M&A Incentives and Outcomes: Evidence from the Mutual Fund Industry

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Job Market Paper

November 12, 2006

Abstract

This paper tests hypotheses about the incentives of acquirers and targets in the merger market. The first hypothesis of this paper is that principal-agent conflicts lead some companies to make acquisitions to obtain private benefits for their management rather than to maximize profits. The second hypothesis is that targets try to avoid being taken over by acquirers that do not maximize profits. I test these hypotheses using data on acquisitions among mutual fund management companies from 1991 through 2004. I find that companies whose managers have recently performed poorly and thus have an incentive to "gamble for resurrection" with the owners' money are more acquisitive than others, yet have significantly worse post-merger operating performance. These findings support the hypothesis that motives other than maximizing profits drive some acquisitions in this industry. I also find that acquirers that do not maximize profits tend to match with lower-quality targets, supporting the hypothesis that targets have an incentive to avoid being acquired by such acquirers. To investigate the role of these incentives in greater depth, I estimate a matching model of the merger market for fund management companies jointly with equations representing the outcomes of mergers. In addition to confirming the findings described above, the estimates show that targets' aversion to inefficient acquirers is a powerful market mechanism that deters many inefficient acquisitions. My counterfactual analysis suggests that eliminating this market mechanism would lead to an allocation in which inefficient acquirers dominate the merger market.

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1 Introduction

A variety of motives may impel firms to pursue an acquisition. Companies may acquire to increase efficiency or to obtain private benefits for managers. It is well understood that the latter can lead to inefficiency in resource allocation. A large literature examines organizational incentives that discourage inefficient acquisitions. This paper studies a market mechanism that can mitigate the degree of inefficiency: Targets may resist being taken over by inefficient acquirers. I explore these ideas in the context of acquisitions among mutual fund management companies.

The first hypothesis of this paper is that some companies acquire at least in part because an acquisition enables their managers to obtain private benefits. I focus on one specific managerial incentive: the idea that managers of a company that performs poorly would want to take risks to improve the company's performance, as would be expected if poor performance increases the odds of manager dismissal (Chevalier and Ellison, 1999; Huson, Parrino, and Starks, 2001; Kaplan and Minton, 2006). As Tirole (2006) notes, it is a common attitude of managers in trouble to take excessive risk and thus "gamble for resurrection."

The second hypothesis of this paper is that targets have an incentive to avoid being taken over by inefficient acquirers. To see why, consider a fund management company that wants to grow in order to market its funds more widely. Suppose the firm has two suitors. One suitor runs its business successfully, and the target expects this suitor to manage the merged fund family skillfully as well. The other suitor has been less successful, and the target suspects that this suitor would fail to bring in new money from investors after the merger. The target manager would prefer the first suitor to the second one because the post-merger performance of the target's assets will be higher when sold to the former than to the latter.

I test these hypotheses using data on acquisitions among mutual fund management companies from 1991 to 2004. The mutual fund industry is an excellent area in which to address the questions posed by this paper. In most other industries, it is difficult to obtain detailed measures of companies' performance after acquisitions. In the mutual fund industry, however, such data are available, including measures of operating performance such as asset flows and fund returns, enabling me to study post-merger performance. Moreover, data are available for all mutual fund management companies, whether private or public, and whether or not they merged. My ability to study companies that could have made an acquisition but did not strengthens my results. The importance of human capital in the mutual fund industry also makes it an interesting place to test my hypotheses because mergers can significantly affect performance via their impact on fund managers. The mutual fund industry also merits study simply for its importance: The industry manages over $9 trillion of assets invested by over 90 million Americans.[2]

The particular type of inefficient acquirer on which I focus has two characteristics: (1) divergence between the incentives of managers and owners and (2) poor recent performance. Divergence of incentives is more likely in public companies than in private ones. Not all public companies, however, suffer from agency conflicts to the same degree, and poor performance could make agency conflicts more acute for the reasons discussed above. Therefore, I identify poorly performing public companies as a group that potentially has non-profit-maximizing motivations for acquisitions, and test empirically whether their behavior differs from others' in a way that suggests that they pursue an acquisition out of managerial motivations. I separately control for public ownership and poor recent performance to ensure that the interaction between these two variables does not represent a systematic difference between public and private companies or between companies with good and poor recent performance.

The first implication of my hypotheses is that companies with managerial motives have a greater desire to undertake acquisitions than companies with only efficiency motives. In support of this implication, I find that among companies who could potentially make an acquisition, public companies with poor recent performance are 71% more likely to make an acquisition than public companies with good recent performance or privately held companies, controlling for differences in firm size and other characteristics that might affect the likelihood of making an acquisition.

The second implication of my hypotheses is that acquirers that do not maximize profits have worse merger outcomes than efficient acquirers. I study asset growth as a merger outcome variable. Marketing economies of scale are important in this industry, and post-merger asset growth is a good measure of the degree to which the newly merged firm captures such scale economies. I find that public acquirers with poor pre-merger performance attract 6.7% less money from fund investors annually (as a percentage of existing assets) than do other acquirers for three years after the merger. Another outcome variable that I study is changes in the return of targets' funds after the merger, because acquirers' skill in overseeing targets' funds may account for changes in their performance. I find that annual returns of funds acquired by poorly performing public companies increase by 0.9-1.8 percentage points less post-merger than returns of funds acquired by other companies.

[2] Investment Company Institute, http://www.ici.org/

The third implication of my hypotheses is that inefficient acquirers' poor ability to manage the merged organization reduces their attractiveness as merger partners. I find that conditional on making an acquisition, poorly performing public companies are more likely to buy a low-quality target compared to other companies. Since I expect that these companies' greater desire for acquisitions would lead to a higher willingness to pay for targets, this empirical pattern suggests that targets' incentive to avoid inefficient acquirers more than offsets inefficient acquirers' relatively high willingness to pay.

To further investigate the role of these incentives in the allocation of targets, and also to explicitly consider match-specific efficiency gains in merger decisions, I estimate a model of the takeover market. The model is a two-sided matching model in which pairings between acquirers and targets arise as part of a stable assignment. I jointly estimate the matching model and equations representing the outcomes of mergers (post-merger asset growth), allowing correlation between the errors of the matching model and the outcome equations. The joint estimation allows me to correct for selection bias in estimating the outcome equations following Sørensen (2006). The interdependence among players in the matching model presents numerical difficulties for the joint estimation. Bayesian methods using Gibbs sampling and data augmentation provide a feasible solution.

My results are as follows. (1) All else equal (holding fixed the amount of efficiency gains from mergers), poorly performing public companies obtain greater utility from buying another fund management company than other companies do. (2) They are much worse at achieving asset growth post-merger, even after controlling for differences in the observed and unobserved characteristics of targets. (3) Targets have an incentive to avoid being taken over by them.

I then use the estimates of the model to show that targets' resistance to inefficient acquirers is a powerful market mechanism that discourages inefficient takeovers. My counterfactual analysis suggests that, in the absence of this behavior, inefficient acquirers would buy most available targets in the merger market. Market discipline arising from targets' preference for efficient acquirers succeeds where organizational discipline fails in curbing inefficient mergers.

Finally, the estimation results reveal an important source of efficiency gains from mergers in this industry: economies of scale in marketing and distributing funds. Whether the acquirer and target have the same channel of distribution (selling funds directly to investors or indirectly through intermediaries) influences both the choice of a merger partner and the outcome of the merger. My results indicate that if two merging companies have the same distribution channel, the merged company annually brings in 7.3% more money from investors for three years after the merger than if the two use different channels of distribution.

This paper contributes to the literature in organizational economics and corporate finance. The idea that managerial incentives might diverge from profit maximization is an old one. In focusing on divergent objectives in making acquisitions, this paper follows the work of Amihud and Lev (1981), Baumol (1959), Jensen (1986), Jensen and Meckling (1976), Mueller (1969), and Shleifer and Vishny (1989) among others. Economists have studied various mechanisms that could discourage the non-profit-maximizing behavior of managers, such as product market competition, labor market competition, compensation schemes, and monitoring by the board of directors. I view the takeover market itself as providing partial discipline for inefficient acquirers. This paper is closely related to the paper of Mitchell and Lehn (1990), which shows that bad acquirers later become takeover targets. The main difference between my paper and theirs is that I study targets' preference for efficient acquirers as a possible market discipline mechanism whereas they focus on efficient acquirers taking over firms who previously made inefficient acquisitions.

A secondary contribution of this paper is to the general empirical literature on the causes and consequences of mergers. This literature identifies conflicts of interest in agency relationships as a possible explanation for the consistent yet puzzling finding that on average, acquisitions do not increase the wealth of acquirers' shareholders (e.g. Datta, Iskandar-Datta, and Raman, 2001; Harford, 1999; Masulis, Wang, and Xie, 2006; Morck, Shleifer, and Vishny, 1990; Shleifer and Vishny, 1988). Unlike most prior work in the merger literature, which studies the reaction of stock prices to merger announcements, this paper measures the benefits of mergers by post-merger operating performance. McGuckin and Nguyen (1995) and Ravenscraft and Scherer (1987) are two of the few papers that use post-merger operating performance for this purpose.

Finally, this paper relates to the mutual fund literature. This literature has analyzed mergers among mutual funds, either within a family of funds or across families (Ding, 2006; Jarayaman, Khorana, and Nelling, 2002; Khorana, Tufano, and Wedge, 2006). Unlike these papers, I analyze mergers between mutual fund management companies – organizations that manage families of funds. Although mergers of funds often follow mergers of fund management companies as management companies streamline their product lines post-merger, the two types of mergers are not equivalent for the purposes of the questions I investigate. My focus on conflicts between shareholders and managers of fund management companies differs from the mutual fund literature that has mainly studied conflicts between fund investors and fund managers or fund management companies (Chevalier and Ellison, 1997; Ding and Wermers, 2006; Khorana, Servaes, and Wedge, 2006; Khorana, Tufano, and Wedge, 2006; Mahoney, 2004).

A brief overview of the rest of the paper follows. Section 2 describes the mutual fund industry and my data. Section 3 presents empirical facts that support my hypotheses and also motivate my model. I discuss my model of the takeover market in Section 4. Section 5 then presents an econometric model of the takeover market and discusses strategies for estimation. Section 6 provides empirical findings from the model and discusses counterfactual exercises I performed. Section 7 concludes the paper.

2 Industry and Data

2.1 Industry

A mutual fund pools capital from many people and invests it in stocks, bonds, or other assets. 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. Examples of fund families include Fidelity funds, managed by Fidelity Management & Research Company, and American funds, managed by Capital Research & Management Co.

Mutual funds are legal entities distinct from the management companies that manage them. They have their own boards of directors or trustees who owe fiduciary obligations to fund investors (also called fund shareholders). Mutual fund management companies register their funds as corporations or trusts, set up the funds' boards, and sell the funds to investors. Hence, although mutual funds are legally separate from the companies that manage them, they resemble products produced by management companies and sold to consumers (fund investors).[3]

Since fund management companies have their own shareholders and boards distinct from their funds' shareholders and boards, I use the term "shareholders" to refer to the shareholders of fund management companies and "fund investors" to refer to the shareholders of individual funds. I

[3] There is an ongoing debate about whether mutual fund investors should be viewed as owners of funds or consumers. See Tkac (2004) for an insightful discussion of this debate.

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.

Many fund management companies are parts of larger financial institutions. Broadly speaking, fund management companies fall into 5 categories: pure mutual fund management companies, full-service brokerage companies, discount brokerage companies, banks, and insurance companies. The presence of vertically integrated firms and conglomerates in this industry complicates my analysis because some companies in my data set may merge for reasons unrelated to their mutual fund subsidiaries. For example, two banks that happen to own mutual fund management companies may merge because of changes in the banking sector and with little regard for the merger's effects on their fund management businesses. My future research will incorporate into this paper's analysis information on fund management companies' affiliations with other financial businesses.

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, 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."[4] Some acquirers may primarily seek assets rather than people (for example, Deutsche Bank laid off huge numbers of fund managers after acquiring Zurich Scudder Investments), but generally the importance of human capital discourages hostile takeovers.

Mergers in this industry may increase efficiency via: (1) economies of scale in production obtained by increasing the number of funds sharing research, back office, or brokerage functions; (2) economies of scale in marketing or distribution of funds, e.g. by providing "one-stop shopping" within a family of funds or spreading fixed costs of marketing and distribution over more investors; and (3) skillful acquirers' superior ability to manage assets or distribute funds. Hendrik du Toit, chief executive of Investec Asset Management, offers anecdotal evidence of the third type of synergy when he says that a rationale for acquisitions in this industry is "to roll up the assets of a loser."[5]

[4] Funds Europe report

[5] Funds Europe report

2.2 Data

I study data on U.S. 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. Thus, I constructed a unique management company identifier. CRSP does not provide information on management companies for years prior to 1992, but I obtained such information for earlier years by matching fund names with another data set from Thomson Financial. I identified management companies as public or private using Thomson Financial's SDC Platinum and the web sites of management companies. Hereafter, I identify 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,[6] but enables me to identify all mergers between fund management companies, big or small, during the sample period. Note that my sample of mergers excludes transfers of ownership from an existing fund management company to a new entrant into the market. My sample includes only mergers of two companies already active in the mutual fund industry.

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.

[6] It is hard to identify the exact month a merger occurs, and an actual integration could happen with some time lag after a merger announcement. I plan to compare a set of the mergers identified using the CRSP data with press releases to see if my results are sensitive to such delays.

I measure the return of fund f during year t using objective-adjusted-returns (OAR). $OAR_{f,t}$ of fund f is defined as

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

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,[7] apparently enough categories to capture systematic differences among different types of funds.

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. To minimize lost observations, I use all funds that have at least 3 months of return information in calculating $WOAR$ for each company. I calculate OAR for each fund assuming that a fund earns the average return of its investment objective category in each month for which we lack return data. My results do not change when I exclude funds that have less than 6 months or less than 9 months of return data. It might seem more intuitive to treat outflows of assets as evidence of poor performance rather than low returns. Constructing a measure of performance using asset flows, however, is more complicated. Since the industry has experienced significant growth during the sample period, firms would experience positive asset inflows even when they perform relatively poorly. Also, the amount of a firm's asset inflows critically depends on the size of the firm's existing assets, so I would have to figure out what would be the right performance benchmark for firms in each size class.

Table 1 presents descriptive statistics for all mutual fund management companies in the market. Table 2 presents summary statistics for the mergers in my sample and compares various attributes of acquirers and targets.

[7] My sample has 27 categories of investment objectives prior to 1992.

3 Empirical Facts

In this section, I present three empirical facts concerning the behavior of poorly performing public companies relative to others. These empirical facts support my hypotheses and also motivate and inform my model of the takeover market.

3.1 Incentives to Make an Acquisition

First, I examine potential acquirers' incentives to undertake an acquisition to see whether companies with incentives to make inefficient acquisitions are more willing than other companies to make acquisitions. Table 3 presents the number of potential (top panel) and actual (bottom panel) acquirers in each of four groups: "private companies with positive $WOAR$ in the previous year," "private companies with negative $WOAR$ in the previous year," "public companies with positive $WOAR$ in the previous year," and "public companies with negative $WOAR$ in the previous year." I calculate the number of potential and actual acquirers in each group in a given year and pool them for all years in the sample period. Potential acquirers in year t include all companies not acquired or liquidated during or prior to that year. Comparing the two panels of Table 3 shows that public companies with bad recent performance are disproportionately more likely to make an acquisition.

Next, I conduct a probit analysis to control for firm size and other characteristics that might affect a firm's likelihood of making an acquisition. The dependent variable of the regression is a dummy variable for making an acquisition; regressors include characteristics of firms such as size and age, and dummy variables representing the year. I measure all regressors in the year before the potential merger. Table 4 presents the estimation results. Table 4 shows that even after controlling for various firm characteristics, public companies with poor recent performance are much more likely to make an acquisition than other companies. Poor performance does not affect a private company's probability of making an acquisition, but poor performance increases the probability that a public company will make an acquisition by about 2 percentage points. Since only about 2.8% of all potential public acquirers make an acquisition in a particular year, poor performance increases a public company's probability of making an acquisition by around 71%. Unreported regressions including interactions between firm size and recent performance yield the same results, indicating that the regressor for poorly performing public companies is not capturing the effect of an interaction between size and recent performance.

These results support the idea that poorly performing public companies, whose managers likely have an incentive to acquire to obtain private benefits, are more eager than other companies to make acquisitions. An alternative explanation is that these companies make more acquisitions than others because acquisitions are a profit-maximizing choice for them. Poorly performing companies may want to maintain corporate profitability through acquisitions or acquire reputational capital by buying funds with good track records. Then, public companies with poor recent performance may be especially likely to acquire because it's profitable for poorly performing companies to make acquisitions and public companies have better access than private companies to capital for financing mergers. Without examining mergers' outcomes, it is impossible to determine poorly performing public companies' motives for acquisitions. Accordingly, I examine merger outcomes in the next subsection.

Note that poorly performing public companies' high propensity to acquire does not contradict the "free cash flow hypothesis," which predicts that cash-rich firms will squander cash on unprofitable investments (Hartford, 1999; Jensen, 1986; Lang, Stulz, and Walkling, 1991). Below-average performance last year does not necessarily mean that a fund management company is short of cash this year. Investors try to invest in "hot" funds with strong recent performance but do not respond as strongly to poor performance by redeeming their investments (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Since fees are typically a fixed proportion of assets under management, even companies with poor performance may have enough free cash to spend on unprofitable investments.

3.2 Outcomes of Mergers

This subsection analyzes whether non-profit-maximizing acquirers have worse merger outcomes than other acquirers do. I first examine the difference between (1) the pre-merger performance of funds previously owned by the target and (2) their performance one year and two years after the merger. My measure of the impact of a merger occurring in year t will be $OAR_{f,t+1} - OAR_{f,t-1}$ (change in OAR of fund f in the year after the merger) and $OAR_{f,t+2} - OAR_{f,t-1}$ (change in OAR of fund f in the two years after the merger). Targets' funds change ownership after a merger, so acquirers' skill in overseeing targets' funds may account for changes in their performance. Changes in the performance of the acquirer's funds, on the other hand, are harder to interpret since I identify potentially inefficient acquirers using acquirers' pre-merger $WOAR$, and mean reversion may mask mergers' impact on the returns of acquirer's funds. My second measure of mergers' impact on performance is net asset inflows (as a percentage of the value of existing assets) into the merged company. An advantage of studying net asset inflows is that they capture economies of scale in marketing and distribution, an important rationale for mergers in this industry.

Change in the Performance of Target Funds

Table 5 compares changes in the return of target funds for different types of acquirers, with no controls. As before, I categorize acquirers on the basis of whether they are public and whether they have negative $WOAR$ in the year preceding the merger, $t-1$. I analyze target funds that are still alive by the end of year $t+2$. The last column in Table 5 reports the number of target funds for each group. It is clear that poorly performing public companies tend to buy targets that own large numbers of funds.

Table 5 shows that funds bought by public acquirers with poor recent performance experience the worst changes in performance post-merger. Funds bought by public acquirers with poor recent performance have lower returns one year and two years after a merger than they did pre-merger, and only these funds' returns consistently decrease post-merger. These funds' cumulative returns in the two years following a merger are 0.9 percentage points lower than pre-merger returns. Returns of funds bought by other acquirers, however, increase post-merger.

Table 6 presents OLS estimation results controlling for characteristics of acquirers and targets and characteristics of the targets' funds. I measure all regressors in the year before the merger. The results in Table 6 show patterns similar to those of Table 5. The results indicate that annual returns of funds acquired by poorly performing public companies increase by 0.9-1.8 percentage points less post-merger than returns of funds acquired by other companies.[8]

I'll briefly address two alternative explanations for the poor post-merger performance of public acquirers with poor pre-merger performance. Since CRSP reports returns net of expenses, one might worry that the results above reflect post-merger changes in expenses varying with the type of acquirer. I have confirmed, however, that post-merger changes in expenses do not explain the results. One might also worry that some funds absorbed the assets of other funds when the

[8] I calculate this number as follows. First, I calculate relative changes in returns for the four categories of acquirers (classifying on the basis of whether or not they are public or have negative $WOAR$) using the estimated coefficients. Then I compute the weighted average of the changes for acquirers other than public companies with negative $WOAR$, using weights equal to the number of funds for each type of acquirer. Finally, I subtract this weighted average from the change for public acquirers with negative $WOAR$.

fund management companies merged. Merging fund management companies commonly merge or liquidate some funds, and absorbing another fund can reduce the absorbing fund's return if fund managers have difficulty managing or reinvesting the assets of the absorbed fund. Funds acquired by poorly performing public companies do in fact absorb other funds' assets more often than funds acquired by other companies. However, I obtain similar results when I analyze only funds that have not absorbed other funds' assets when their fund management companies merged.

Net Asset Inflows into the Merged Company

My second measure of post-merger performance is the net flow of assets into the merged company. 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. Unlike in most papers on mutual funds, I do not calculate inflows net of reinvestments of dividends and distributions, because I view high reinvestments due to superior post-merger fund performance as part of merger outcomes. For each company formed by a merger in year t, I calculate net asset inflows during years $t+1$, $t+2$, and $t+3$. I use these three measures of annual net asset inflows to compute the average annual net asset inflows after the merger for each of the four types of acquirers.

Three results of my calculations of average net asset inflows (reported in Table 7[9]) deserve mention. First, note that all types of acquirers experience positive net asset inflows on average post-merger. The reason is that the mutual fund industry grew significantly during the sample period. The total value of assets under management at the end of the sample period is about 5.5 times the total value at the beginning of the sample period. Second, acquirers with below average pre-merger performance tend to attract less money from investors after a merger than do acquirers with above average pre-merger performance, reflecting investors' tendency to chase recent past performance. Third, the discrepancy in the post-merger asset inflows of acquirers

[9] 1. The total number of observations is 489. The number of observations is less than 798 (=266 (number of acquisitions) $\times$ 3 (for three years after the acquisition), because I exclude observations if the acquirer disappears (as a result of being acquired or liquidated) within three years after the merger, and the sample lacks at least one net asset inflow for the three years after a merger that occurs in the last three years of the sample. Moreover, net asset inflows for a given year and an acquirer appear in the sample only once, even if the acquirer makes multiple acquisitions in that year (Recall that I analyze the net asset inflows at the fund management company level, so multiple acquisitions by the same acquirer need not generate distinct observations). Rather than double count observations corresponding with 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.

2. I cap the maximum and minimum net asset inflows at 100% and -50% to ensure that a few outliers do not distort the results. The sample includes 12 observations with net asset inflows exceeding 100% and 6 observations with net inflows below -50%.

with positive and negative $WOAR$ is much larger when the acquirer is public than when the acquirer is private. The post-merger net asset inflows of private acquirers with good pre-merger performance are 0.12 percentage points higher than those of private acquirers with poor pre-merger performance. For public acquirers, the difference is 9.31 percentage points. This suggests that the post-merger underperformance of public companies with negative pre-merger $WOAR$ relative to public companies with positive pre-merger $WOAR$ is not simply due to past performance influencing future asset inflows.

Table 8 presents OLS estimation results using net asset inflows as the dependent variable and controlling for characteristics of the acquirer and target that might affect net inflows. The first column includes a few basic controls, such as dummies for the year of the acquisition and the log of the value of existing assets. The second column adds expenses and loads, in the year before the dependent variable is measured, as controls. The third column adds a few more characteristics of the acquirer and target and match-specific characteristics such as whether the acquirer and target use the same channel for distributing and marketing funds. The last column adds the growth rates of acquirers' assets under management in the one and two years before the merger as controls, to distinguish the impact of pre-existing growth trends from the impact of mergers. Here, I simply note that the coefficient on the dummy variable indicating poorly performing public acquirers is negative and significant in all specifications, and reserve a full discussion of merger outcomes for Section 6, where I use similar outcome equations in the model estimation.

These results regarding the impact of mergers and the results presented in the previous subsection regarding incentives to make an acquisition suggest that a subset of fund management companies acquire for motives other than maximizing profits. If poorly performing public companies make acquisitions often to achieve efficiencies, we would not expect to find consistently worse post-merger performance by these companies.

It is not clear exactly why these inefficient acquirers perform relatively poorly post-merger, and I plan to investigate it in future work. My conjecture is that organizational diseconomies of scale might be part of the story, given that human assets are the key to success in this industry. These non-profit-maximizing acquirers may be likely to make acquisitions under pressure without a clear blueprint for successful post-merger integration, increasing their risk of losing key fund managers post-merger and rendering them more vulnerable to internal conflicts. The following two quotes suggest that the human-capital-intensive nature of the mutual fund industry makes it vulnerable to such problems during mergers. "The focus can go away from asset management towards dealing with the corporate politics of the merger. In effect, the threat is to both houses. M&A is a time-consuming distraction, and the corporate-political fall-out can hit buyer as well as seller."[10] "If a company loses a good (fund) manager who prefers the certainty of another offer to the probability of a job with the merged firm, it might lose a whole department or be left with no obvious successor."[11] Moreover, fund managers' expectations may be self-fulfilling: If fund managers expect an acquirer to mismanage the surviving company, they may flee to avoid reductions in the portion of their compensation that depends upon the company's profitability (Farnsworth and Taylor, 2004). Losing good fund managers harms post-merger performance, possibly prompting additional fund managers to leave the company.

3.3 Targets' Incentives

In this subsection, I analyze patterns of matching between actual acquirers and targets to infer targets' preferences regarding merger partners. I have shown above that poorly performing public companies are more willing to acquire than other companies. It seems plausible to infer that these companies' greater willingness to acquire would translate into a higher willingness to pay for targets. Previous research found that acquirers seeking private benefits for managers indeed tend to pay more (Morck, Shleifer, and Vishny, 1990; Slusky and Caves, 1991). Therefore, targets should prefer these companies to other acquirers, all else equal, *unless* targets have other incentives to avoid these companies.

Targets, however, may have an incentive to avoid inefficient acquirers. The results from the merger outcome regressions showed inefficient acquirers' difficulty in attracting new money from investors post-merger. Thus, the expected value of the assets that a target is selling would be higher when sold to an efficient acquirer than when sold to an inefficient acquirer. This would provide targets with an incentive to prefer an efficient acquirer to an inefficient one. If this effect dominates the effect of the higher willingness to pay of inefficient acquirers, we would expect that inefficient acquirers would match with lower-quality targets than efficient acquirers do.

Table 9 shows the distribution of target quality (measured by the target's performance in the

[10] Todd Ruppert, president and CEO of T. Rowe Price Global Investment Services, "Harnessing talent post-merger," http://www.funds-europe.com
[11] Robert Kovach, managing director of management psychologists RHR International, quoted in a Funds Europe report.

year before it is acquired) across different types of acquirers. Each cell shows, for the specified type of actual acquirer, the percentage of actual acquirers who matched with a target that had a negative $WOAR$ in the year before it was acquired. For instance, the number in the upper left cell means that 53% of actual acquirers that are private and had positive $WOAR$ in the year before the merger matched with a target that had a negative $WOAR$ in the year before it was acquired. Hence, the table shows that public companies with poor recent performance tend to match with low-quality targets more often than do other acquirers. The difference in the likelihood of matching with a low-quality target is not large, however, and the average $WOAR$s of target companies for the four categories of acquirers (not reported) show that while public acquirers with poor pre-merger performance tend to match with lower-quality targets than do public acquirers with good pre-merger performance, the same pattern is true for private acquirers.

Since simple binary classifications (above average v. below average) are unlikely to reflect closely the companies' preferences concerning merger partners and therefore the equilibrium matching, I construct rankings to use in a regression. I rank actual targets in each year based on their $WOAR$ in the year prior to the merger. A higher ranking indicates better recent performance. Next, I normalize the rankings by dividing them by the total number of actual targets in the year in question. For example, if we have 20 actual targets, the worst-performing target receives a ranking of $\frac{1}{20}$, and the best-performing target receives a ranking of 1. Similarly, I rank actual acquirers in each year based on their pre-merger $WOAR$ and compute normalized rankings. I then predict the ranking of the actual target matched with each actual acquirer using the acquirer's characteristics (including its ranking), the target's characteristics, and interactions between the two companies' characteristics. As before, I measure all characteristics of the target and acquirer in the year preceding the merger.

Table 10 reports the results of the regression. The results indicate that public companies with poor recent performance are more likely to buy low-quality targets than are public companies with good recent performance. If an acquirer is private, there is no such positive correlation (rather there is a negative correlation) between the acquirer's pre-merger performance and the quality of its matched target. The negative coefficient for Public Acquirer means public acquirers tend to match with lower-ranked targets than do private acquirers, and the negative coefficient for Acquirer's Ranking means that an acquirer's ranking and the matching target's ranking are negatively correlated when the acquirer is private. Neither of the two coefficients is statistically significant. Since the interaction of Public Acquirer and Acquirer's Ranking has a positive coefficient whose magnitude is larger than that of the coefficient for Acquirer's Ranking, there is a positive correlation between an acquirer's ranking and the matching target's ranking when the acquirer is public.

Thus, public acquirers with poor recent performance tend to match with lower-quality targets than do public acquirers with good recent performance, while for private acquirers, poor recent performance does not impose any disadvantage on them in the matching market compared to other private acquirers. I interpret this empirical pattern as evidence that targets' incentive to avoid being taken over by inefficient acquirers more than offsets the effect of inefficient acquirers' higher willingness to pay. When a public company with poor recent performance bids for targets, the targets suspect that the bidder may be unable to manage the merged company effectively and seek other matches. If private companies bid for targets, the targets face no such concerns about the bidder's motive.

4 Model

This section develops a model of the takeover market as a two-sided matching game 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.

A natural question that arises at this point is why we need a model at all. The purpose of this model is fourfold. First, the two incentives of interest here are conflicts of interests (1) between the owners and managers of potential acquirers and (2) between acquirers and targets. A single-agent model cannot address both incentives, so I employ a matching model. Second, a matching model facilitates analysis of the efficiency gains, frequently match-specific, resulting from acquisitions. Third, a model enables me to correct for selection bias in estimating the outcome equations by jointly estimating the matching model and outcome equations. If acquirers with a particular characteristic tend to match with targets that are desirable for unobservable reasons, the estimated coefficient for the acquirer's characteristic in the outcome equations will reflect the effects of the unobserved target characteristics, biasing the coefficient upward. Following Sørensen (2006), and more generally Berry, Levinsohn, and Pakes (1995) and Bresnahan (1987), I use characteristics of other companies in the takeover market as an instrument to correct for such a bias. The rationale is that the characteristics of other companies in the market affect the set of feasible merger partners for each company, providing exogenous variation that affects matching, but not merger outcomes directly. Fourth, the model allows me to perform counterfactual analysis to investigate the precise determinants of market outcomes.

4.1 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,[12] 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. Searching for matches is costless in this model, and players observe the lists of potential acquirers and potential targets.

Managers of potential acquirers and targets are the decision makers in my model. 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 imposed by the shareholders.[13]

4.2 Preferences

Let $S_{i,j,t}$ be a *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 the sum of the efficiency gains from the acquisition and the private gains the manager obtains from the deal. This assumption 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 efficiency, the company's valuation S assigns no weight to managers' private benefits.

[12] I relax this assumption later when I estimate the model. 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.

[13] Managers maximize their expected utility subject to constraints imposed by employment contracts and oversight by independent directors or significant shareholders. A large literature devises optimal contracts for principal-agent relationships to align agents' interests with those of principals (See Laffont and Martimort (2001) for a list of important contributions to this literature).

Both efficiencies and private benefits resulting from mergers depend upon companies' characteristics. Increases in efficiency from acquiring target company j depend upon various characteristics of the target and acquirer, and interactions between these characteristics reflecting match-specific synergies.

A dummy variable, M, indicates whether managers' private benefits enter the acquirer's valuation. If I just include the variable M in S but not interactions between M and other characteristics of the acquirer or target, the coefficient on M, which I denote α_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 will allow the value of private benefits from a merger to vary with these characteristics, helping us to identify attributes of acquirers that encourage them to make inefficient acquisitions. Interactions between M and targets' characteristics allow inefficient acquirers and efficient acquirers to assign different values to merger partners.

A target and an acquirer split the acquirer's valuation of the match: Potential acquirer i obtains a portion $\lambda_{i,j,t}$ of the valuation and potential target j receives a portion $(1-\lambda_{i,j,t})$ of the valuation. Hence, *potential acquirer i's utility* from buying potential target company j is

$$U_{i,j,t} = \lambda_{i,j,t} S_{i,j,t}.$$

Potential target j's utility from being acquired by company i is $(1-\lambda_{i,j,t})S_{i,j,t}$ *unless* targets have a specific incentive to avoid inefficient acquirers. To allow such an incentive of targets, I model *potential target j's utility from being acquired by company i* as

$$V_{i,j,t} = (1-\lambda_{i,j,t})S_{i,j,t} + \beta_M M_{i,t}.$$

Note that α_M, which reflects inefficient acquirers' urge to merge, enters both $U_{i,j,t}$ and $V_{i,j,t}$. α_M enters targets' utility function $V_{i,j,t}$ because inefficient acquirers' greater willingness to make an acquisition implies a higher willingness to pay for acquisitions. These acquirers' higher willingness to pay, in turn, increases their value to targets, so α_M appears in $V_{i,j,t}$.

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 strict preferences so that no acquirer is indifferent between two targets, and no target is indifferent between two acquirers.

The signs and magnitudes of α_M and β_M affect the set of merger partners available to each acquirer. If managers obtain private benefits of control from making an acquisition, α_M will be positive. A positive α_M (higher willingness to pay) expands the set of targets willing to match with the inefficient acquirers. If targets have an incentive to avoid inefficient acquirers for the reasons discussed earlier ($\beta_M < 0$), the targets' utility from matching with an inefficient acquirer decreases by the magnitude of β_M. A negative β_M thus 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 uniform sharing to generate a simple and 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.[14] 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 the targets with which they match. 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 test the sensitivity of my results to the assumption of a fixed sharing rule in Section 6.

4.3 Stable Matchings

An equilibrium concept used for one-to-one, 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. Appendix A provides a proof.[15]

[14] See Legros and Newman (2002, 2004) and Chiappori and Reny (2005) for progress on this topic.

[15] The intuition behind the uniqueness of equilibrium is simple. If β_M is zero, equilibrium is unique because preferences of targets are aligned with those of acquirers (Sørensen, 2006). A non-zero β_M does not introduce any cycles into preferences because it shifts the utility of every target by the same amount. Therefore, a non-zero β_M in targets' utility function, V, 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

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 μ. Then, matching μ is stable if and only if the following inequalities hold.

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

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. Let acquirer i's "effective choice set" be the set of targets that cannot find an acquirer willing to match with them that they prefer to i. Define a target's effective choice set analogously. Then equilibrium is an allocation in which each acquirer chooses the optimal target from its effective choice set and each target chooses the optimal acquirer from its effective choice set.

5 The Econometric Model

My econometric model consists of two parts: a matching model and outcome equations. In this section, I discuss their empirical specifications. I then discuss identification of the model and my estimation strategies.

5.1 Model Specification

Since mutual funds are sold nationwide, no boundaries divide mutual fund management companies into different geographic markets. Accordingly, in my model each period of time defines a market. All mutual fund management companies that exist in a given year participate in the market for that year. I choose periods of a year rather than a shorter period because I often do not observe the exact month in which a merger occurs.

The set of potential targets J_t consists of all fund management companies actually acquired 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 limit the number of acquisitions in each year to the number

on j.

of targets, making the econometric model more tractable. When I estimate the model, I try an alternative specification that partially relaxes the exogeneity of the set of potential targets.

5.1.1 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. The utility of an acquirer or a target from a match depends on the characteristics of the acquirer and target, interactions between these characteristics, and a constant.[16] 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 $M_{i,t}$ ($X_{i,j,t}M_{i,t}$). Table 11 lists the variables. All the variables are measured in the year before the merger.

Acquirers' utility function ($U_{i,j,t}$) and targets' utility function ($V_{i,j,t}$) are as follows.[17]

$$
\begin{aligned}
&U_{i,j,t} = \lambda_t S_{i,j,t} = \lambda_t \left[X'_{i,j,t}\alpha_X + \alpha_M M_{i,t} + X'_{i,j,t}M_{i,t}\alpha_{XM} + \omega_{i,j,t} \right] \\
&V_{i,j,t} = (1-\lambda_t)S_{i,j,t} + \beta_M M_{i,t} + \epsilon_{i,j,t} \\
&= (1-\lambda_t) \left[X'_{i,j,t}\alpha_X + \alpha_M M_{i,t} + X'_{i,j,t}M_{i,t}\alpha_{XM} + \omega_{i,j,t} \right] + \beta_M M_{i,t} + \epsilon_{i,j,t}
\end{aligned}
$$

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 $V_{i,j,t}$. If we do not impose any restrictions on $\epsilon_{i,j,t}$, the errors can introduce a cycle into preference rankings so that the set of stable matchings is not a singleton. 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.

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 (α_M) *and* di-

[16] Estimated coefficients for the dummies for the year of the acquisition turn out to be insignificant, so I exclude them to minimize the time required to estimate the model.

[17] Recall that $S_{i,j,t}$ is the measure of the deal's attractiveness from the perspective of the acquiring manager. The acquirer and target share $S_{i,j,t}$.

vergence of interests between inefficient acquirers and targets (β_M).[18] I can separately identify these two effects using two related but distinct pieces of information from the observed matchings: which potential acquirers actually make an acquisition and who matches with whom conditional on making an acquisition or being acquired. Since not all potential acquirers prefer acquiring to not acquiring, potential acquirers' decisions to acquire convey information regarding which characteristics increase the utility of a match, helping to identify α_M. The pattern of matching between *actual* acquirers and targets helps separately identify β_M. Two sources of variation in the pattern of matching help identify β_M. Some variation comes from within a given matching market: Inefficient acquirers may match with their preferred targets more often or less than do efficient acquirers. This lets us draw inferences regarding targets' preferences. Additional variation comes from across matching markets: The degree to which inefficient acquirers match with their preferred targets depends on the proportion of inefficient acquirers in the matching market. This second source of variation helps identify β_M since β_M is more relevant in markets in which targets have sufficient numbers of efficient acquirers as alternative matches.

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.[19] 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 α_M and β_M.[20] Finally, I normalize λ_t to 0.5.

Since the number of potential acquirers exceeds 600 in some years, it would be computationally burdensome to use all potential acquirers in estimation. I therefore reduce the set of potential acquirers in two ways. First, I eliminate some companies that have nearly zero probability of making an acquisition. For example, companies born in year t will almost certainly not make an acquisition in that year, and companies that are very small are unlikely to make an acquisition.

[18] 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.

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

[20] 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 α_M and β_M are not separately identified. Since my identification argument relies on 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 to making an acquisition.

I check the minimum age and size (measured by value of assets under management) of all *actual* acquirers and delete from the set of potential acquirers companies that do not surpass these thresholds. Second, I randomly choose about 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.

5.1.2 Merger Outcome Equations

To measure mergers' impact, I use post-merger asset growth. As in Section 3.2, I use annual net asset inflows 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 net asset inflows into the combined company during years $t+1$, $t+2$, and $t+3$, respectively. For each potential match between $i \in I_t$ and $j \in J_t$, the net asset inflows are functions of the characteristics of the acquirer and target, interactions between the two companies' characteristics, and dummies representing the year of the acquisition.

$$\Delta F_{i,j,t+1} = Z'_{i,j,t+1}\theta$$
$$\Delta F_{i,j,t+2} = Z'_{i,j,t+2}\theta$$
$$\Delta F_{i,j,t+3} = Z'_{i,j,t+3}\theta$$

$Z_{i,j,t+1}$, $Z_{i,j,t+2}$, and $Z_{i,j,t+3}$ are identical except that the dummies representing the year of the acquisition and some control variables depend on the year the dependent variable is measured. The impact of overall industry growth on asset flows into fund management companies 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. As before, I separately include a dummy variable to indicate a public acquirer and a dummy variable to indicate an acquirer with a negative pre-merger $WOAR$. To simplify notation, I summarize these outcome equations as $\Delta F_{i,j,t} = Z'_{i,j,t}\theta$. In estimation, I use the same sample used to generate the results appearing in Table 8 of Section 3.2. Section 3.2 also explains how I overcome some problems with the data – e.g. outliers and acquirers who make more than one acquisition in a year.

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

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

The unobserved factors that affect the utility functions in the matching model also affect the outcome equations through ρ.

5.2 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. Hence, 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 a feasible solution, so I use Bayesian techniques developed earlier by Albert and Chib (1993), Chen (2005), Cohen and Einav (2006), Geweke, Gowrisankaran, and Town (2003), Kenneth (2003), Logan, Hoff, and Newton (2001, 2006), and Sørensen (2006). Appendix B provides a brief overview of the Bayesian approach, and the likelihood function and posterior distribution to be used in my estimation.

6 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.

6.1 Estimation Results

Tables 12 and 13 report the estimates of the model. The first column of Table 12 reports the estimated coefficients of the utility functions in the matching model. The second column of Table 12 reports marginal probabilities associated with the estimated coefficients.[21] Table 13 reports

[21] The estimated coefficients of the matching model are not directly interpretable because they are measured against the assumed scale of the errors in the utility functions. To quantify the strength of the estimated preference coefficients, I compute marginal probabilities. For targets' characteristics, marginal probabilities report a change in the probability that acquirer i will prefer target j to target $j\prime$, when we increase one of j's attributes by one unit (using an infinitesimal change for a continuous variable), evaluated at the mean of X. For acquirers' characteristics,

the estimated coefficients of the outcome equations. The bottom of Table 13 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.[22] In the data, about 15% of all actual acquirers make multiple (mostly two) acquisitions in a year.

I first discuss the results from the matching model. 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 (pension plans, corporations, bank trust departments, etc.) hold more than half of all money market fund assets, this positive coefficient suggests that companies prefer as merger partners those that serve a similar market segment and investor clientele. Because institutional investors and retail investors have different needs and require different styles of marketing and distribution, 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 to the latter is 72.9%, a marginal increase of 22.9 percentage points from a 50-50 random chance. 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 result 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 $j\prime$, when only j has the same distribution channel as the acquirer and otherwise j and $j\prime$ are identical, is 56.8%, a marginal increase of 6.8 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 players' matching decisions. The positive α_M implies that given fixed

marginal probabilities report a change in the probability that target j will prefer acquirer i to acquirer $i\prime$, when we increase one of i's attributes by one unit (using an infinitesimal change for a continuous variable), evaluated at the mean of X.

[22] I 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.

efficiency gains, acquirers that do not maximize profits are more eager to make an acquisition than profit-maximizing ones, since the former obtain private benefits as well. β_M is negative and significant, suggesting that targets have an incentive to avoid inefficient acquirers. As we will see when we discuss the outcome equations below, inefficient acquirers attract significantly less money from fund investors post-merger than do efficient acquirers. Hence, the negative β_M may reflect targets' reluctance to allow an unskillful acquirer to manage the merged company. This incentive almost entirely offsets the effect of the inefficient acquirers' greater willingness to pay (Note that $(1 - \lambda_t)\alpha_M$ enters the target's utility function, and λ_t is normalized to 0.5). Some coefficients for the interactions of M with acquirer or target characteristics are significant. The positive coefficient on "$M \times Target\ TNA$" suggests that inefficient acquirers particularly like large targets. 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 12 are intuitively 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-unvarying 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 to avoid targets that performed badly pre-merger.

Table 13 reports the estimation results for the outcome equations. First, the results show 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 7.3% 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, but not significant. I did not impose any cross-equation restrictions between the matching utility functions and the outcome equations, because I wanted to test whether efficiency gains that influence matching decisions also affect merger outcomes in the expected manner, and vice versa. My results show that this is the case.

Second, I find that inefficient acquirers receive less favorable post-merger asset flows than do efficient acquirers, controlling for differences in the observed and unobserved characteristics of targets. The estimated coefficient on M in the outcome equations is negative and significant, and its magnitude indicates that inefficient acquirers receive 6.7% less capital from investors annually than do other acquirers for three years after the merger.[23] 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.

The estimated correlation (calculated using the estimated ρ) does not differ significantly from zero, indicating that the errors in the matching utility functions and the outcome equations are not closely correlated. The magnitudes of θ_M obtained from the joint estimation and from separate estimations 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.

6.2 Alternative Specifications

6.2.1 Alternative Definition of Potential Target Sets

My primary model assumes that the set of potential targets is identical to the set of actual targets. I made this restrictive assumption to make the model tractable. To check the sensitivity of my estimation results to this assumption, I redefined the set of potential targets and adjusted the set of potential acquirers accordingly (because a company cannot appear in both sets). 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. To allow each potential target the outside option of not being acquired, I model

[23] The difference is not 12.6% because of the difference-in-difference structure of the regression. I calculate the difference as follows. First, I use the estimated coefficients to calculate net asset inflows for "public, negative pre-merger $WOAR$ acquirers," "public, positive pre-merger $WOAR$ acquirers, " and "private, negative pre-merger $WOAR$ acquirers" *relative to* "private, positive pre-merger $WOAR$ acquirers" (the omitted group). Then, I compute the weighted average of the inflows for acquirers with $M = 0$ (i.e. everyone except for public acquirers with negative $WOAR$), using weights equal to the number of observations for each type of acquirer. Finally, I subtract that weighted average from the net asset inflows of acquirers with $M = 1$.

a target's reservation utility as a function of its characteristics, such as age, ownership, recent performance, and size. Although in this model targets do not compare their utility of a sale this period against the expected utility of a sale next period, one can interpret the reservation utility function as reflecting targets' expectations about the option value of awaiting a sale in a future period.

This alternative specification generates similar results to those of my primary model. All variables reflecting match-specific efficiency gains have the same signs as those obtained from my primary model and similar magnitudes. Moreover, the signs of α_M and β_M remain the same as in the primary model, and these coefficients remain statistically significant. The magnitudes of α_M and β_M change only slightly. The only coefficients that differ substantially from those obtained from the primary model are those for some target characteristics. These changes occur because under the new specification, both the matching pattern and targets' participation decision determine the coefficients for target characteristics.

6.2.2 Relaxation of Uniform Sharing Rule

Another important assumption of my primary model was the uniform sharing rule. The uniform 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 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 require 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 actual 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 actual acquirers and lie between -0.1 and 0.1. Then I set the transfer of acquirer i equal to its normalized ranking. Targets' utility function changes in each iteration, so transfers also change with each iteration. Given the scale of utility, the transfers are large enough to change some targets' rankings of acquirers. I set the transfer of a potential acquirer that does not make an acquisition to 0. The results from this specification are similar to the results from my primary model.

6.2.3 Conflicts of Interest at Targets

So far, I have ignored potential principal-agent conflicts at targets. Target companies are not immune to agency conflicts, however. Target managers sometimes stifle attempted takeovers – e.g. with poison pills, greenmail, or appeals to rival bidders more favorable to the incumbent management ("white knights") – even when doing so may harm target shareholders (Jensen, 1988; Shleifer and Vishny, 1986; Walkling and Long, 1984). Since most of the mergers in my sample are friendly (i.e. received the approval of the target's management), attempts to resist hostile acquisitions aren't very relevant. However, shareholders and managers may disagree regarding by whom they should be acquired. Acquirers may differ in their ability to confer private benefits upon managers of acquired companies, e.g. by guaranteeing the managers' positions in the merged company or contractually committing to generous salaries, bonuses or other perks. If target managers are willing to accept a lower sale price in return for greater private benefits, ignoring the conflict of interest at targets could be problematic.

To investigate such conflicts using the available data, I allow separate β_Ms for public and private targets. One might think that acquirers motivated by private benefits for their management would be more willing to confer private benefits on the target's managers. Alternatively, one could argue that managers who are faithful to their shareholders' interests will be especially eager to bribe the target's management to reduce the price of acquiring the target. In either case, β_M for public targets would differ from β_M for private targets. A problem with empirically testing this idea is that the stable matching may no longer be unique, because the second term of V (representing the divergence of interests between target and acquirer) is now match-specific. I estimate the model with separate β_Ms for public and private targets, recognizing that equilibrium might cease to be unique. Varying the initial coefficient values did not affect the results of the estimation at all, suggesting that if there are multiple stable matchings, corresponding coefficients are similar across the stable matchings. The estimation results, not reported, show that β_M for public targets and

β_M for private targets are very similar.

6.3 Goodness of Fit and Counterfactual Analysis

In this section, I use the estimated parameters reported in Table 12 to check how well the model explains the data and perform three counterfactual analyses.

To test goodness of fit, I use the point estimates of the parameters of the matching utility functions in Table 12 to compute $U_{i,j,t}$ and $V_{i,j,t}$ for each possible match. I use the computed Us and Vs 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 14 shows the actual data and the second panel shows the model's prediction. Comparing the two panels indicates that the model does a good job of predicting who will make an acquisition.

One theme of this paper is that targets have an incentive to avoid an acquirer who will mismanage the merged company, and that such an incentive shrinks the set of targets that are willing to match with inefficient acquirers, which the targets expect to struggle post-merger. Targets' response to this incentive acts as a market mechanism to discourage inefficient takeovers. My first counterfactual analysis examines the impact of eliminating this market mechanism by calculating the stable matching that would occur if $\beta_M = 0$.

The third panel in Table 14 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, and indeed would end up buying most available targets. This counterfactual result suggests that targets' incentive to avoid inefficient acquirers deters a large number of inefficient mergers.

In my second counterfactual analysis, I set α_M, β_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 M&A market. Companies would pursue an acquisition only based on efficiency reasons. The fourth panel of Table 14 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 made decisions regarding acquisitions to maximize profits. 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. If the match-specific efficiency gains outweigh the acquirers' incompetence in running the merged company, the acquirers will still make acquisitions. Another reason why inefficient acquirers remain active is that setting $\beta_M = 0$ in this counterfactual analysis eliminates targets' resistance to being acquired by inefficient acquirers.

My last counterfactual analysis considers what will happen if inefficient acquirers cannot raise their bids to reflect anticipated private benefits but targets still shun these acquirers. I set α_M and all other coefficients for the interactions of M in the matching model equal to zero, but leave β_M at its estimated value. The last panel of Table 14 reports the stable matching under this scenario. The results show that since targets have a strong incentive to avoid inefficient acquirers, these acquirers will not be active in the merger market if they cannot make up for their unattractiveness by paying higher prices.

7 Conclusion

This paper tests two hypotheses about incentives in the merger market. The first hypothesis is about the incentives of acquirers' management: Managers' pursuit of private benefits drives some acquisitions. The second hypothesis is about targets' incentives: Targets do not want to be taken over by acquirers they expect to be unable to manage the merged company successfully. I tested these hypotheses using acquisitions among mutual fund management companies, exploiting rich data on post-merger operating performance and an exhaustive list of potential participants in this industry's merger market.

My analysis provides empirical evidence for these hypotheses. I find that companies whose managers have recently performed poorly and thus have an incentive to gamble with the owners' money to avoid dismissal are especially eager to make an acquisition, all else equal. At the same time, these companies are significantly worse at attracting new money from investors post-merger. These findings support the hypothesis that objectives other than maximizing profits drive some acquisitions. I also find empirical evidence that targets have an incentive to avoid takeovers by acquirers that do not maximize profits, providing some market discipline that discourages inefficient takeovers.

Similar patterns may emerge in other industries. The importance of human capital in the mutual fund industry and of senior management's influence on the performance of the merged company, especially during the integration process, lead me to expect that we might observe less dramatic results in other manufacturing industries, in which plants might keep operating without much change under new ownership. Nonetheless, the underlying divergence of managers' and owners' incentives, and targets' incentive to avoid unpromising acquirers likely exist in other markets.

Given the magnitude of inefficient acquirers' post-merger underperformance, it may be fruitful to look inside the merged companies and investigate exactly how acquirers destroy value in these organizations. Do they lose key fund managers during the integration process? Are they ineffective at streamlining their product lines after the merger? Do they tend to fire target fund managers regardless of performance and retain bad fund managers from the acquiring side? My future research will investigate changes that occur within the merged organizations to gain an insight into how one creates or destroys value in putting two organizations together.

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Appendix A: Uniqueness of Equilibrium

First, I discuss a few results from Roth and Sotomayor (1990) regarding stable matchings, which I use in my proof of uniqueness. Let $\mu >_M \mu'$ indicate that all men like matching μ at least as well as matching μ', and that at least one man prefers μ to μ' outright.

Definition (Roth and Sotomayor, 1990). For a given marriage market, a stable matching μ is M-optimal if every man likes it at least as well as any other stable matching: that is, if for every other stable matching μ', $\mu \geq_M \mu'$. Similarly, a stable matching ν is W-optimal if every woman likes it at least as well as any other stable matching, that is, if for every other stable matching ν', $\nu \geq_W \nu'$.

Theorem 1 (Gale and Shapley, 1962). When all men and women have strict preferences, there always exists an M-optimal stable matching, and a W-optimal stable matching.

Theorem 2 (Knuth, 1976). When all agents have strict preferences, the common preferences of the two sides of the market are opposed on the set of stable matchings: if μ and μ' are stable matchings, then all men like μ at least as well as μ' if and only if all women like μ' at least as well as μ. That is, $\mu >_M \mu'$ if and only if $\mu' >_W \mu$.

A corollary of theorem 2 is that when preferences are strict, the set of stable matchings is a singleton if and only if $\mu_M = \mu_W$.

Theorem 3 (Knuth, 1976). In a market with strict preferences, the set of people who are single is the same for all stable matchings.

Proof of the uniqueness of stable matchings:

I prove this result by contradiction. Suppose that the acquirer-optimal stable matching μ_A and the target-optimal stable matching μ_T are not the same in year t. If so, we can identify is and js whose partners under μ_A are different from their partners under μ_T. Let $S(i)$ be the collection of such is and $S(j)$ be the collection of such js. Theorem 3 implies that 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 μ_A differs from μ_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 js 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 $S(i)$. QED.

Appendix B: Estimation Methods

Brief Overview of the Bayesian Approach

Bayesian estimation requires two functions: a prior distribution of parameters, $k(\theta)$, and the likelihood of the data (in my application, matching and merger outcomes) given the parameters, $L(Y|\theta)$. By Bayes' rule, the posterior distribution of the parameters given the data is $K(\theta|Y) = \frac{L(Y|\theta)k(\theta)}{L(Y)}$. Since $L(Y)$ does not depend on θ, $L(Y)$ is simply the normalizing constant that ensures the posterior density integrates to 1, and we can write the posterior distribution concisely as $K(\theta|Y) = C \times L(Y|\theta)k(\theta)$.

Thus, once I specify a prior distribution and the likelihood function, I can obtain the posterior distribution and use the mean and variance of the posterior distribution for inference. According to the Bernstein-von Mises theorem (1917, 1931), the mean of the posterior distribution $\overline{\theta} = \int \theta K(\theta|Y)d\theta$ has the same asymptotic sampling distribution as the maximum likelihood estimator, since the influence of the prior disappears asymptotically. The theorem also states that asymptotically the variance of the posterior distribution equals the asymptotic variance of the Bayesian estimator $\overline{\theta}$. Hence, a researcher can perform inference entirely by using moments of the posterior: The mean of the posterior provides the point estimates, and the standard deviation of the posterior provides the standard errors of the estimates (Train, 2003).

If we could analytically compute the mean and variance of the posterior or readily simulate draws from the posterior, Bayesian estimation would be simple. Bayesian methods are computationally burdensome when it is hard to simulate draws from the posterior. In such cases, Bayesian methods use an iterative process that converges, after a significant number of iterations, to draws from the correct posterior. As Train (2003) puts it, the Bayesian procedures trade the difficulties of convergence to a maximum (under classical estimation procedures) for the difficulties of convergence to a posterior distribution. Markov Chain Monte Carlo simulation methods (MCMC) are commonly used iteration procedures for Bayesian estimation.

One widely used method of MCMC is the Gibbs sampling algorithm. Gibbs sampling exploits the fact that in some cases, it is difficult to draw directly from a joint density and yet easy to draw from the conditional density of each element (or each block) given the values of the other elements (blocks). I'll illustrate Gibbs sampling using an example from Chib and Greenberg (1995). Consider three random variables x_1, x_2, and x_3. The Gibbs sampling algorithm is as follows: Specify starting values for x_1, x_2, and x_3, $(x_1^{(0)}, x_2^{(0)}, x_3^{(0)})$, and set $i = 0$. Simulate $x_1^{(i+1)}$ using

$\pi(x_1|x_2^{(i)}, x_3^{(i)})$, simulate $x_2^{(i+1)}$ using $\pi(x_2|x_1^{(i+1)}, x_3^{(i)})$, and simulate $x_3^{(i+1)}$ using $\pi(x_3|x_1^{(i+1)}, x_2^{(i+1)})$. Set $i = i + 1$ and repeat the simulation process. This process converges to draws from the joint density $\pi(x_1, x_2, x_3)$, and we can use draws obtained after a significant number of iterations to compute the mean and variance of x_1, x_2, and x_3.

Likelihood Function

I re-write the utility functions and outcome equations as follows to collect parameters.

$$U_{i,j,t} = \lambda_t \left[X'_{i,j,t}\alpha_X + \alpha_M M_{i,t} + X'_{i,j,t}M_{i,t}\alpha_{XM} + \omega_{i,j,t}\right] = \lambda_t \left[X'_{i,j,t}\alpha + \omega_{i,j,t}\right]$$
$$V_{i,j,t} = (1-\lambda_t)\left[X'_{i,j,t}\alpha + \omega_{i,j,t}\right] + \beta_M M_{i,t} + \epsilon_{i,t} = \tfrac{1-\lambda_t}{\lambda_t}U_{i,j,t} + \beta_M M_{i,t} + \epsilon_{i,t}$$
$$\Delta F_{i,j,t} = Z'_{i,j,t}\theta + \rho\omega_{i,j,t} + \nu_{i,j,t}$$

The new $X_{i,j,t}$ contains $X_{i,j,t}$, $M_{i,t}$, and $X_{i,j,t}M_{i,t}$, and α contains α_X, α_M, and α_{XM}. 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 $\nu_{i,j,t} \sim IIDN(0,\sigma_\nu)$ and $\omega_{i,j,t} \perp \nu_{i,j,t}$. The assumed error structure does not allow autocorrelations in the outcome equations. My future research will allow a more flexible error structure. The parameters of the model I need to estimate are α, β_M, θ, ρ, and σ_ν. To simplify notation, let $\Theta = (\alpha, \beta_M, \theta, \rho, \sigma_\nu)$. Denote the observed matching in year t by μ_t. Let the set of utilities (U_t, V_t) for which μ_t is the equilibrium be Γ_{μ_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 4.2. 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 μ_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. Hence,

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

The third equality follows because conditional on U_t, X_t, and Θ, knowing $\epsilon_{i,t}$ determines $[V_{i,1,t}, V_{i,2,t},..., V_{i,|J_t|,t}]$. The likelihood function is therefore

$$L(\mu, \Delta F \mid X, Z, \Theta) = C \times \prod_t \int_{(U_t,V_t)\in\Gamma_{\mu_t}} \{ \prod_{i\in I_t, j\in J_t\cup\{0\}} \phi(\frac{U_{i,j,t}-\lambda_t X'_{i,j,t}\alpha}{\lambda_t}) \times \prod_{i\in I_t} \phi(\frac{\epsilon_{i,t}}{1-\lambda_t})$$
$$\times \prod_{i,j\in o_t} \phi\left(\frac{\Delta F_{i,j,t}-Z'_{i,j,t}\theta-\rho(U_{i,j,t}/\lambda_t - X'_{i,j,t}\alpha)}{\sqrt{\sigma_\nu}}\right) dG(\omega,\epsilon,\nu)\}.$$

$(U_t, V_t) \in \Gamma_{\mu_t}$ which enters the region of integration in the likelihood function is the set of inequalities required for stability, as discussed in Section 4.3.

Prior: I assume that prior distributions of α, β_M, θ, and ρ 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 θ and ρ are set at 1000 since the variance of net asset inflows 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 σ_ν is inverted gamma with $v = 2$ degrees of freedom and scale $s = 1$. Hence, the prior density of σ_ν is $k(\sigma_\nu) = C \times \frac{1}{\sigma_\nu^{3/2}} \exp\left[-\frac{1}{\sigma_\nu}\right]$. I choose these priors to simplify the simulation process since given the assumption of normally distributed error terms, these are conjugate priors.

Posterior: The posterior distribution of the parameters is
$K(\Theta \mid X, Z, \mu, \Delta F) = C\times\ k(\alpha) \times k(\beta_M) \times k(\theta) \times k(\rho) \times k(\sigma_\nu) \times L(\mu, \Delta F \mid X, Z, \Theta)$

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 Θ. If we do so, computation of the marginal posterior distributions of Θ using Gibbs sampling requires only the posterior distributions of Θ *conditional on* U, V, and the data, and the posterior distributions of U and V *conditional* on Θ 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

$$K(U, V, \Theta \mid X, Z, \mu, \Delta F) = C \times k(\Theta) \times \prod_t L(\mu_t, U_t, V_t, \Delta F_t \mid X_t, Z_t, \Theta)$$
$$= C \times k(\Theta) \times \prod_t I_{\{(U_t,V_t)\in\Gamma_{\mu_t}\}} p(U_t, \epsilon_t, \Delta F_t \mid X_t, Z_t, \Theta),$$

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 α is a normal distribution with the following mean and covariance matrix:

$$\tilde{\alpha} = \tilde{\Omega} \sum_t \sum_{i \in I_t, j \in J_t \cup \{0\}} \tfrac{1}{\lambda_t} U_{i,j,t} X_{i,j,t} - \tilde{\Omega} \sum_t \sum_{i,j \in o_t} \tfrac{1}{\sigma_\nu} \left(\Delta F_{i,j,t} - Z'_{i,j,t}\theta - \tfrac{\rho U_{i,j,t}}{\lambda_t} \right) \rho X_{i,j,t}$$

$$\text{and } \tilde{\Omega} = \left[\tfrac{1}{20} I + \sum_t \sum_{i \in I_t, j \in J_t \cup \{0\}} X_{i,j,t} X'_{i,j,t} + \sum_t \sum_{i,j \in o_t} \tfrac{1}{\sigma_\nu} \rho^2 X_{i,j,t} X'_{i,j,t} \right]^{-1}.$$

Similarly, the conditional posterior distributions of θ and ρ are normal. The conditional posterior distribution of σ_ν is inverted gamma with an updated degree of freedom and scale. The conditional posterior distribution of β_M is truncated normal, because conditional on U, ϵ, and the data, a draw of β_M determines $V_{i,j,t}$ for $\forall i, j, t$, and these Vs should satisfy the stability conditions. Accordingly, the stability conditions for all js determine the truncation points of the conditional posterior distribution of β_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 $\epsilon_{i,t}$. Appendix C outlines sampling procedures for $U_{i,j,t}$, $\epsilon_{i,t}$, and β_M.

I base my estimates on 200,000 iterations of the sampling procedure. I discard the initial 100,000 draws to allow time for the conditional distributions to converge to the correct joint posterior distribution and use the last 100,000 draws to compute coefficient estimates and standard errors. Inspection of the posterior means and variances at various points in the iteration process shows that in most cases they stabilize long before the 100,000th iteration.

Appendix C: Sampling Procedure for U, ϵ, and β_M

$\mathbf{U}_{i,j,t}$**:** The sampling procedure for the fully conditional distribution of $U_{i,j,t}$ is as follows (Logan, Hoff, and Newton, 2001).

case 1) unmatched pairs ($j \neq \mu(i)$) and $j = 0$. Sample $U_{i,0,t}$ from the normal distribution with mean 3 and variance λ_t^2, conditional upon $U_{i,0,t} < U_{i,\mu(i),t}$.

case 2) unmatched pairs ($j \neq \mu(i)$) and $j \neq 0$. Sample $U_{i,j,t}$ from the normal distribution with mean $\lambda_t X'_{i,j,t}\alpha$ and variance λ_t^2, conditional upon $U_{i,j,t} < \max(U_{i,\mu(i),t}, U_{\mu(j),j,t} + \frac{\lambda_t}{1-\lambda_t}(\beta_M M_{\mu(j),t} - \beta_M M_{i,t} + \epsilon_{\mu(j),t} - \epsilon_{i,t}))$.

case 3) matched pairs ($j = \mu(i)$) and $j = 0$. Sample $U_{i,0,t}$ from the normal distribution with mean 3 and variance λ_t^2, conditional upon $U_{i,0,t} > \max_{j' \neq 0 \text{ and } j' \in C(i)} U_{i,j',t}$, where $C(i) = \{j' | V_{i,j',t} > V_{\mu(j'),j',t}\}$.

case 4) matched pairs ($j = \mu(i)$), $j \neq 0$, and $i, j \in o_t$. Sample $U_{i,j,t}$ from the normal distribution with mean $\left[\frac{1}{\lambda_t^2} + \frac{1}{\lambda_t^2 \sigma_\nu}\rho^2\right]^{-1} \times (\frac{1}{\lambda_t} X'_{i,j,t}\alpha + \frac{\rho}{\lambda_t \sigma_\nu}(\Delta F_{i,j,t} - Z'_{i,j,t}\theta + \rho X'_{i,j,t}\alpha))$ and variance $\left[\frac{1}{\lambda_t^2} + \frac{1}{\lambda_t^2 \sigma_\nu}\rho^2\right]^{-1}$, conditional upon $U_{i,j,t} > \max[U1, U2]$, where $U1 = \max_{j' \neq j \text{ and } j' \in C1(i)} U_{i,j',t}$ with $C1(i) = \{j' | V_{i,j',t} > V_{\mu(j'),j',t}\}$, and $U2 = \max_{i' \neq i \text{ and } i' \in C2(j)} (U_{i',j,t} + \frac{\lambda_t}{1-\lambda_t}[\beta_M M_{i',t} - \beta_M M_{i,t} + \epsilon_{i',t} - \epsilon_{i,t})$ with $C2(j) = \{i' | U_{i',j,t} > U_{i',\mu(i'),t}\}$.

$\boldsymbol{\epsilon}_{i,t}$: The sampling procedure for the fully conditional distribution of $\epsilon_{i,t}$ is as follows.

Sample $\epsilon_{i,t}$ from the normal distribution with mean 0 and variance $(1-\lambda_t)^2$, conditional upon $E1 < \epsilon_{i,t} < E2$, where $E1 = \max_{i' \neq i \text{ and } U_{i',\mu(i),t} > U_{i',\mu(i'),t}} \left[\frac{1-\lambda_t}{\lambda_t}(U_{i',\mu(i),t} - U_{i,\mu(i),t}) + \beta_M M_{i',t} - \beta_M M_{i,t} + \epsilon_{i',t}\right]$, and $E2 = \max_{j \neq \mu(i) \text{ and } U_{i,j,t} > U_{i,\mu(i),t}} \left[\frac{1-\lambda_t}{\lambda_t}(U_{\mu(j),j,t} - U_{i,j,t}) + \beta_M M_{\mu(j),t} - \beta_M M_{i,t} + \epsilon_{\mu(j),t}\right]$.

$\boldsymbol{\beta}_M$: The sampling procedure for the fully conditional distribution of β_M is as follows.

Sample β_M from the normal distribution with mean 0 and variance 20, conditional upon $B1 < \beta_M < B2$, where $B1 = \max_{(i,j) \text{ s.t. } j \neq \mu(i),\ M_{\mu(j),t} > M_{i,t}, \text{ and } U_{i,j,t} > U_{i,\mu(i),t}} \left[\frac{1-\lambda_t}{\lambda_t}(U_{i,j,t} - U_{\mu(j),j,t}) + \epsilon_{i,t} - \epsilon_{\mu(j),t}\right]$ and $B2 = \max_{(i,j) \text{ s.t. } j \neq \mu(i),\ M_{\mu(j),t} < M_{i,t}, \text{ and } U_{i,j,t} > U_{i,\mu(i),t}} \left[\frac{1-\lambda_t}{\lambda_t}(U_{\mu(j),j,t} - U_{i,j,t}) + \epsilon_{\mu(j),t} - \epsilon_{i,t}\right]$.

Table 1
Descriptive Statistics for All Companies/Years

	No. Obs	Mean	Std. Dev	Min	Max
Year	8557	1997.877	3.914	1991	2004
Total Net Assets (*TNA*), billions	8557	6.473	33.767	0	826.687
Number of Funds	8557	19.097	45.880	1	706
Number of Money Market Funds	8557	2.399	6.956	0	105
Number of Institutional Funds	8557	2.644	8.913	0	120
Number of Retirement Funds	8557	0.340	5.304	0	222
Public Company	8404	0.329	0.470	0	1
Load Company	8557	0.391	0.488	0	1
Young Company	8557	0.205	0.404	0	1

Total Net Assets for a fund is the market value of all securities owned by the fund minus its total liabilities. Total Net Assets 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
Descriptive Statistics for Companies That Are Actual Acquirers or Targets

YEAR		Number	*TNA*, billions	Number of Funds	Public Company	Load Company	Young Company	Pre-Merger *WOAR*
1991	Acquirer	19	9.74 (26.74)	21.89 (39.59)	0 .59 (0.51)	0.89 (0.32)	0.05 (0.23)	-0.000 (0.017)
	Target	22	0.29 (0.53)	3.09 (3.28)	0.1 (0.31)	0.5 (0.51)	0.18 (0.39)	-0.014 (0.051)
1992	Acquirer	14	4.28 (5.99)	16.14 (12.06)	0.57 (0.51)	0.71 (0.47)	0.14 (0.36)	0.021 (0.067)
	Target	19	0.22 (0.35)	3.37 (2.87)	0.29 (0.47)	0.53 (0.51)	0.16 (0.37)	-0.022 (0.112)
1993	Acquirer	13	13.92 (24.96)	35 (36.26)	0.77 (0.44)	0.92 (0.28)	0 (0)	0.003 (0.014)
	Target	15	2.24 (5.18)	14.27 (26.45)	0.4 (0.51)	0.53 (0.52)	0.2 (0.41)	-0.013 (0.045)
1994	Acquirer	14	19.50 (25.01)	66.14 (68.15)	0.79 (0.43)	0.64 (0.50)	0 (0)	0.010 (0.025)
	Target	15	2.28 (3.39)	16.13 (16.71)	0.54 (0.52)	0.67 (0.49)	0.13 (0.35)	-0.002 (0.032)
1995	Acquirer	12	11.06 (8.62)	56.67 (40.67)	0.58 (0.51)	0.83 (0.39)	0 (0)	0.003 (0.008)
	Target	13	1.74 (3.10)	10.85 (10.84)	0.5 (0.52)	0.54 (0.52)	0.23 (0.44)	-0.011 (0.013)
1996	Acquirer	16	17.83 (28.76)	68.19 (90.29)	0.86 (0.36)	0.81 (0.40)	0.06 (0.25)	-0.003 (0.022)
	Target	17	2.47 (3.72)	11.06 (12.18)	0.29 (0.47)	0.41 (0.51)	0.29 (0.47)	-0.021 (0.036)
1997	Acquirer	26	15.32 (22.04)	66.85 (71.71)	0.65 (0.49)	0.73 (0.45)	0 (0)	-0.001 (0.031)
	Target	31	3.74 (10.75)	19.97 (25.72)	0.58 (0.50)	0.68 (0.48)	0.10 (0.30)	0.006 (0.034)
1998	Acquirer	8	10.85 (14.17)	65.63 (77.89)	0.88 (0.35)	0.88 (0.35)	0.13 (0.35)	0.024 (0.034)
	Target	9	1.28 (1.45)	12.89 (14.61)	0.38 (0.52)	0.67 (0.5)	0.11 (0.33)	-0.049 (0.163)
1999	Acquirer	19	21.20 (29.48)	83.37 (80.55)	0.74 (0.45)	0.79 (0.42)	0.16 (0.37)	-0.002 (0.042)
	Target	23	6.80 (12.49)	25.30 (38.36)	0.48 (0.51)	0.57 (0.51)	0.13 (0.34)	-0.045 (0.100)
2000	Acquirer	21	18.67 (33.98)	71.57 (92.28)	0.71 (0.46)	0.81 (0.40)	0.14 (0.36)	0.001 (0.099)
	Target	23	2.38 (3.44)	16.26 (16.16)	0.52 (0.51)	0.39 (0.50)	0.09 (0.29)	-0.023 (0.137)
2001	Acquirer	20	60.98 (129.92)	98.1 (85.64)	0.7 (0.47)	0.55 (0.51)	0.05 (0.22)	-0.030 (0.062)
	Target	26	4.73 (13.77)	19.31 (31.80)	0.48 (0.51)	0.42 (0.50)	0.23 (0.43)	-0.027 (0.139)
2002	Acquirer	23	31.71 (43.73)	95.74 (99.99)	0.74 (0.45)	0.65 (0.49)	0 (0)	0.015 (0.064)
	Target	32	3.48 (7.15)	24.16 (33.26)	0.42 (0.50)	0.5 (0.51)	0.03 (0.18)	0.007 (0.076)
2003	Acquirer	10	29.88 (46.20)	75.7 (82.52)	0.5 (0.53)	0.8 (0.42)	0 (0)	0.020 (0.060)
	Target	11	2.87 (5.30)	27 (42.93)	0.55 (0.52)	0.45 (0.52)	0 (0)	-0.011 (0.042)
2004	Acquirer	10	16.72 (23.64)	58.9 (65.34)	0.5 (0.53)	0.6 (0.52)	0 (0)	0.029 (0.116)
	Target	10	1.26 (3.32)	6.8 (9.60)	0.44 (0.53)	0.3 (0.48)	0.2 (0.42)	0.006 (0.066)

The number of acquirers is often smaller than the number of targets since some acquirers make multiple acquisitions in a year.

Table 3

Among Potential Acquirers (pooled over years)

	private	public
positive *WOAR*	2670 (53%)	1426 (56%)
negative *WOAR*	2371 (47%)	1122 (44%)
total	5041 (100%)	2548 (100%)

Among Actual Acquirers (pooled over years)

	private	public
positive *WOAR*	47 (57%)	81 (44%)
negative *WOAR*	35 (43%)	103 (56%)
total	82 (100%)	184 (100%)

Potential acquirers in year *t* are companies that are not acquired or liquidated in that year.
Actual acquirers in year *t* are companies that actually make an acquisition in year *t*.
In year *t*, a company *i* belongs to the first cell (private/positive *WOAR*) if the company is a private company and its *WOAR* is positive in year *t-1*.

Table 4

Probit for Acquisition Decision

Dependent Variable = 1 if the company makes an acquisition in year *t*, = 0 o/w

	dF/dX		
	Specification 1	Specification 2	Specification 3
Public	0.033 (0.006) ***	0.005 (0.004)	0.002 (0.004)
Negative *WOAR*	-0.005 (0.005)	-0.001 (0.004)	-0.004 (0.004)
Public × Negative *WOAR*	0.019 (0.010) **	0.013 (0.008) **	0.021 (0.010) ***
Young Company	No	-0.005 (0.004)	-0.009 (0.004)
Size Variables	No	Yes	Yes
Other Characteristics	No	No	Yes
Year Dummies	Yes	Yes	Yes
No. Obs	7589	7589	6237
Pseudo R^2	0.076	0.16	0.179

I report marginal probabilities rather than coefficients.
Inside the parentheses are standard errors.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level
Public = 1 if the company is public, = 0 otherwise.
Negative *WOAR* = 1 if the company has a negative *WOAR* in the previous year, = 0 o/w.
Young Company = 1 if the company is less than 3 years old, = 0 o/w.
Size Variables: 4 dummies for having *TNA* of more than $100 million, $500 million, $1 billion, and $10 billion, number of funds, square of the number of funds.
Other Characteristics: load company dummy, number of money market funds, number of institutional funds, number of retirement funds, weighted average of the expense ratios of funds offered by the company and its square, weighted average of the turnover ratios of funds offered by the company and its square. Expense ratio is the percentage of the total investment that fund investors pay for the fund's operating expenses. The turnover ratio of a fund is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average *TNA* of the fund.

Table 5

Acquirer Type	Mean Change in *OAR* of Target Funds			No. Obs
	1 year after the merger	2 years after the merger	cumulative	
Private & Positive *WOAR*	0.009	0.017	0.018	107
Private & Negative *WOAR*	-0.001	0.014	0.043	107
Public & Positive *WOAR*	0.011	0.005	0.016	536
Public & Negative *WOAR*	-0.010	-0.005	-0.009	1123

First column: $OAR_{f,t+1} - OAR_{f,t-1}$

Second column: $OAR_{f,t+2} - OAR_{f,t-1}$

Third column: $(1+ OAR_{f,t+1}) \times (1+OAR_{f,t+2}) - (1+ OAR_{f,t-1})$

The last column shows the number of target funds used in the computation for each type of acquirer.

Table 6

OLS Regression for Merger Outcome (Δ in target fund's *OAR*)

	Specification 1		Specification 2		Specification 3	
	1 Year Later	2 Years Later	1 Year Later	2 Years Later	1 Year Later	2 Years Later
Public Acquirer	0.016 (0.012)	0.002 (0.010)	0.020 (0.010) *	-0.006 (0.013)	0.021 (0.012) *	-0.010 (0.016)
Negative *WOAR* Acquirer	0.036 (0.023)	0.035 (0.021) *	0.040 (0.019) **	0.039 (0.018) **	0.041 (0.020) **	0.034 (0.019) *
Public Acquirer × Negative *WOAR* Acquirer	-0.056 (0.025) **	-0.042 (0.023) *	-0.059 (0.021) ***	-0.041 (0.020) **	-0.061 (0.022) ***	-0.035 (0.021) *
Target Fund *OAR* Negative, pre-merger	-0.002 (0.004)	0.005 (0.007)	-0.002 (0.004)	0.005 (0.008)	-0.001 (0.004)	0.005 (0.008)
Target Fund *OAR*, pre-merger	-1.081 (0.052) ***	-1.102 (0.056) ***	-1.074 (0.054) ***	-1.099 (0.057) ***	-1.078 (0.053) ***	-1.093 (0.056) ***
Public Target			-0.020 (0.007) ***	-0.008 (0.009)	-0.023 (0.008) ***	-0.011 (0.011)
Negative *WOAR* Target			-0.007 (0.005)	-0.006 (0.008)	-0.009 (0.005) *	-0.007 (0.007)
Size Ratio			0.052 (0.027) *	0.043 (0.028) **	0.044 (0.028)	0.058 (0.026) **
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Size Variables	No	No	Yes	Yes	Yes	Yes
Age Variables	No	No	No	No	Yes	Yes
Fund Characteristics	No	No	No	No	Yes	Yes
Robust s.e.	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	1920	1873	1798	1751	1783	1783
R^2	0.577	0.487	0.59	0.493	0.639	0.595

Inside the parentheses are standard errors.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level
The dependent variable for "1 Year Later" columns is $OAR_{f,t+1}$ - $OAR_{f,t-1}$.
The dependent variable for "2 Years Later" columns is $OAR_{f,t+2}$ - $OAR_{f,t-1}$.
Target fund's pre-merger *OAR* and a dummy for the target fund having a negative pre-merger *OAR* (Target Fund *OAR* Negative, pre-merger) are included to control for a difference in target funds' quality.
Size Ratio = Target's *TNA* / Acquirer's *TNA*.
Size Variables: 4 dummies for having *TNA* of more than $100 million, $500 million, $1 billion, and $10 billion, number of funds, square of the number of funds. Both the acquirer and target.
Age Variables: young company dummy, both the acquirer and target.
Fund Characteristics: fund's *TNA*, fund's *TNA* squared, a dummy for being a growth fund, fund's expense ratio and its square, a dummy for being a load fund, a dummy for being a money market fund, a dummy for being an institutional fund.
Robust s.e. is a standard error calculated by clustering error terms by merger.

Table 7

Average Annual Net Asset Inflows for 3 Years after the Merger

(as % of existing asset size)

Acquirer Type	private	public
positive W*OAR*	13.82% (85)	16.74% (147)
negative W*OAR*	13.70% (72)	7.43% (185)

Net Asset Inflows for year t = 100 × (TNA_t – TNA_{t-1}) / TNA_{t-1}
Inside the parentheses are the numbers of observations in each cell.

Table 8

OLS Regression for Merger Outcome (annual net asset inflows)

	Specification 1	Specification 2	Specification 3	Specification 4
Public Acquirer	6.487 (3.662) *	6.370 (3.664) *	7.401 (3.729) *	6.713 (3.701) *
Negative *WOAR* Acquirer	-0.440 (4.094)	-0.313 (4.096)	1.763 (4.148)	2.298 (4.116)
Public Acquirer × Negative *WOAR* Acquirer	-10.113 (4.967) **	-10.043 (4.970) **	-11.732 (5.022) **	-11.563 (4.959) **
Public Target	-2.875 (2.587)	-2.958 (2.592)	-1.831 (2.869)	-2.128 (2.842)
Negative *WOAR* Target	-0.859 (2.582)	-0.478 (2.606)	-1.703 (2.665)	-1.933 (2.627)
Log(*TNA*)	-1.365 (0.652) **	-1.344 (0.653) *	-1.270 (0.709) *	-1.071 (0.710)
Price 1 (Expense Ratio)		-0.031 (0.292)	-0.712 (0.772)	-0.635 (0.787)
Price 2 (Load)		-0.658 (0.513)	-0.728 (0.654)	-0.696 (0.649)
Size Ratio			0.474 (0.417)	0.433 (0.427)
Similarity in proportion of MM Funds			9.309 (8.444)	8.305 (8.343)
Similarity in proportion of Institutional Funds			13.173 (8.761)	12.541 (8.687)
Same Public Status			-2.073 (2.679)	-1.750 (2.643)
Same Distribution Channel			5.719 (3.028) *	5.859 (2.989) *
Other Characteristics	No	No	Yes	Yes
Previous Growth Rates	No	No	No	Yes
Year Dummies	Yes	Yes	Yes	Yes
No. Obs	489	489	489	489
R^2	0.178	0.181	0.207	0.208

Inside the parentheses are standard errors.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level
<u>Log(*TNA*)</u>: natural logarithm of the sum of the acquirer's and target's *TNA* in the year before the merger.
<u>Price 1 (Expense Ratio)</u>: weighted average of the expense ratios of funds offered by the merged company (in the year before the dependent variable is measured).
<u>Price 2 (Load)</u>: weighted average of the loads of funds offered by the merged company (in the year before the dependent variable is measured).
<u>Size Ratio</u> = Target's *TNA* / Acquirer's *TNA* in the year before the merger.
<u>Similarity in proportion of MM Funds</u> = 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.
<u>Similarity in proportion of Institutional Funds</u> = minus of the absolute difference between the acquirer and target in the proportion of institutional funds.
<u>Same Public Status</u> equals one if the acquirer and target are both public or both private and zero otherwise.
<u>Same Distribution Channel</u> equals one if the acquirer and target are both load companies or both no-load companies and zero otherwise.
<u>Other Characteristics</u>: young company dummy and load company dummy. Both the acquirer and target.
<u>Previous Growth Rates</u>: Net asset inflows (as % of existing asset size) of the acquirer in one and two years before the merger.

Table 9

Acquirer Type	private	public
positive *WOAR*	53.33% (47)	54.32% (81)
negative *WOAR*	54.55% (35)	61.17% (103)

In year *t*, an actual acquirer *i* belongs to the private/positive *WOAR* acquirer type if the company is a private company and its *WOAR* is positive in year *t-1*.
Each cell reports the proportion of actual acquirers of the given type who are matched with targets that have a negative *WOAR* in the year before the merger.
Inside the parentheses are the numbers of observations in each cell.
For example, the numbers in the upper left cell mean that there are 47 actual acquirers during my sample period who are private and have a positive *WOAR* in the year before the merger. 53% of them are matched with targets that have a negative *WOAR* in the year before the merger.

Table 10

Dependent Variable = Target's Ranking

	Specification 1	Specification 2	Specification 3
Public Acquirer	-0.134 (0.084)	-0.125 (0.090)	-0.111 (0.088)
Acquirer's Ranking	-0.152 (0.102)	-0.158 (0.104)	-0.150 (0.101)
Public Acquirer × Acquirer's Ranking	0.258 (0.138) *	0.284 (0.142) **	0.253 (0.139) *
Public Target	0.006 (0.040)	0.018 (0.047)	0.014 (0.046)
Size & Age Variables	No	Yes	Yes
Interactions	No	Yes	Yes
Other Characteristics	No	No	Yes
Year Dummies	Yes	Yes	Yes
No. Obs	246	246	246
R^2	0.017	0.055	0.137

A target's ranking is determined by its *WOAR* in the year preceding the merger, relative to those of other actual targets in the same year. A higher ranking indicates better recent performance.
An acquirer's ranking is determined by its *WOAR* in the year preceding the merger, relative to those of other actual acquirers in the same year. A higher ranking indicates better recent performance.
Inside the parentheses are standard errors.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level
<u>Size Variables</u>: acquirer's *TNA*, target's *TNA*, acquirer's number of funds, and target's number of funds.
<u>Age Variables</u>: young company dummy, both the acquirer and target.
<u>Interactions</u>: a dummy for the acquirer and target having the same public status, a dummy for the acquirer and target having the same distribution channel, the ratio of the target's *TNA* to the acquirer's *TNA*.
<u>Other Characteristics</u>: weighted average of the expense ratios of funds offered by the company, weighted average of the loads of funds offered by the company, and weighted average of the turnover ratios of funds offered by the company. Both the acquirer and target.

Table 11
List of variables in the matching model (all measured in the year before the merger)

1. $X_{i,j,t}$
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. $M_{i,t}$
M = Acquirer Public Company × Acquirer Negative *WOAR*

3. $X_{i,j,t}M_{i,t}$
M × Acquirer *TNA*
M × Acquirer Young Company
M × Acquirer Past Acquisition
M × Target *TNA*
M × Target Young Company

Interactions of *M* with acquirer and target characteristics enter both *U* and *V*. $\beta_M \times M$ is the only variable in *V* that does not enter *U*.

Table 12
Estimates of the Matching Model

		Coefficient Estimate	Marginal Probability
Interaction Effects	Size Ratio	-0.0005 (0.0003)	-0.0001
	Similarity in proportion of MM Funds	0.862 (0.233) ***	0.229
	Similarity in proportion of Institutional Funds	0.103 (0.232)	0.029
	Same Public Status	0.073 (0.079)	0.020
	Same Distribution Channel	0.241 (0.078) ***	0.068
Target Characteristics	*TNA*	2.842 (1.819)	0.758
	TNA^2	-0.271 (0.388)	
	Number of Fund	-0.044 (0.020) **	-0.012
	Number of MM Funds	0.175 (0.209)	0.050
	Number of Institutional Funds	-0.078 (0.158)	-0.022
	Public Company	2.240 (0.953) **	0.443
	Young Company	0.358 (0.974)	0.100
	Load Company	1.353 (0.520) ***	0.331
	*WOAR*ranking	1.735 (0.582) ***	0.390
Acquirer Characteristics	*TNA*	-0.017 (0.039)	-0.002
	TNA^2	0.00003 (0.0006)	
	Number of Fund	-0.0002 (0.002)	-0.00002
	Number of MM Funds	0.024 (0.007) ***	0.003
	Number of Institutional Funds	0.007 (0.005)	0.0009
	Public Company	0.316 (0.153) **	0.040
	Young Company	0.114 (0.246)	0.014
	Past Acquisition	0.751 (0.161) ***	0.094
	Load Company	0.489 (0.118) ***	0.061
	Negative *WOAR*	-0.067 (0.148)	-0.008
	M (α_M)	2.214 (0.541) ***	
	M × Acquirer *TNA*	0.003 (0.037)	
	M × Acquirer Young Company	0.046 (0.446)	
	M × Acquirer Past Acquisition	-0.628 (0.262) **	
	M × Target *TNA*	0.189 (0.112) *	
	M × Target Young Company	-0.034 (0.231)	
	β_M	-0.918 (0.252) ***	

Inside the parentheses are standard errors.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level
Variable definitions are provided in Table 11.

Table 13
Estimates of the Outcome Equations

		Coefficient Estimate
Interaction Effects	Size Ratio	0.092 (0.162)
	Similarity in proportion of MM Funds	1.720 (3.668)
	Similarity in proportion of Institutional Funds	3.102 (4.884)
	Same Public Status	-2.239 (2.672)
	Same Distribution Channel	7.323 (3.088) **
Target Characteristics	Public Company	-2.845 (2.933)
	Young Company	6.476 (4.044)
	Load Company	-3.448 (3.155)
	Negative *WOAR*	-0.768 (2.680)
Acquirer Characteristics	Public Company	7.016 (3.983) *
	Young Company	-6.238 (5.893)
	Past Acquisition	0.917 (3.042)
	Load Company	3.221 (3.500)
	Negative *WOAR*	2.923 (4.378)
	M (θ_M)	-12.624 (5.365) **
Target + Acquirer	Log(Pre-merger *TNA*)	-1.172 (0.795)
	Constant	9.720 (9.246)
	Year Dummies	Included
	Controls	Included
	σ_V	608.341
	Correlation	0.088 (0.070)

Inside the parentheses are standard errors.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level
Log(Pre-merger *TNA*) = (target's *TNA* + acquirer's *TNA*)
Year dummies: adjusted depending on the year the dependent is measured.
Controls: price 1 (expense ratio) and price 2 (load).
Price 1 (Expense Ratio): 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): 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.

Table 14
Goodness of Fit and Counterfactual Analysis

Actual Data

Acquirer Type	private	public
positive *WOAR*	47	81
negative *WOAR*	35	103

Model Prediction

Acquirer Type	private	public
positive *WOAR*	49	81
negative *WOAR*	37	99

If $\beta_M = 0$

Acquirer Type	private	public
positive *WOAR*	4	20
negative *WOAR*	4	238

If $\alpha_M = \beta_M = 0$

Acquirer Type	private	public
positive *WOAR*	41	113
negative *WOAR*	36	76

If $\alpha_M = 0$

Acquirer Type	private	public
positive *WOAR*	79	140
negative *WOAR*	41	6