned \( 1 \).

### C. Acquirer’s Characteristics

- \( TNA \)
- \( TNA^2 \)
- Number of Funds
- Number of Money Market Funds
- Number of Institutional Funds
- Public Company
- Young Company
- Load Company
- Negative \( WOAR \) equals one if the company has a negative pre-merger \( WOAR \) and zero otherwise.
- Past Acquisition equals one if the company made an acquisition in the past three years and zero otherwise.

2. \( M_{ij} \)

\( M = \) Acquirer Public Company \( \times \) Acquirer Negative \( WOAR \)

3. \( X_{ijt}M_{ij} \)

\( M \times \) Acquirer \( TNA \)
\( M \times \) Acquirer Young Company
\( M \times \) Acquirer Past Acquisition
\( M \times \) Target \( TNA \)
\( M \times \) Target Young Company

Interactions of \( M \) with acquirer and target characteristics enter both \( U \) and \( V \). \( \beta_{ij} \times M \) is the only variable in \( V \) that does not enter \( U \).
Table 3
Estimates of the matching model.

<table>
<thead>
<tr>
<th>Interaction Effects</th>
<th>Size Ratio</th>
<th>Marginal Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interaction Size Ratio</td>
<td>-0.000 (0.000) *</td>
<td>0.000</td>
</tr>
<tr>
<td>Effects</td>
<td>Similarity in proportion of MM Funds</td>
<td>0.851 (0.247) ***</td>
</tr>
<tr>
<td>Similarity in proportion of Institutional Funds</td>
<td>0.118 (0.238)</td>
<td>0.033</td>
</tr>
<tr>
<td>Same Public Status</td>
<td>0.054 (0.081)</td>
<td>0.015</td>
</tr>
<tr>
<td>Same Distribution Channel</td>
<td>0.235 (0.079) ***</td>
<td>0.066</td>
</tr>
<tr>
<td>Target Characteristics</td>
<td>TNA</td>
<td>3.119 (1.856) *</td>
</tr>
<tr>
<td></td>
<td>TNA$^2$</td>
<td>0.444 (0.295)</td>
</tr>
<tr>
<td></td>
<td>Number of Fund</td>
<td>-0.046 (0.029)</td>
</tr>
<tr>
<td></td>
<td>Number of MM Funds</td>
<td>0.099 (0.276)</td>
</tr>
<tr>
<td></td>
<td>Number of Institutional Funds</td>
<td>0.113 (0.198)</td>
</tr>
<tr>
<td></td>
<td>Public Company</td>
<td>4.896 (1.411) ***</td>
</tr>
<tr>
<td></td>
<td>Young Company</td>
<td>0.134 (1.135)</td>
</tr>
<tr>
<td></td>
<td>Load Company</td>
<td>0.786 (1.013)</td>
</tr>
<tr>
<td></td>
<td>WOAR ranking</td>
<td>3.31 (1.095) ***</td>
</tr>
<tr>
<td>Acquirer Characteristics</td>
<td>TNA</td>
<td>-0.024 (0.034)</td>
</tr>
<tr>
<td></td>
<td>TNA$^2$</td>
<td>0.0003 (0.0005)</td>
</tr>
<tr>
<td></td>
<td>Number of Fund</td>
<td>-0.0009 (0.002)</td>
</tr>
<tr>
<td></td>
<td>Number of MM Funds</td>
<td>0.016 (0.006) **</td>
</tr>
<tr>
<td></td>
<td>Number of Institutional Funds</td>
<td>0.011 (0.005) **</td>
</tr>
<tr>
<td></td>
<td>Public Company</td>
<td>0.390 (0.143) ***</td>
</tr>
<tr>
<td></td>
<td>Young Company</td>
<td>0.105 (0.240)</td>
</tr>
<tr>
<td></td>
<td>Past Acquisition</td>
<td>0.809 (0.169) ***</td>
</tr>
<tr>
<td></td>
<td>Load Company</td>
<td>0.609 (0.113) ***</td>
</tr>
<tr>
<td></td>
<td>Negative WOAR</td>
<td>-0.079 (0.137)</td>
</tr>
<tr>
<td></td>
<td>$M$ ($\alpha_0$)</td>
<td>4.093 (1.193) ***</td>
</tr>
<tr>
<td></td>
<td>$M \times$ Acquirer $TNA$</td>
<td>0.036 (0.036)</td>
</tr>
<tr>
<td></td>
<td>$M \times$ Acquirer Young Company</td>
<td>0.195 (0.467)</td>
</tr>
<tr>
<td></td>
<td>$M \times$ Acquirer Past Acquisition</td>
<td>-0.609 (0.278) **</td>
</tr>
<tr>
<td></td>
<td>$M \times$ Target $TNA$</td>
<td>0.177 (0.113)</td>
</tr>
<tr>
<td></td>
<td>$M \times$ Target Young Company</td>
<td>-0.059 (0.231)</td>
</tr>
<tr>
<td></td>
<td>$\beta_M$</td>
<td>-1.827 (0.577) ***</td>
</tr>
</tbody>
</table>

Notes: Inside the parentheses are the standard deviations of the posterior distribution. Variable definitions are provided in Table 2.

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.
Table 4
Estimates of the outcome equations.

<table>
<thead>
<tr>
<th>Interaction / Effects</th>
<th>Coefficient Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size Ratio</td>
<td>0.083 (0.159)</td>
</tr>
<tr>
<td>Similarity in proportion of MM Funds</td>
<td>1.628 (3.665)</td>
</tr>
<tr>
<td>Similarity in proportion of Institutional Funds</td>
<td>1.667 (4.717)</td>
</tr>
<tr>
<td>Same Public Status</td>
<td>-2.317 (2.666)</td>
</tr>
<tr>
<td>Same Distribution Channel</td>
<td>7.260 (3.056) **</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Target Characteristics</th>
<th>Coefficient Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Company</td>
<td>-3.132 (2.892)</td>
</tr>
<tr>
<td>Young Company</td>
<td>5.491 (3.999)</td>
</tr>
<tr>
<td>Load Company</td>
<td>-2.944 (3.151)</td>
</tr>
<tr>
<td>Negative WOAR</td>
<td>-0.585 (2.645)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Acquirer Characteristics</th>
<th>Coefficient Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Company</td>
<td>6.195 (3.863)</td>
</tr>
<tr>
<td>Young Company</td>
<td>-6.347 (5.719)</td>
</tr>
<tr>
<td>Past Acquisition</td>
<td>0.554 (3.021)</td>
</tr>
<tr>
<td>Load Company</td>
<td>2.708 (3.476)</td>
</tr>
<tr>
<td>Negative WOAR</td>
<td>2.704 (4.275)</td>
</tr>
<tr>
<td>$M (\theta_{id})$</td>
<td>-12.496 (5.199) **</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Target + Acquirer Characteristics</th>
<th>Coefficient Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Pre-merger TNA)</td>
<td>-1.231 (0.845)</td>
</tr>
</tbody>
</table>

| Year Dummies                              | Included             |
|Controls                                   | Included             |
|$\sigma_v$                                 | 602.784              |
|Correlation                                | 0.036 (0.027)        |

Notes: Standard deviations of the posterior distributions are inside the parentheses. $\log(\text{Pre-merger TNA}) = (\text{target’s TNA} + \text{acquirer’s TNA})$. Year dummies are adjusted depending on the year the dependent is measured. Controls include price 1 (expense ratio) and price 2 (load). Price 1 (Expense Ratio) is weighted average of the expense ratios of funds offered by the merged company (in the year before the dependent variable is measured). Price 2 (Load) is weighted average of the loads of funds offered by the merged company (in the year before the dependent variable is measured). All variables are measured in the year before the merger. The only exceptions are price variables that are measured in one year before the dependent variable is measured, and year dummies that adjust depending on the year the dependent variable is measured.

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.
Table 5
Goodness of fit and counterfactual analysis.

<table>
<thead>
<tr>
<th></th>
<th>Actual data</th>
<th>Model prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>private</td>
<td>public</td>
</tr>
<tr>
<td>positive WOAR</td>
<td>47</td>
<td>81</td>
</tr>
<tr>
<td>negative WOAR</td>
<td>35</td>
<td>103</td>
</tr>
</tbody>
</table>

If $\beta_M = 0$

|          | private | public |
| positive WOAR | 1       | 4      |
| negative WOAR | 1       | 260    |

If $\alpha_M = \beta_M = 0$

|          | private | public |
| positive WOAR | 51      | 106    |
| negative WOAR | 35      | 74     |

If $\alpha_M = 0$

|          | private | public |
| positive WOAR | 72      | 141    |
| negative WOAR | 52      | 1      |

Notes: The number in each cell reports the number of acquirers that have the specified type. For instance, in the actual data, there are 47 acquirers which are private companies with positive WOAR in the year before the merger, while the model predicts that there are 41 such acquirers.
I prove this result by contradiction. Suppose that the acquirer-optimal stable matching $\mu_A$ and the target-optimal stable matching $\mu_T$ are not the same in year $t$. If so, we can identify $i$s and $j$s whose partners under $\mu_A$ are different from their partners under $\mu_T$. Let $S(i)$ be the collection of such $i$s and $S(j)$ be the collection of such $j$s. Since the set of people who are single is the same for all stable matchings in a market with strict preferences (Knuth, 1976), self-matched acquirers or targets will not be in $S(i)$ or $S(j)$. We also have $|S(i)| = |S(j)|$, where $|X|$ represents the number of elements in set $X$. Using the assumption that $\mu_A$ differs from $\mu_T$, we conclude that $S(i)$ and $S(j)$ are non-empty. By the definition of an acquirer-optimal stable matching and the assumption of strict preferences, we have $U_{i,\mu_A(i),t} > U_{i,\mu_T(i),t} \forall i \in S(i)$, and by the definition of a target-optimal stable matching, $V_{\mu_T(j),j,t} > V_{\mu_A(j),j,t} \forall j \in S(j)$. Recall that $V_{i,j,t} = \frac{(1-\lambda_t)}{\lambda_t} U_{i,j,t} + \beta_M M_{i,t}$. Summing the inequality conditions for $j$s and plugging in the expression for $V$ yields $\sum_{j \in S(j)} \left[ \frac{(1-\lambda_t)}{\lambda_t} U_{\mu_T(j),j,t} + \beta_M M_{\mu_T(j),t} \right] > \sum_{j \in S(j)} \left[ \frac{(1-\lambda_t)}{\lambda_t} U_{\mu_A(j),j,t} + \beta_M M_{\mu_A(j),t} \right]$, which reduces to $\sum_{j \in S(j)} U_{\mu_T(j),j,t} > \sum_{j \in S(j)} U_{\mu_A(j),j,t}$, or equivalently, $\sum_{i \in S(i)} U_{i,\mu_T(i),t} > \sum_{i \in S(i)} U_{i,\mu_A(i),t}$. But the previous inequality cannot hold because $U_{i,\mu_A(i),t}$ is bigger than $U_{i,\mu_T(i),t}$ for each $i$ in $S(i)$.

**Online Appendix 2: Estimation Methods**
I re-write the utility functions and outcome equations as follows to collect parameters.

\[
U_{i,j,t} = \lambda_t \left[ X'_{i,j,t} \alpha_X + \alpha_M M_{i,t} + X'_{i,j,t} M_{i,t} \alpha_X M + \omega_{i,j,t} \right] = \lambda_t \left[ X'_{i,j,t} \alpha + \omega_{i,j,t} \right]
\]

\[
V_{i,j,t} = (1 - \lambda_t) \left[ X'_{i,j,t} \alpha + \omega_{i,j,t} \right] + \beta_{M} M_{i,t} + \epsilon_{i,t} = \frac{1 - \lambda_t}{\lambda_t} U_{i,j,t} + \beta_{M} M_{i,t} + \epsilon_{i,t}
\]

\[
\Delta F_{i,j,t} = Z'_{i,j,t} \theta + \rho \omega_{i,j,t} + \nu_{i,j,t}
\]

The new \(X_{i,j,t}\) contains \(X_{i,j,t}\), \(M_{i,t}\), and \(X_{i,j,t} M_{i,t}\), and \(\alpha\) contains \(\alpha_X\), \(\alpha_M\), and \(\alpha_X M\). I assume \(\omega_{i,j,t} \sim IIDN(0,1)\), \(\epsilon_{i,t} \sim IIDN(0,(1 - \lambda_t)^2)\), and \(\omega_{i,j,t} \perp \epsilon_{i,t}\). I also assume \(\nu_{i,j,t} \sim IIDN(0,\sigma_\nu)\), \(\omega_{i,j,t} \perp \nu_{i,j,t}\), and \(\epsilon_{i,t} \perp \nu_{i,j,t}\). The assumed error structure does not allow autocorrelations in the outcome equations, which is a restrictive assumption but simplifies the estimation procedure. The parameters of the model I need to estimate are \(\alpha, \beta_M, \theta, \rho,\) and \(\sigma_\nu\). To simplify notation, let \(\Theta = (\alpha, \beta_M, \theta, \rho, \sigma_\nu)\). Denote the observed matching in year \(t\) by \(\mu_t\). Let the set of utilities \((U_t, V_t)\) for which \(\mu_t\) is the equilibrium be \(\Gamma_{\mu_t}\), where \(U_t\) is a stack of \(U_{i,j,t}\) and \(V_t\) is a stack of \(V_{i,j,t}\) as defined in Section 3.2. We observe merger outcomes only for actual matches. \(i, j \in o_t\) means we observe merger outcomes for a match between \(i\) and \(j\) \((\neq 0)\). Below, \(C\) represents a generic constant.

Likelihood: The likelihood function for year \(t\) is the probability of getting values of \((U_t, V_t)\) that are consistent with \(\mu_t\) (i.e., values of \((U_t, V_t)\) such that \((U_t, V_t) \in \Gamma_{\mu_t}\)) and observing
\( \Delta F_{i,j,t} \) for actual matches.

\[
L(\mu_t, \Delta F_t|X_t, Z_t, \Theta) = \int_{(U_t, V_t) \in \Gamma_{\mu_t}} p(U_t, V_t, \Delta F_t|X_t, Z_t, \Theta) dG(\omega, \epsilon, \nu) \\
= \int_{(U_t, V_t) \in \Gamma_{\mu_t}} p(U_t|X_t, \Theta)p(\epsilon_t|U_t, X_t, \Theta)p(\Delta F_t|U_t, X_t, Z_t, \Theta)dG(\omega, \epsilon, \nu)
\]

(2)

The second equality follows because conditional on \( U_t, X_t, \) and \( \Theta \), knowing \( \epsilon_{i,t} \) determines \([V_{i,1,t}, V_{i,2,t}, \ldots, V_{i,J_t,t}]\). The likelihood function is therefore as follows.

\[
L(\mu, \Delta F|X, Z, \Theta) = C \times \prod_{t} \int_{(U_t, V_t) \in \Gamma_{\mu_t}} \left\{ \prod_{i \in I_t, j \in J_t \setminus \{0\}} \phi\left(\frac{U_{i,j,t} - \lambda_t X_{i,j,t}}{\lambda_t} \right) \times \prod_{i \in I_t} \phi\left(\frac{\epsilon_{i,t}}{1-\lambda_t} \right) \times \prod_{i,j \in \alpha_t} \phi\left(\frac{\Delta F_{i,j,t} - Z_{i,j,t} - \rho(U_{i,j,t}/\lambda_t - X_{i,j,t}/\alpha)}{\sqrt{\sigma_v}} \right) \right\} dG(\omega, \epsilon, \nu)
\]

(3)

\((U_t, V_t) \in \Gamma_{\mu_t}\) which enters the region of integration in the likelihood function is the set of inequalities required for stability, as discussed in Section 3.3.

Prior: I assume that prior distributions of \( \alpha, \beta_M, \theta, \) and \( \rho \) are normal with large variances. \( \alpha \sim N(0, 20I) \) and \( \beta_M \sim N(0, 20) \), where \( I \) is an identity matrix of appropriate dimension. Prior variances of \( \theta \) and \( \rho \) are set at 1000 since the variance of net asset growth rates is large. Hence, \( k(\alpha) = C \times \exp\left[ -\frac{1}{40} \alpha' \alpha \right] \) and \( k(\beta_M) = C \times \exp\left[ -\frac{1}{40} \beta_M^2 \right] \), and so on. I assume that the prior distribution of \( \sigma_v \) is inverted gamma with \( v = 2 \) degrees of freedom and scale \( s = 1 \). Hence, the prior density of \( \sigma_v \) is \( k(\sigma_v) = C \times \frac{1}{\sigma_v^{1/2}} \exp\left[ -\frac{1}{\sigma_v} \right] \). I choose these priors to simplify the simulation process since given the assumption of normally distributed error terms, these are conjugate priors.
Posterior: The set of inequalities in the region of integration of the likelihood function, \((U_t, V_t) \in \Gamma_{\mu_t}\), makes it computationally very slow to draw directly from the posterior. Gibbs sampling, when combined with a device called “data augmentation,” makes drawing easier.

The idea of data augmentation is to treat latent variables \(U\) and \(V\) as parameters along with \(\Theta\). If we do so, computation of the marginal posterior distributions of \(\Theta\) using Gibbs sampling requires only the posterior distributions of \(\Theta\) conditional on \(U, V,\) and the data, and the posterior distributions of \(U\) and \(V\) conditional on \(\Theta\) and the data (Albert and Chib, 1993). Drawing from these fully conditional distributions is easy because they have standard forms, such as normal, truncated normal, or inverted gamma. As Geweke (1998) observes, a key feature of data augmentation is that since Bayesian inference conditions on the observables \((X, Z, \mu, \Delta F)\), parameters and latent variables have the same standing as unknown entities whose joint distribution with the observables the model determines. The augmented posterior distribution in my model is

\[
K(U, V, \Theta|X, Z, \mu, \Delta F) = C \times k(\alpha) \times k(\beta_M) \times k(\theta) \times k(\rho) \times k(\sigma_v) \times \prod_t L(\mu_t, U_t, V_t, \Delta F_t|X_t, Z_t, \Theta)
\]

where \(I_{\{\}}\) is an indicator function. From this expression, we can derive conditional posterior densities to use in estimation with Gibbs sampling.

Conditional Posterior: The fully conditional posterior distribution of \(\alpha\) is a normal dis-
tribution with the following mean and covariance matrix.

\[ \tilde{\alpha} = \tilde{\Omega} \sum_{t} \sum_{i \in I, j \in J \cup \{0\}} \frac{1}{\lambda_t} U_{i,j,t} X_{i,j,t} - \tilde{\Omega} \sum_{t} \sum_{i,j \in \alpha_t} \frac{1}{\sigma_v} \left( \Delta F_{i,j,t} - Z'_{i,j,t} \theta - \frac{\rho U_{i,j,t}}{\lambda_t} \right) \rho X_{i,j,t} \]

\[ \tilde{\Omega} = \left[ \frac{1}{20} I + \sum_{t} \sum_{i \in I, j \in J \cup \{0\}} X_{i,j,t} X'_{i,j,t} + \sum_{t} \sum_{i,j \in \alpha_t} \frac{1}{\sigma_v} \rho^2 X_{i,j,t} X'_{i,j,t} \right]^{-1} \]  

(5)

Similarly, the conditional posterior distributions of \( \theta \) and \( \rho \) are normal. The conditional posterior distribution of \( \sigma_v \) is inverted gamma with an updated degree of freedom and scale. The conditional posterior distribution of \( \beta_M \) is truncated normal, because conditional on \( U, \epsilon, \) and the data, a draw of \( \beta_M \) determines \( V_{i,j,t} \) for \( \forall i, j, t \), and these \( V \)'s should satisfy the stability conditions. Accordingly, the stability conditions for all \( j \)'s determine the truncation points of the conditional posterior distribution of \( \beta_M \). Similarly, the conditional posterior distribution of \( U_{i,j,t} \) is a truncated normal distribution because it is a normal distribution constrained by the stability conditions. The same is true for \( \epsilon_{i,t} \).

I base my estimates on 200,000 iterations of the sampling procedure. I discard the initial 150,000 draws to allow time for the conditional distributions to converge to the correct joint posterior distribution and use the last 50,000 draws to compute the means and standard deviations of the posterior distribution. Inspection of the posterior means and variances at various points in the iteration process shows that in most cases they stabilize long before the 150,000th iteration.