Returns to Scale from Labor Specialization: Evidence from Asset Management Mergers

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We study human capital synergies in asset management mergers that stem from the improved ability to assign fund managers to more specialized tasks in larger firms. More specialized task assignment allows rotated managers to focus on their investment expertise and leads to incremental $54 million of value added per deal per year on average. The effects are concentrated in mergers that lead to a large increase in firm size and in funds whose management appears less specialized prior to the merger. Our results provide direct evidence on the role of firms in the assignment of tasks to fund managers.

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Scale economies have been at the center of research interest in asset management at least since the theoretical model of Berk and Green (2004) that prominently features diseconomies of scale at the fund level and the empirical evidence of Chen et al. (2004) who document a negative relationship between fund size and fund performance. Diseconomies of scale at the fund level have been subject to several studies since.[1] However, much less is known about potential economies of scale at the asset management firm level. This is surprising as Chen et al. (2004) also document a positive relationship between firm size and fund performance: funds managed in larger firms outperform funds managed in smaller firms.

In this paper, we study a particular source of firm level economies of scale in the asset management industry: labor specialization. We hypothesize that fund managers can be assigned more specialized tasks in larger than in smaller firms and that such specialized task assignment improves managerial productivity. We examine this conjecture in the context of mergers between asset management firms. We focus on mergers because they increase firm size in a large and discrete fashion and we ask if the post-merger reorganizations of the buyer and target firms are characterized by increases in managerial turnover leading to more specialized task assignment for fund managers, and ultimately improved performance and value creation in the sense of Berk and van Binsbergen (2015).

Several observations lead us to expect significant human capital synergies following mergers between asset management firms. First, human capital is the most important production input in asset management because asset management firms do not own the (financial) capital they manage on behalf of outside investors (Berk, van Binsbergen, and Liu 2017). Second, past literature has shown how specialization can positively affect fund performance. Third, notwithstanding the benefits of specialization, asset management firms also have incentives to engage in fund proliferation and offer many differentiated funds,[2] giving rise to the possibility that especially managers in smaller asset management firms may end up less specialized because they manage funds across multiple investment objectives. If so, mergers could give rise to

[1] For example, Pollet and Wilson (2008), Yan (2008), Elton, Gruber, and Blake (2012), Reuter and Zitzewitz (2021) or Zhu (2018). A related literature examines diseconomies of scale at the industry level, e.g., Pastor and Stambaugh (2012), Pastor, Stambaugh, and Taylor (2015).
[2] We review the relevant literature at the end of the introduction.

significant human capital synergies because fund managers can be assigned more specialized tasks in larger firms which could increase managerial productivity.

We test our hypothesis using an extensive hand-collected sample of asset management mergers worldwide between 2001 and 2013. We identify 176 merger deals across 30 different buyer and target countries, affecting 8,524 distinct funds, 4.6 trillion USD in assets under management (AUM), and 5,739 individual fund managers employed by target and buyer firms.

Our main findings are as follows. First, turnover of fund managers increases by more than 30% in the post-merger period relative to a control group of comparable funds not affected by a merger. This result is a net effect of two opposing changes in managerial turnover. On the one hand, managerial rotations that affect existing fund managers who already worked for the buyer and target firms before the deal increase strongly while, on the other hand, managerial turnover events that involve new external fund managers decline. In other words, the post-merger periods are characterized by the reallocation of existing fund managers, coupled with a decrease in external hiring. Related to that, we find no changes in the overall headcount of fund managers of buyer and target firms, confirming that merging firms focus on reallocating (rather than replacing or shrinking) their existing group of fund managers.

Second, such turnover events lead to more specialized task assignment for rotated managers, but only following mergers of two asset management firms of similar size (in terms of number of fund managers, but also AUM). In such deals, the combined entity experiences a large increase in size compared to the two stand-alone firms, increasing the ability to reallocate existing fund managers which could unlock human capital synergies. This stands in contrast to mergers that involve the acquisition of a smaller firm by a larger one, where the scope for comparable human capital synergies through reallocation is limited. In mergers leading to a large increase in firm size, managerial turnover events are concentrated in funds with "generalist" fund managers who manage funds across different investment objectives in the pre-merger periods. In such deals, rotated managers become more specialized: following their rotation, they stop managing funds in some investment styles but may be assigned new funds in styles they already manage.

As a result, the collection of funds they manage is concentrated in fewer different investment objectives while managing on average a similar level of AUM.

Third, we document improved fund performance in the post-merger periods but again only in mergers that lead to a large increase in firm size. Within these mergers, performance improvements are concentrated in funds with generalist managers prior to the merger. Overall, this translates into an additional $54 million in value added per deal per year on average. In mergers that lead to a large increase in firm size, the same statistic amounts to $104 million while it is absent in the remaining sample. And within this subset of mergers, 60% of the change in value creation is attributable to the 38% of funds managed by generalist managers prior to the merger.

Fourth, we investigate the channels by which fund performance improves and find that post-merger, fund managers refocus their portfolio policies in what are likely their “areas of expertise”: areas in which they have created the most value over their entire career. In those areas, managers increase their active share, their industry concentration, and portfolio differentiation relative to peer funds. Furthermore, when we decompose the improvements in overall fund performance, we find them to be entirely driven by improved performance in precisely those “areas of expertise”. We interpret these results in light of the theory of “specialized learning” by van Nieuwerburgh and Veldkamp (2009, 2010) that predicts both the changes in portfolio policies and fund performance in areas in which the manager has an information advantage. Therefore, and in light of our hypothesis, we argue that mergers between asset managers can alleviate organizational constraints that prevented optimal specialization for some managers.

Our empirical design is closely aligned with the literature that examines the impact of corporate transactions (e.g., mergers, private equity buyouts, etc.) on outcomes and operational activities of target or buyer firms.[3] We follow the standard in that literature and examine changes in managerial turnover, task assignment, portfolio policies, performance and value creation pre- versus post-merger in a difference-in-

[3] For similar approaches see the reviews of Andrade, Mitchell, and Stafford (2001), Betton, Eckbo, and Thorburn (2008) or the studies of Bena and Li (2014) or Tookes and Yimfor (2021) in the M&A literature. Examples in the private equity literature include Bharath, Dittmar and Sivadasan (2014), Davis et al. (2014), Biesinger, Bircan, and Ljungqvist (2020) among others.

differences framework relative to various control groups, including control groups of fund managers from withdrawn mergers as in Bena and Li (2014). We sharpen our analysis by conducting “across-deal” tests that exploit cross-sectional heterogeneity in deal characteristics (specifically, deals that lead to a large versus a small increase in firm size). In doing so, we seek to understand if asset management mergers give rise to a particular form of value creation (or “synergy”) which in turn informs our understanding of scale economies in asset management. We complement this analysis with “within-deal” tests that focus on how managerial turnover and performance improvement are concentrated for funds with generalist managers.

Furthermore, we argue that the asset management industry’s heavy reliance on human capital carries empirical benefits that at least partially attenuate concerns about confounding effects from other factors that may accompany the reallocation of human capital in a growing or larger firm. We view an asset management firm as a collection of mutual funds. For each fund, we observe the manager(s) in charge of portfolio decisions and the outcomes associated with those decisions. This level of data granularity allows us to track the assignment of tasks for each manager over time and to measure outcomes at the fund, manager, or firm level. Finally, these outcomes are readily transformed into a dollar measure of added value (Berk and van Binsbergen 2015).

Despite these benefits and our efforts to compare treated funds to different control groups throughout, we are cognizant of the fact that mergers are not random events but instead driven by expected synergies from the matching of buyer and target firms. Therefore, we directly examine the matching of buyer and target firms to understand (and rule out) some plausible merger motivations between asset managers and to guide our overall interpretation of the results. We investigate the selection of observed target firms relative to hypothetical targets to assess likely motivations behind these asset management mergers. For example, asset management mergers could be driven by the desire to acquire investment expertise. In this case, we would expect differences in observable characteristics (e.g., product offering, style specialization, etc.) between buyer and target firms. Alternatively, mergers could be driven by buyer firms with strong fund performance acquiring target firms with low fund performance to replace underperforming target fund managers. In such a “Q-theory” related motivation (e.g., Jovanovic and Rousseau 2002), we would expect performance differences between buyer and target funds to predict the target choice. Furthermore, we would also expect (i) increased managerial turnover in the post-merger period that would, however, be driven by departures of existing fund managers and (ii) differences in post-merger outcomes for target versus buyer funds. In contrast to both, our proposed synergy is based on the notion of asset complementarities that would predict mergers between asset management firms that are similar in terms of size and product offerings. In other words, our hypothesis predicts that "like-buys-like" (Rhodes-Kropf and Robinson 2008) because a merger between two identical firms allows for the greatest room to re-assign tasks.[4] Therefore, we also expect our main results to be symmetric for target and buyer funds.

Our findings reject the first two motivations and support the hypothesis that asset management mergers are driven by asset complementarities. In other words, we find that "like-buys-like": buyers tend to select target firms that are similar not only in terms of size but also in terms of product offerings and other dimensions such as geographical proximity. In addition, we show that changes in managerial task specialization and improvements in fund performance benefit both buyer and target funds. Combined with the prior results on the reallocation of existing fund managers, the drop in external hiring, and the overall constant fund manager headcount suggests that these mergers are neither driven by a motive to acquire and reallocate missing investment expertise nor by a motive to take over and restructure under-performing target firms. Rather, and consistent with our hypothesis, target selection appears to be driven by asset complementarities, substantiating our argument of human capital synergies as one source of scale economies in asset management.

Our study makes three main contributions to the literature. First, we contribute to the debate on (dis)economies of scale in the asset management industry. Chen et al. (2004) document both diseconomies of scale at the fund level (i.e., a negative relationship between fund size and fund performance) and economies of scale at the family (or "firm") level (i.e., a positive relationship between family size and fund performance). While diseconomies of scale at the fund level are much debated in the literature (e.g., Berk

[4] We discuss this intuition in more detail in Section 1 where we formulate and elaborate on our hypothesis.

and Green 2004; Chen et al. 2004; Pollet and Wilson 2008; Yan 2008; Elton, Gruber, and Blake 2012; Reuter and Zitzewitz 2021; Zhu 2018), potential economies of scale at the family level have received less attention. Related to that, consolidation within the asset management industry has raised concerns on multiple dimensions.[5] We point to a benefit of consolidation: the ability to better allocate valuable human capital in a larger firm and the associated value creation.

Second, an active literature discusses the role of asset management firms in the assignment and allocation of fund managers. Khorana (1996) studies the mutual fund firing decisions and Drazin and Rao (2002) examine the allocation of existing managers to new funds. Fang, Kempf, and Trapp (2014) show that families efficiently allocate the most skilled fund managers to market segments where investment skill can generate the largest rewards. Cici et al. (2018) show how families exploit the industry expertise their fund managers have acquired in prior employment across fund strategies. Berk, van Binsbergen, and Liu (2017) find that at least 30% of the value added by mutual funds is due to the firm's ability to better observe manager skill and to promote and demote managers as a function of that. Recently, Zambrana and Zapatero (2021) show how families optimally allow some managers to be specialists and others to be generalists as a function of their stock picking versus market timing abilities. At the same time, Chen, Xie, and Zhou (2020) document how multi-tasking negatively affects fund performance and how families use team assignment to alleviate such negative effects. Complementary to that, we focus on the firms' role in designing the scope and the degree of task specialization of each manager. We hypothesize that how efficiently a firm can perform this role is a function of firm size and that especially small firms face constraints that prevent the allocation of some managers to their most efficient employment. These constraints can arise because of the well documented incentives of mutual fund firms to engage in product proliferation and offer a large variety of funds with different investment objectives (e.g., Gruber 1996; Khorana and Servaes 1999; Nanda, Narayanan, and Warther 2000; Massa 2000, 2003; Mamaysky and

[5] Such concerns include the impact of mergers on product market competition (He and Huang 2017; Azar, Schmalz, and Tecu 2018), on financial stability (Massa, Schumacher, and Wang 2021), or the interaction between asset management companies and banks within financial conglomerates (Ferreira, Matos, and Pires 2018).

Spiegel 2002; Cvitanic and Huggonnier 2022). For example, Kostovetsky and Warner (2020) and Betermier, Schumacher, and Shahrad (Forthcoming) document differences in fund launching decisions between large and small firms. They show that especially small firms face incentives to build broad and differentiated fund menus to compete with incumbent firms. Our results suggest that these incentives may interfere with optimal managerial task allocation, and we show how increases in firm size due to mergers can relax these constraints and give rise to significant human capital synergies and, by extension, scale economies.

Third, we contribute to the literature that studies how mergers affect corporate outcomes and value creation. Examples include Hoberg and Phillips (2010), Sheen (2014) or Bena and Li (2014). In terms of human capital synergies, Tookes and Yimfor (2023) show how mergers can have disciplining effects on the labor force by reducing employee misconduct. In that sense, our study contributes to the broader literature on the human capital implications in mergers (e.g., Tate and Yang 2015, Forthcoming; Lee, Mauer, and Xu 2018; Ouimet and Zarutskie 2020; Bach et al. 2023). Our results emphasize the importance of asset complementarities in the context of asset management mergers (i.e., the like-buys-like result of Rhodes-Kropf and Robinson 2008) and our global sample of mergers between asset management firms allows us to document strong evidence that similarities rather than differences in observable firm characteristics appear to play an important role in the matching of buyer and target firms.

The paper proceeds as follows. We discuss our hypothesis in more detail in Section 1. Section 2 presents the data and summary statistics. We analyze managerial turnover and task assignment around mergers in Section 3 and associated changes in fund performance and value creation in Section 4. Section 5 explores the mechanisms of how managerial specialization improves fund performance and Section 6 discusses alternative interpretations and competing explanations for our results. A short conclusion follows.

1 Hypothesis and Empirical Predictions

Our main hypothesis states that mergers between asset management firms create value because the combined entity can assign fund managers to more specialized tasks compared to the two stand-alone firms. To illustrate, suppose there are two firms: a buyer and a target. For simplicity, each firm employs one fund manager (B and T, respectively), and offers funds with different investment objectives – say, domestic and international ones. If the firms are separate, each fund manager is a "generalist" who manages funds in two investment objectives. Instead, if the firms merge, the combined entity can assign each manager to become a "specialist": manager B can manage the domestic funds only, while manager T manages the international funds only (all while keeping the total number of funds constant). In doing so, each manager now carries out a more specialized task because the investment opportunity set (i.e., the set of different investment objectives) s/he follows is smaller and more concentrated. While clearly illustrative, our toy example makes several assumptions about the role of individual fund managers and asset management firms that merit further discussion and that will inform our empirical analysis.

1.1 Specialization in Asset Management

First, the example assumes that specialization is valuable in asset management. There is ample theoretical and empirical evidence for this assumption. Theories of portfolio choice under asymmetric information emphasize the role of strategic information acquisition / learning (e.g., van Nieuwerburgh and Veldkamp 2009, 2010), predicting specialized learning and superior performance by fund managers. Prior empirical literature on mutual fund performance indicates that various dimensions of specialization are associated with superior fund performance (e.g., Kacperczyk, Sialm, and Zheng 2005; Cremers and Petajisto 2009; Amihud and Goyenko 2013; Schumacher 2018).

At the same time, past literature has also shown the value of generalist fund managers that manage funds across different investment objectives. Zambrana and Zapatero (2021) show that managers with market timing ability are best assigned a generalist role whereas managers with stock picking ability perform better when employed as specialists. Going beyond fund management, the empirical corporate finance literature also recognizes the value of generalist CEOs (e.g., Custodio, Ferreira, and Matos 2013).

While our hypothesis does not discount the value of generalist fund managers per se, we conjecture that becoming a "generalist" in the sense of Zambrana and Zapatero (2021; i.e., managing funds in multiple investment objectives) may at times be the result of necessity, at least in smaller asset management firms. Simply put, if a small firm seeks to offer a variety of funds across investment objectives, some fund managers may have to act as generalists to help the firm realize its product market strategy. As a result, mergers may allow firms to reallocate some fund managers to assign more specialized tasks to them. Empirically, we ask which funds or managers are more likely to be affected by managerial turnover events as a function of their generalist versus specialist profile prior to the merger, and how managerial turnover affects the task assignment of managers in mergers of different types of firms. Under our hypothesis, we expect differences in the type of turnover events: For a merger that will lead to a large increase in firm size, we expect turnover events that assign managers to more specialized tasks and that especially affect funds with generalist managers. In contrast, the same may not be true in a merger involving a large and a small firm – we expect managerial tasks to be already optimally assigned at least in the large firm.

1.2 Fund Proliferation and Product Market Behavior

Second, our illustrative example rests on the premise that the two stand-alone firms offer an assortment of funds with different investment objectives, rather than a specialized menu with only one investment objective per firm. In other words, if having specialist managers clearly dominates generalist ones, why would a small firm want to offer an assortment of different but ultimately underperforming funds?

In this respect, the incentives of mutual fund families to engage in menu proliferation are well documented in the literature. There are multiple reasons for families to launch many funds: having multiple small funds could help performance generation (e.g., Berk and Green 2004), launching many funds improves the chances of having an outperforming one that creates positive spillovers to the family (e.g., Nanda, Wang, and Zheng 2004). Other motives beyond performance maximization include creating differentiated fee structures, avoiding capital gains overhang, or simply meeting investor demand for a particular style (Khorana and Servaes 1999). Yet additional motives are anchored in the industrial organization of the mutual fund industry and evolve around the incentive to segment the market for mutual funds by giving investors plenty of options to invest with the same family (while erecting barriers to switch families) and to complement the offering of investment products with other, non-performance related services (e.g., Khorana and Servaes 1999; Massa 2000, 2003; Mamaysky and Spiegel 2002). Recently, Betermier, Schumacher, and Shahrad (Forthcoming) show that product proliferation can be a potent strategy by incumbent firms to deter market entry and that especially small firms seek to grow their product portfolios not by specializing in few investment objectives but by covering the full range of investment objectives. We will further discuss this assumption when presenting the summary statics of merging firms across different deal types to understand if manager specialization generally appears lower in mergers that involve smaller firms.

1.3 Size and Boundaries of the Firm

Third, our example assumes that as stand-alone entities, both firms only employ one manager full-time who needs to oversee funds in different investment objectives. A reason for such an outcome might be that the total number of fund managers the firm can afford to hire is a function of its overall size (e.g., firm AUM) because the overall level of firm resources is a direct function of the size of the firm. This might leave smaller firms with fewer "managers per investment objective", creating a tension if such firms seek to offer a differentiated fund menu.

Clearly, there are alternatives to this assumption. For example, the firm could hire more fund managers "part-time". Indeed, the practice of sub-advising portfolio management (where an asset management firm hires an unaffiliated sub-advisor firm to manage the portfolio of some of its funds) is well documented in the literature (Chen et al. 2013; Del Guercio and Reuter 2014; Chuprinin, Massa, and Schumacher 2015). We discuss this possibility further in Section 6 but note here that asset management firms are known to hire subadvisors to compensate for missing investment expertise (Massa and Schumacher 2020). In contrast, our hypothesis links value creation to the reassignment of human capital and subsequent specialization and not to the acquisition of missing expertise.

Another alternative states that small firms optimally hire generalist managers in the first place, seeking to benefit from economies of scope in generalist manager's ability (e.g., Zambrana and Zapatero 2021) to grow the firm. In the end, we concur that alterative assumptions are tenable when it comes to the questions on the boundary of and the optimal size for an asset management firm. Our answer will be empirical in that we will examine "managers per investment objective" statistics when discussing our sample of merging firms of different sizes. Ultimately, we are motivated by the understudied result of Chen et al. (2004) that funds managed in large firms perform better, suggesting that these funds benefit from some firm level scale economies. We test for one such benefit: the possibly better ability to assign fund managers their optimal degree of specialization in a larger compared to a smaller firm.

1.4 Testable Predictions

These considerations allow us to lay out three testable empirical predictions that will form the core of our empirical analysis: First, we expect that mergers are followed by increased managerial turnover that is driven by the re-allocation of existing fund managers, is concentrated in funds whose management appears less specialized a priori, and results in the assignment of more specialized tasks to rotated fund managers. Second, the assignment of more specialized tasks leads to improved productivity and more added value, especially for funds whose management appears less specialized a priori. And third, we expect these effects to be concentrated in mergers that lead to a large increase in firm size and muted in mergers between a large and a small firm.

We also consider several extensions of our hypothesis. First, we interpret our findings in light of the theoretical literature on "specialized learning" by van Nieuwerburgh and Veldkamp (2009, 2010), which offers more detailed predictions as to "how" fund manager specialization may improve fund performance. Specifically, these authors predict that a fund manager will optimally specialize in areas in which s/he has an information advantage and such specialization will manifest itself not only in superior performance but also in observable portfolio policies including a higher degree of portfolio concentration, activeness, and differentiation. Also, those authors predict improved value creation from specialization to be driven by superior risk-adjusted returns (which are one component of Berk and van Binsbergen's (2015) measure of value-added). Second, the merger theory of Rhodes-Kropf and Robinson (2008) predicts that "like-buys-like", and implies that expected merger benefits will accrue to both merger parties because of asset complementarities. In other words, under their framework, we expect our core results to be symmetric across funds from buyer and target firms. This stands in contrast to alternative merger theories (e.g., Jovanovic and Rousseau 2002) that suggest post-merger changes to be concentrated in target funds because e.g., high-skill bidders acquire and restructure low-skill target firms.

2 Data and Variables

2.1 Sample Construction

We combine information from a range of sources: the SDC Platinum and Zephyr Mergers and Acquisitions databases, FactSet Ownership institutional holdings, the Morningstar Direct database, Global Open-End Funds Section, as well as international stock return data and accounting information from Thomson Datastream / WorldScope.

The starting point of our analysis is a sample of mergers between asset managers worldwide, retrieved from the SDC Platinum and Zephyr-Bureau van Dijk Mergers and Acquisitions databases. We consider deals completed from 2001 up to and including 2013, because ownership data from FactSet is too sparse for earlier periods. We restrict the attention to completed deals in which both the buyer and the target belong to the financial industry, and in which the buyer controls less than 50% of the target's shares before and more than 50% after the deal.[6]

[6] We classify "financial industry" based on the sector classification by SDC or Zephyr ("Banks, insurance companies, other services"), SIC primary code (60 to 67), NAICS primary code (52 and 53), NACE Rev.2 primary code (63 to 70), or Zephyr classification ("Banking, insurance & financial service").

We merge the M&A deals with the FactSet ownership database by manually screening buyer and target names. FactSet reports security-level holdings for mutual funds (as well as a variety of other entities, e.g., insurance, closed-end, and pension funds, excluded from our analysis) and the organizational structure in which a fund is managed (its portfolio management company, and that firm's ultimate parent company). Wherever possible, we match the buyer or target in the M&A deals data directly to a management company in FactSet. In several deals, ultimate parents are directly involved in the merger: for example, in July 2001, Bank of America Corp. (parent company) takes over Marsico Capital Management LLC (management company). In all such cases, all management companies associated with Bank of America Corp. in FactSet are treated as buyers, and their funds as buyer funds (and likewise, reversing roles, when the target is in turn a parent company). In addition, we require available holdings data for both buyer and target prior to the merger. These filters result in an overall sample of 176 mergers.

We match FactSet to the Morningstar Direct mutual fund database to obtain fund characteristics (e.g., investment objectives, returns, fees, information on share classes) and individual fund manager information.[7] To define measures of task specialization, we rely on the Morningstar classification of investment objectives, specifically the Morningstar "Global Category" metric. This metric classifies funds into investment objectives based on the geographic investment focus of the fund (by country, region, or global) and further along the size-value dimension for larger markets such as e.g., the "US", the "UK", the "Global", or "Europe" regions. It also designates industry objectives if the fund is specialized on a particular industry. We emphasize that our sample is global on two important dimensions: First, our sample of mergers is global, which increases the power of our test, and allows us to consider cross-country similarities (e.g., culture and language) with regard to our hypothesis that stresses the importance of asset complementarities to predict the matching between buyer and target firms. Second, our sample includes a large heterogeneity

[7] A partial linking table between FactSet and Morningstar is provided by FactSet directly. We complement this list using a fuzzy string-matching computer program, and manually screen the code output to obtain a complete matching table between the two databases. Overall, we obtain a match in the Morningstar database for 90% of the FactSet funds in our sample. We retrieve the individual manager names from Morningstar. In addition, Morningstar provides a separate file that contains unique manager identifiers linked to the manager names which ensures the accuracy of our manager-fund mappings.

in global investment objectives. In total, we count 86 different Morningstar investment objectives in the full sample, allowing for a rich span of manager specialization.

We also require that portfolio holdings information is available in the FactSet database for both asset managers at least one year prior to the merger completion date. Following Chuprinin, Massa, and Schumacher (2015), we focus on semi-annual holdings information throughout the analysis, to maximize coverage. In addition, we restrict attention to open-ended, actively managed mutual funds,[8] and we further require that the funds are classified as "Equity" by Morningstar or have at least 80% of their total net assets (TNA) in equity if the Morningstar identifier is missing. These filters result in a final sample of 135 deals.

Finally, to complement the holdings information and to construct benchmark portfolios, we download stock price and accounting information on all global stocks from Thomson Datastream and Worldscope, to which we apply the screens of Ince and Porter (2006) to detect data errors.

The resulting overall sample comprises 8,524 funds managed by 5,739 individual managers that are affiliated with 507 management companies (or their parent companies). Out of 8,524 funds overall, 7,383 are buyer funds, and 1,741 are target funds. 600 funds appear as buyer funds in one deal and target funds in a separate deal. Similarly, out of 507 management companies, 397 are buyers, 162 are targets, and 52 management companies appear as buyers in one deal and targets in a separate deal. Throughout the main analysis, we work on a subset of the data restricted to active equity funds, comprising 3,121 funds (2,650 buyer funds and 746 target funds) with 3,904 individual managers, affiliated with 385 management companies (297 buyers and 122 targets).

Figure 1 here

Our sample highlights consolidation in the global asset management industry. Figure 1 displays strong growth in the volume of M&A transactions between global asset management companies. Over our sample period, the M&A deals covered by our analysis are associated with a cumulative $4.6 trillion of AUM and include buyer and target firms from 30 different countries.

[8] We drop the index funds based on the "Index" flag provided by Morningstar.

2.2 Key Variable: $Large\Delta_d$

Most variables we use in our empirical tests are defined following the literature. We introduce them as we go through the analysis and present a complete overview in the Appendix.

Our key variable to test our prediction on scale economies is $Large\Delta_d$. This variable exploits cross-sectional heterogeneity in deal characteristics and separates our merger sample in deals that lead to a large increase in firm size versus those that do not. We define $Large\Delta_d$ as an indicator equal to 1 if in deal d, the number of individual target fund managers pre-merger divided by the sum of individual target and buyer fund managers pre-merger is above the sample average and 0 otherwise. In other words, we classify deals in which the pre-merger target firm is large (in terms of individual fund managers) relative to the buyer firm as deals that are expected to lead to a large change in firm size.

There are several important elements to discuss in this definition. First, this definition reflects the observation from Berk, van Binsbergen, and Liu (2017) that human capital is the most important production input for an asset management firm. Hence, the number of managers should be a key variable to measure the size of asset management firms especially if the role of the firm is to assign managers to funds.

Second, in our count of individual fund managers, we focus on active equity fund managers throughout because we expect the firms' ability to re-assign managers to be limited by the types of funds they already manage: an equity fund manager may be re-assigned to another equity fund but may not be suitable to oversee e.g., a fixed income fund.

Third, we count individual fund managers in the buyer and target firms prior to the merger because we seek to focus on pre-determined deal characteristics and would like to avoid introducing an endogenous look ahead based on observed changes in the post-merger periods.

Fourth, our definition focuses on the relative increase in firm size to classify our deals as opposed to the absolute increase in size of bidder and target firms. Intuitively, the larger the target firm relative to the buyer, the larger the increase in firm size (recognizing that it is empirically very rare that a target firm is substantially larger than a buyer firm).[9] Such mergers provide the most opportunities to re-assign existing human capital to funds and alter the matching of human to investment capital. By scaling the pre-merger size of the target firm by the sum of the pre-merger buyer and target sizes, we also seek to emphasize that the size of the target relative to the size of the buyer is likely important to capturing possible asset complementarities. In fact, a "merger of equals" in which buyer and target are of equal size may afford the most opportunities to re-assign fund managers in the combined entity. Therefore, such deals may offer the greatest relief to pre-merger organizational constraints in the firms' ability to assign tasks to managers.

Fifth, we recognize that there are plausible alternative definitions of this key variable and we implement several of them in robustness tests in Section 6.4. One alternative uses the stand-alone absolute size of the target firm, others also consider the number of funds or the number of different investment styles in the buyer or target firm in addition to the number of individual fund managers to define this important cross-sectional variable.

2.3 Summary Statistics

Table 1 here

Table 1 reports descriptive statistics for our main sample. Column 1 of Panel A shows that the average firm involved in a merger employs almost 17 managers that oversee close to 15 funds across 6 different investment objectives, managing a total of $7.9 billion. In columns 2 and 3, we separate our deals in two groups along the $Large\Delta_d$ indicator. We highlight important differences between these two groups of firms prior to the merger and put those into comparison to the average mutual fund firm in FactSet (column 4).

Firms involved in a merger that leads to a large increase in firm size (i.e., where $Large\Delta_d = 1$, column 2) are ex-ante smaller in terms of AUM, number of funds and fund managers compared to other merging firms (column 3) or the average FactSet firm (column 4), in line with our working assumption that human capital constraints are potentially more severe in smaller firms. To that end, Panel A also documents the

[9] The clear exception to this is the merger between BlackRock and BGI in 2009 that forms part of our sample. In Table IA.13, we remove this deal from our sample and find that none of our results are affected.

number of different investment styles in which these firms offer funds prior to the merger. Importantly, the ratio fund managers-to-investment styles is almost 28% (18%) lower in column 2 compared to column 3 (4) (2.2 "managers per style" in column 2 versus 2.9 in column 3 or 2.7 in column 4). Given the broad nature of the Morningstar investment objectives which can contain dozens of sub-categories themselves,[10] this indicates that a merger between two such firms can significantly improve this ratio, which may allow firms to significantly change the allocation of tasks to some managers.

In Panel B of the same table, we report average firm characteristics separately for buyer and target firms across these two groups of deals. The average buyer and target firm in $Large\Delta_d = 1$ deals are similar to each other across several size-related metrics: they each employ about 11 fund managers and manage 10 funds across 5 investment styles (i.e., about 2.2 "managers per style"). In contrast, the typical buyer firm in the remaining mergers is substantially larger than the target firm: the average buyer employs 5 times as many fund managers, manages 5 times as many funds (but only 3 times as many investment objectives), and almost 8 times as much AUM. In other words, mergers that lead to a large increase in firm size are mergers between two smaller but similar asset managers, as postulated in our toy example from Section 1.

A second insight from Panel B is how the average degree of manager specialization varies across firms of different size groups. The smallest firms in our sample (target firms in $Large\Delta_d = 0$, column 6) employ 1.9 managers per style, the second group of firms (buyer and target firms in $Large\Delta_d = 1$, columns 1 and 2) employ about 2.2 managers per style, whereas the largest firms in our sample (buyer firms in $Large\Delta_d = 0$, column 5) employ 3.1 managers per style. We also view this as consistent with the working assumptions from our toy example from Section 1.

A third insight from Panel B compares other firm characteristics across buyer and target firms in both sub-samples, and in particular differences in the average past fund returns. It is again notable that in $Large\Delta_d = 1$ deals, average past fund returns as well as dispersion of fund returns across funds in the same

[10] For example, the entire investment space of "Global Equity" is represented by 2 different Morningstar investment objectives only (see Table IA.1 in the Internet Appendix) but Morningstar further provides more granular style classifications that would differentiate across multiple sub-categories with different benchmarks within those.

firm are statistically indistinguishable between buyer and target firms, suggesting that similarities in observables extend beyond size-related metrics. In contrast, in $Large\Delta_d = 0$ deals, funds managed by buyer firms register significantly higher average fund returns in the past compared to funds managed by target firms. We view these summary statistics as suggestive evidence that indicates how asset complementarities could be an important driver for some mergers in our sample. We will build on this first evidence in Section 6 where we explicitly analyze the matching of buyer and target firms along these as well as other observable firm characteristics.

Panel C of the same table reports complementary descriptive statistics at the fund level that are comparable to other studies that use a worldwide sample of funds from FactSet and Morningstar (e.g., Schumacher 2018). We present additional descriptive statistics in the Internet Appendix, Table IA.1. Specifically, to illustrate the global dimension of our data, we summarize the distribution of our main sample funds along the top 25 location countries and the top 25 investment objectives in terms of TNA. On both dimensions, our data span the global equity mutual fund universe in the sense that funds are located around the world and cover a large variety of investment objectives. The same appendix table provides additional summary statistics of our sample of mergers. Specifically, we decompose mergers into deals that involve only stand-alone asset management firms versus deals that involve other organizational types including parent or subsidiary firms. We show that this dimension appears uncorrelated with our $Large\Delta_d$ indicator, suggesting that we are not implicitly comparing mergers between stand-alone firms with mergers between conglomerate-affiliated firms.

3 Reallocating Existing Fund Managers

3.1 Empirical Design

We begin and examine how managerial turnover changes after the merger completion. According to our first prediction, we expect an increase in managerial turnover that is driven by the reallocation of managers that already work for the buyer and target firms rather than by turnover events involving external managers.

To test this prediction, we estimate linear probability models of the form:

$$Rotation_{dpft} = \alpha_{dpt} + \alpha_{dpf} + \beta_1 Post_{dt} + \beta_2 Treat_{dpf} + \beta_3 Treat_{dpf} \times Post_{dt} + \mu' x_{ft-1} + \varepsilon_{dpft}, \tag{1}$$

where the subscript d indicates merger deals, f indicates funds, t indicates semi-annual time periods, and p indicates matching fund pairs, each consisting of a fund affected by a merger (a "treated" fund) and a comparable fund not affected by a merger (a "control" fund). We introduce these matching pair indicators to focus on differences in the outcome variables between treated and control funds within each deal, accounting for the fact that some control funds may be chosen for multiple treated funds and some treated funds are affected by more than 1 merger deal (see Section 2 for summary statistics). We consider two different groups of control funds.

First, for each treated fund, we select a matching fund out of all active equity funds that are neither involved in a merger nor managed by an affiliated firm of our sample firms throughout the sample period. Out of those, we select the one that shares the same investment objective, is managed in the same country, and closest in terms of portfolio holdings, firm size, and fund size one year prior to the merger.[11] We identify matching funds for 77% of the funds affected by mergers that are present one year prior to mergers in our sample.

Second, as an alternative and following Bena and Li (2014), we construct a control group from funds that are subject to withdrawn deals. We obtain mergers involving asset management firms that are ultimately withdrawn (i.e., mergers that were announced but then cancelled) from Thomson SDC and Zephyr and match them to FactSet. We identify 8 such withdrawn deals. After applying the same data requirements as for our regular deals, we are left with 5 withdrawn deals. For each of those withdrawn deals, we select a completed deal to serve as its treatment counterpart. From the completed deals, we select those that (i) are completed within the one-year window centered around the withdrawal date of the

[11] Specifically, we create a measure of portfolio distance between any two funds as the sum of squared differences in portfolio weights and select as the matching fund the one closest in fund size from all funds in the same investment objective and country and that are in the closest quintile in terms of portfolio distance and firm size. In unreported tests, we add expenses as an additional matching criterion and obtain similar results.

withdrawn deals; and (ii) are closest in terms of the relative size ratio (i.e., target firm's total assets divided by buyer's total assets). As Bena and Li (2014), we posit that this is a suitable control group because the firms involved in the deal had the intention to perform a merger that ultimately did not happen.

Table 2 here

In Table 2, we compare fund characteristics between the treatment and control samples. For the main sample where the control group is constructed from matching funds, the treatment and control sample have statistically similar observable characteristics as one would expect. However, for the sample from withdrawn deals, there remain statistically significant differences in observables. We attribute these differences to the small set of possible control funds we have in the small number of withdrawn deals; we control for those observables and focus our main analysis on the first control group of matching funds drawn from the overall universe.

To implement the tests, we define several measures of managerial rotation that the management team of fund f in the matching pair p of merger d may experience in period t: $NewManager_{dpft}$ is an indicator equal to 1 if a new manager appears in the management team of the fund and 0 otherwise, $InternalNewManager_{dpft}$ is an indicator equal to 1 if a new manager who has already managed a fund in the buyer or the target before the merger appears in the management of the fund and 0 otherwise, and $ExternalNewManager_{dpft}$ is an indicator equal to 1 if a new manager who did not previously manage a fund in the buyer or the target before the merger appears in the management of the fund and 0 otherwise. This decomposition allows us to investigate if merging firms re-allocate their existing set of fund managers or if managerial turnover events involve external hiring. Our hypothesis predicts that merging firms should re-allocate their existing workforce and that managerial turnover events should not involve newly hired fund managers. In a complementary test, we will further examine the overall headcount of fund managers: our hypothesis predicts this headcount should stay constant whereas a "Q-theory" motivated alternative would predict that some (target) managers are replaced with (buyer) managers.

Equation (1) is a stacked difference-in-differences specification that includes all asset management merger events. We include granular deal × pair × time and deal × pair × fund fixed effects, where again the matching pair indicators capture a particular pair consisting of a treated and a control fund for a particular merger. The key coefficient of interest is β_3, the coefficient on $Treat_{dpf} \times Post_{dt}$, the interaction term between the indicators $Treat_{dpf}$ that is equal to 1 for treated fund f in pair p in deal d and 0 for the control fund and $Post_{dt}$ that is equal to 1 for all periods following and including the completion period of deal d and 0 otherwise. Note that while we include the level effects for both indicators in equation (1) for completeness, the granular fixed effects absorb both in the estimation, leaving only the interaction term to be reported. We furthermore include standard, time varying lagged fund-level control variables in the vector x_{ft-1} including: $Fund\ size_{ft-1}$ as the natural logarithm of the AUM of fund f in million \$, $Firm\ size_{ft-1}$ as the natural logarithm of the AUM of all the funds of the pre-merger stand-alone firm managing fund f in billion \$, excluding fund f itself, $Volatility_{ft-1}$ as the annualized standard deviation of the trailing 12 month gross returns of fund f, $Expenses_{ft-1}$ as the management expense ratio of fund f in percentage points per year, and $Past\ return_{ft-1}$ as the trailing 12 month cumulative gross return of fund f. We estimate Equation (1) at the semi-annual frequency over a symmetric 6-year window centered on the completion date of deal d and double cluster standard errors at the deal and period level.

Table 3 here

3.2 Fund Manager Rotations: Results

Table 3 presents the results. Column 1 shows that the probability of a new manager joining a fund in any given half-year period following the deal completion date increases by 3.4%, significant at the 1% level, relative to control funds. Compared to the unconditional probability of a change in the management team of about 10% in the pre-merger period, this corresponds to an increase in the intensity of managerial rotation following a merger by over 30%. Columns 2 and 3 decompose this first result into the arrival of external versus internal managers. We find that the effect in column 1 is the net effect of two opposing developments: first, column 2 shows that the arrival of new external managers (i.e., managers who have not worked for the buyer or target firm before the merger), drops by about 6.2% relative to matching funds whereas the arrival of a new internal manager who has already managed funds in the buyer or target firm before the merger increases by over 9.3% per period relative to control funds. Using the alternative (and much smaller sample) in which control funds are drawn from withdrawn deals, we find the same strong increase internal manager reallocations in column 4.

Figure 2 here

To examine if this result is possibly driven by pre-existing trends, we decompose these overall effects into period-by-period estimates to understand if changes in managerial rotation intensity coincide sharply with the deal completion dates (i.e., if they change around the event). We re-estimate Equation (1) but include granular period-effects instead of only the $Post_{dt}$ indicator and present the results of this estimation in Figure 2. Panel A (B) displays the estimates for rotations of internal (external) fund managers. We find no significant difference in managerial rotation intensities between treatment and control funds in any pre-event period but a sharp increase (drop) immediately following the deal completion dates. We cautiously interpret this as evidence that these turnover events are brought about by the mergers (i.e., that they would not have happened without the mergers), recognizing that the mergers themselves are endogenous events that could be motivated by the desire to reallocate fund managers in the first place.

3.3 Fund Manager Rotations: Across and Within Deal Heterogeneity

We now sharpen our empirical strategy along two dimensions. First, we examine differences in managerial turnover activity across different merger types, in particular mergers that lead to a large increase in firm size versus those that do not. Second, we examine within-deal heterogeneity in managerial turnover by analyzing if turnover events are concentrated for funds managed by generalist fund managers.

We first explore turnover heterogeneity across deals. We classify mergers into those that lead to a large versus small increase in firm size: as indicated in Section 2, we define $Large\Delta_d$ as an indicator equal to 1 for deals that lead to an above-average increase in the number of individual fund managers.

Table 4 here

Having classified the sample of mergers in this way, we re-estimate Equation (1) and add the triple interaction term $Treat_{dpf} \times Post_{dt} \times Large\Delta_d$ to the specification and present the results in Table 4, column 1.[12] We find no significant difference in the overall increase in managerial turnover across deals that lead to a large versus a small increase in firm size. Instead, the volume of managerial turnover seems to increase following all mergers.

Therefore, we turn our attention to differences in managerial turnover events within deals. Our hypothesis predicts that increases in turnover volume reflect the opportunity to assign more specialized tasks to managers in deals that lead to a large increase in firm size. As such, we would expect that in those deals, turnover events are concentrated for funds managed by generalist managers, i.e., managers who manage funds in more than 1 investment objective. In contrast, in deals involving a large buyer and a small target, the same is less likely to be the case.

To test this, we define an indicator $Generalist_{dp}$ to equal 1 if, over the year prior to the deal, the management of the treated fund in pair p in deal d includes only generalist fund managers who manage funds in more than 1 Morningstar investment objective and 0 otherwise. We postulate that in firms involved in $Large\Delta_d = 1$ deals, some of those managers are "generalists by necessity" and the merger affords the now larger firm the opportunity to re-assign some of those to a more specialist role. For ease of interpretation, rather than including quadruple interaction term to Equation (1), we add a triple interaction term $Treat_{dpf} \times Post_{dt} \times Generalist_{dp}$, and re-estimate the specification separately for both subsamples of deals with $Large\Delta_d = 1$ and $Large\Delta_d = 0$.

We present the results in the remaining parts of Table 4. In column 2, the estimates show that in the sample of $Large\Delta_d = 1$ deals, managerial turnover events are heavily concentrated in funds managed by generalist managers – the entire significance of the original $Treat_{dpf} \times Post_{dt}$ term moves to the triple interaction term. In those deals, funds with a generalist manager are 8.8% more likely to experience a

[12] Note again that all other dual interaction terms and the level effect of $Large\Delta_d$ are absorbed by the granular fixed effects.

turnover event (compared to the 3.4% overall sample estimate from Table 3, column 1). In contrast, the same estimation for the remaining $Large\Delta_d = 0$ deals in column 3 shows that this is not the case in all other mergers – the triple interaction term is insignificant, indicating that the composition of the fund management team in terms of specialist versus generalist manager is not associated with differential turnover frequency. Additional tests in the Internet Appendix, Table IA.2 show that this result is driven by the sample of existing "internal" managers. All these results support our hypothesis.

3.4 Rotations and Task Specialization: Manager Level Evidence

We now complement the fund level results with manager level tests to directly examine how turnover events affect the degree of task specialization and overall workload of rotated managers. Under our hypothesis, we expect rotated fund managers to be assigned more specialized tasks, especially for managers experiencing turnover events in $Large\Delta_d = 1$ deals.

To accomplish that, we change the unit of analysis to the individual fund manager level, track the assignment of tasks to each manager, and estimate the following specification:

$$
\begin{gathered}
Task_{dmt} = \alpha_{dt} + \alpha_{dm} + \beta_1 Post_{dt} + \beta_2 Large\Delta_d + \beta_3 Treat_{dm} + \beta_4 Treat_{dm} \times Post_{dt} + \\
\beta_5 Large\Delta_d \times Post_{dt} + \beta_6 Large\Delta_d \times Treat_{dm} + \beta_7 Treat_{dm} \times Post_{dt} \times Large\Delta_d + \\
\mu' x_{mt-1} + \varepsilon_{dmt},
\end{gathered} \tag{2}
$$

where $Task_{dmt}$ measures various dimensions of the tasks assigned to managers m. We define four measures that capture the specialization of tasks assigned to manager m in period t: $Log(\#\ of\ styles)_{dmt}$ is the natural logarithm of the count of different Morningstar investment objectives in which manager m is managing funds in deal d at period t; $Concentration_{dmt}$ is a Herfindahl-Hirschman-Index over the share of funds in each investment objective for manager m in deal d at period t; $Log(\#\ of\ removed\ styles)_{dmt}$ is the natural logarithm of 1 plus the number of investment styles that were removed from manager m in deal d at period t; and $Log(\#\ of\ added\ styles)_{dmt}$ is correspondingly the natural logarithm of 1 plus the number of investment styles that were added to manager m in deal d at period t relative to period $t-1$. We also define two measures of the overall "workload" assigned to each manager: $Log(AUM)_{dmt}$ is the natural logarithm of the total AUM of manager m in deal d at period t, defined as the sum of AUM across all funds under his/her management (regardless of if the fund is single- or team-managed). Alternatively, $Log(AUM\ per\ capita)_{dmt}$ is the natural logarithm of total AUM of manager m in deal d at period t defined as the sum of "AUM per manager" across all funds under his/her management. In the case of team-managed funds, "AUM per manager" is the ratio of fund AUM divided by the number of managers on the management team. The vector x_{mt-1} contains lagged manager controls, which are the same control variables as in Equation (1), now averaged across all funds managed by manager m and the specification further includes deal × time and deal × manager fixed effects, denoted by α_{dt} and α_{dm}. We use as control managers the managers from the matching sample of control funds used in all prior tests so far. Standard errors are double clustered by deal and time as before.

Table 5 here

Table 5 presents the results. We focus on the degree of task specialization in columns 1 to 4 and find that in deals that lead to a large increase in firm size, the tasks of rotated managers become more specialized. In such deals, managers begin managing funds in fewer different investment objectives (column 1) and the collection of funds they oversee becomes more concentrated across investment styles (column 2). Columns 3 and 4 further clarify how this increase in task specialization comes about: in such deals, managers are more likely to see investment styles removed from their task allocations (column 3) but do not experience a corresponding increase in new styles being added to their workload (column 4).

These results also rule out the alternative possibility that rotated managers are re-matched to an entirely new set of tasks. For example, we do not observe that a hypothetical manager from our toy example from Section 1 who previously managed domestic and international funds would be rotated to manage, say, value and growth funds. Such a complete re-matching would imply that rotated managers receive funds in new styles. Instead, we observe that they only give up certain styles without gaining new ones. In other words, these results confirm that rotated fund managers are disproportionately generalist fund managers for which turnover events lead to more specialization.

In columns 5 to 6 of the same table, we also track the overall "workload" of each manager and find that across both our measures, it does not change on average in the post-merger period. This suggests that the increase in specialization for managers in deals that lead to a large increase in firm size is not driven by a simultaneous reduction in overall workload which could confound our subsequent interpretation of our test on changes in fund performance or managerial productivity.

3.5 Changes in Overall Headcount of Fund Managers

Finally, we examine if the post-merger periods are characterized by changes in the overall headcount of fund managers in the combined entities. We view this as a complementary test to rule out that our results are driven by the departures of some fund managers who are subsequently replaced by other existing fund managers. While the results of Section 3.4 that show no changes in the average workload for rotated fund managers make this unlikely, we nevertheless seek to rule out explicitly that the post-merger periods are characterized by departures rather than re-assignment of the existing fund manager work force.

To test this, we estimate the following specification at the deal level:

$$Headcount_{dt} = \alpha_t + \alpha_d + \beta_1 Post_{dt} + \beta_2 Large\Delta_d + \beta_3 Large\Delta_d \times Post_{dt} + \mu' x_{dt-1} + \varepsilon_{dt}, \tag{3}$$

where $Headcount_{dt}$ is the natural logarithm of 1 plus the number of individual fund managers affected in deal d in period t and x_{dt-1} is a vector of average fund characteristics across all funds affected by deal d. We add time and deal fixed effects, denoted by α_t and α_d, and double cluster the standard errors by deal and time. We present the results in the Internet Appendix, Table IA.3. In short, we find no changes in the overall headcount of fund managers in the post-merger periods, confirming the prior interpretation that managerial turnover events are primarily characterized by the reallocation of existing fund managers.

These results are also interesting as they speak to potential cost synergies as a driver of scale economies. While we cannot compare our estimates to potential cost synergies for a lack of data on e.g., back-office functions and other firm attributes that may be affected by rationalization, we argue that it seems unlikely that cost synergies would interact with or affect the conclusions we draw from our tests for several reasons.

First, the result of this subsection does not point towards cost synergies stemming from the rationalization of fund managers. Second, in unreported tests, we also find no evidence that merging firms streamline their product offering: we find no evidence of rationalization at the fund level and only few fund mergers in the post-merger periods. Third, general cost synergies would in principle affect all funds, yet our results indicate strong within-deal heterogeneity in managerial turnover. Fourth, cost synergies carry no direct predictions on improved fund performance which is the topic of the next section.

4 Fund Performance, Value Creation, and Firm Size

4.1 Changes in Fund Performance

Motivated by prior work in Chen et al. (2004) who show that risk-adjusted fund returns are negatively related to fund size but positively related to asset management firm size, we first examine if changes in firm size induced by the merger are associated with improved fund performance.[13] We re-estimate the specification in Table 4, column 1 (i.e., Equation (1) augmented with a triple interaction term $Treat_{dpf} \times Post_{dt} \times Large\Delta_d$), but use fund-level performance measures as the dependent variables.

We consider different measures of risk-adjusted fund returns including overall net-of-style fund returns, factor-corrected fund returns relative to different factor models, as well as holdings-based returns in excess of various benchmark portfolios. All fund returns are before fees and (in keeping with the frequency of the analysis so far), at the semi-annual frequency. The detailed definition of all fund return measures is provided in the Appendix. We iterate that while all regressions include the full set of level and dual interaction terms, we report only those that are not absorbed by the granular fixed effects.

Table 6 here

We present the results in Table 6. Columns 1 to 3 present specifications with overall risk-adjusted fund returns while columns 4 to 6 focus on holdings-based excess returns. We find that the coefficient of the

[13] As a preliminary test, we replicate the main results of Chen et al. (2004) using the full FactSet sample during the years from 2000 to 2013. Table IA.4 in the Internet Appendix confirms that fund performance is negatively related to fund size but positively to firm size.

triple interaction term $Treat_{dpf} \times Post_{dt} \times Large\Delta_d$ is positive and significant across all columns, suggesting that fund performance improves by about 70 to 90 basis points per half year (i.e., about 1.4% to 1.8% per year) in the post-merger periods, relative to control funds, and in particular for funds in $Large\Delta_d = 1$ deals. The effect is consistent for performance measures based on fund gross returns (columns 1 to 3) or benchmark-adjusted holdings-based returns (columns 4 to 6), suggesting that performance improvements are primarily driven by better stock-picking decisions – an ability past literature has attributed to specialist fund managers (Zambrana and Zapatero 2021).[14]

The results of Table 6 clearly indicate that improvements in fund performance are concentrated in mergers that lead to a large increase in firm size and absent in all other mergers. We base this observation on the insignificant (in fact, at times negative) coefficient on the simple interaction term $Treat_{dpf} \times Post_{dt}$ that measures performance improvements for funds in mergers for which $Large\Delta_d = 0$. The lack of significance indicates no improvements in average fund performance in those deals, which again connects well to our hypothesis in the sense that these deals do not lead to a large increase in firm size and as such are unlikely to generate the same human capital synergies that are hypothesis focusses on.

4.2 Changes in Fund Performance: Within Deal Heterogeneity

In Table 7, we dig deeper into the performance results from Table 6 and examine within-deal heterogeneity in changes in fund performance. Specifically, we pick up on the analysis from Section 3.3 that shows how changes managerial turnover are concentrated in funds with generalist managers prior to the merger. We now ask if those same funds also register stronger improvements in fund performance. We use the same specification as in Table 4, columns 2 and 3 but use as dependent variable the ETF-adjusted holdings return introduced in Table 6, column 6. We focus on ETF-adjusted holdings returns because (i) it is a measure of stock picking ability associated with specialist fund managers and (ii) in anticipation of our

[14] In the Internet Appendix, Table IA.5, we find no improvement in timing ability (i.e., benchmark timing does not contribute to the overall improvement in fund returns), which is again consistent with the findings of Zambrana and Zapatero (2021) that show factor timing to be a skill of generalist managers. We also note that since total fund returns are net of transaction costs while holding-based returns are gross of transaction costs, possible changes in trading costs cannot explain our performance results of Table 6.

following tests on changes in value-added that build on Berk and van Binsbergen (2015) who also use ETF-adjusted fund returns to measure value added. However, our results are similar if we use alternative benchmark portfolios such as a market benchmark or a size-value-momentum benchmark.

Table 7 here

Results in Table 7 confirm our hypothesis. Column 1 shows how in mergers that lead to a large increase in firm size, improvements in fund performance are concentrated in funds with generalist managers prior to the merger. In fact, the entire significance of the simple interaction term shifts to the triple term, suggesting that funds who were already managed by specialists register no change in fund performance relative to control funds in the post-merger periods. Column 2 of the same table shows that the same is not true for the remaining sample of funds in $Large\Delta_d = 0$ deals – neither generalist nor specialist managed funds seem to register changes in fund performance following such mergers.

4.3 Changes in Value Added

Improvements in benchmark-adjusted fund returns are a first indication that the post-merger human capital reorganizations are beneficial in mergers that lead to a large increase in firm size. However, these improvements do not quantify how much value is created in the sense of Berk and van Binsbergen (2015). Or from a mergers & acquisitions point of view, these results do not quantify the synergies that are accomplished and that potentially contributed to the merger motivation in the first place.

To address this, we complement the fund performance result with a quantification of the changes in value-added by implementing the measure of Berk and van Binsbergen (2015). We directly compute value-added at the deal and fund level in the pre- versus post-merger periods. To correct for risk, we employ the benchmark portfolio constructed from the holdings of all physical-replication ETFs in FactSet that track the same benchmark index as the fund in question. This benchmark comes closest to the one proposed by Berk and van Binsbergen (2015), who use total fund returns from Vanguard ETFs that track the same benchmark index to correct total fund returns. As a first step, we focus on value-added before fees and expenses, as we are interested in how much incremental value is created.

Table 8 here

Table 8 presents simple deal-level summary statistics, comparing value added at the deal level in the pre- versus post-merger periods. We find that total value-added increases by about $54 million per year (i.e., by about $27 million per semi-annual period, column 3, row 1) in the post-merger period for the average merger. Expressed on a per-fund basis (column 4), this implies that the average fund creates an additional $2 million per year in value in the post-merger period compared to the pre-merger period.

When we split the sample along the $Large\Delta_d$ indicator, we find that this result is heavily concentrated in deals that lead to a large increase in firm size. For those deals, total value-added increases by about $104 per year following the merger completion ($52 million per semi-annual period, column 3, row 2). The average fund in those deals creates almost $4.4 million in additional value per year over the same period (column 4, row 2). In contrast, we find no significant change in value creation in the remaining sample (columns 3 and 4, row 3), in line with earlier results.

We confirm this result in multi-variate tests by repeating the specification of Table 6 but using value added as the dependent variable instead of risk-adjusted fund returns. We use the same risk-corrections and benchmarks introduced in Table 6 and conduct this test both at the fund and at the aggregate deal level. For brevity, we present these results in the Internet Appendix, Table IA.6 and 7. Consistent with the simple univariate tests presented in Table 8, we find that fund level value added improves by between $3.1 and $5.8 million per year (depending on the risk-correction) relative to control funds but only for funds in $Large\Delta_d = 1$ deals. Our multivariate tests show no changes in value-added for funds in in $Large\Delta_d = 0$ deals, again consistent with the univariate tests. Conducting the same multi-variate tests on the aggregate deal level also delivers estimates consistent with the univariate ones.

Continuing in Table 8, in rows 4 and 5, we decompose changes in value added along the characteristics of the fund management teams prior to the merger. In row 4, we find that improvements in value added are entirely concentrated in funds managed by generalists prior to the merger. The average generalist fund registers an additional $3.4 million on value per year following the merger whereas we detect no changes in value added for funds managed by specialists prior to the merger.

Finally, the remaining rows perform the 2-dimensional split (i.e., by generalist versus specialist and by $Large\Delta_d = 1$ versus $Large\Delta_d = 0$) and as suspected, changes in value-added are heavily concentrated in funds managed by generalists and subject to a merger that leads to large increase in firm size. The average such fund creates an additional $7.2 million per year in value in the post-merger periods (column 4, row 6) whereas we detect no such evidence for all other funds.

Before closing this subsection, we highlight one additional insight from Table 8. Column 1 indicates the average value added for different sub-samples of funds prior to any merger. Row 6 indicates that funds managed by generalists and (ultimately) subject to a merger that leads to large increase in firm size are the only group who register significant negative value-added in the pre-merger periods. We view this as supportive evidence to our conjecture that some of those managers assumed generalist roles "by necessity" with negative implications for value creation. Contrasting this with row 9, we find that specialist fund managers (ultimately) subject to a merger that does not lead to large increase in firm size are the only group of manages who collectively already create positive value prior to the merger, supporting the assumption that specialization is indeed conducive of value creation, at least on average in larger firms.

4.4 Changes in Value Added After Fees and in Risk-adjusted Returns

We provide two additional tests on improved value-creation in the post-merger periods. First, we examine how the additional value is shared between the firm and fund investors. From the perspective of merging firms, expected synergies should motivate a merger only if the firm can appropriate a significant part of the value creation (rather than passing it on entirely to fund investors). To assess how the incremental value added is shared, we re-compute the results presented in Section 4.3 but on an after-fee basis and present the results in the Internet Appendix, Table IA.8. The table mirrors Table 8 but uses fund returns after expenses in the calculations. The results still show an improvement in value added. However, on an after-fee basis, this improvement is substantially smaller and significant only for mergers that lead to a large increase in firm size. In those cases, the improvement drops from about $104 million per year before fees (column 3, row 2) to $62 million per year, suggesting that merging firms in such deals manage to appropriate about 40% of the incremental value added via fees, leaving a large fraction to fund investors.

Second, value-added is the product of fund AUM multiplied by risk-adjusted returns. In the context of our hypothesis and the general theory of "specialized learning", one would expect that changes in value added are driven by improvements in risk-adjusted returns that allow managers to create positive (and absolute) outperformance. While our results in Table 8 indicate positive value added in the post-merger periods for "Generalist" funds in $Large\Delta_d = 1$ deals, our estimates in Table 6 only indicate relative improvements in risk-adjusted returns. To clarify, we re-compute Table 8 but tabulate risk-adjusted returns instead of value-added and report the results in the Internet Appendix, Table IA.9. We find corresponding patterns to the ones reported in Table 8: "Generalist" funds in $Large\Delta_d = 1$ deals register positive absolute risk-adjusted returns of about 2.2% per year in the post-merger periods, indicating that improved managerial specialization enables managers to generate positive risk-adjusted returns, as the theory of van Nieuwerburgh and Veldkamp (2009, 2010) would suggest.

5 How Does Fund Performance Improve?

In this section, we explore the channels of "how" improved managerial specialization improves fund performance and value creation. To do so, we test extended predictions from our main hypothesis that are motivated by the theory of specialized learning of van Nieuwerburgh and Veldkamp (2009, 2010). In their theory, managers optimally specialize in investment areas in which they have an information advantage. Such specialization manifests itself not only in superior risk-adjusted returns but also in particular portfolio policies, namely higher levels of activeness, portfolio concentration, and differentiation from peer funds which in turn drive superior risk-adjusted returns. The premise of our main hypothesis is that pre-merger, organizational constraints limited the degree of fund manager specialization. However, post-merger, such constraints are relaxed, allowing us to test for changes in those portfolio policies and link those changes to changes in risk-adjusted fund returns.

To implement this test, we require one additional piece of information for each manager: the areas in which a manager would like to specialize a priori. In the spirit of van Nieuwerburgh and Veldkamp (2009, 2010), we need a proxy for the manger's "information advantage" that will drive his/her learning decisions going forward.

We put forward the following proxy to identify each manager's "Expertise Areas": For each manager, we identify all funds the manager ever managed in our data and partition the portfolio holdings of all those funds into country-industry sub-portfolios. We then compute the cumulative value-added for each sub-portfolio over the manager's entire career path prior to the merger and we designate the top 25% country-industry sub-portfolios in which the manager has created the most value over his/her career as the manager's investment "Expertise Areas". All other country-industries are labelled "Non-Expertise Areas".

Several ideas are embedded in this proxy: First, by considering the full career path of each manager, we hope to recover the areas in which the manager has created most value. Second, even though a manager may have faced constraints in the degree of his/her specialization pre-merger, we assume that the manager's desired specialization can still be inferred from the manager's past portfolio allocations across the history of all his/her different funds. Third, we identify the expertise areas by sorting them on value added which combines both AUM allocations and the risk-adjusted returns the manager earned, two central ingredients that should reflect the manager's information advantages. Fourth, we choose to partition portfolio holdings into country-industry sub-portfolios because the country and/or industry dimensions are established sources of information advantages (e.g., Coval and Moskowitz 1999, 2001, Cici et al., 2018, Schumacher 2018).

Having designated each manager's possible "Expertise Areas", we measure portfolio policies and risk-adjusted returns in both expertise and non-expertise areas and test for changes using the same specifications as before. Our measures of portfolio policies include the Active Share measure of Cremers and Petajisto (2009), the industry concentration index of Kacperzcyk et al. (2004) as well as a measure of portfolio differentiation from peer funds that we label "Distance to Peers". It is the portfolio distance between fund f and the average active equity fund in the same investment style. Our measures of risk adjusted returns are the same holdings-based return measures used throughout, only now computed separately for expertise and non-expertise areas for each manager.

Table 9 here

We report the results in Table 9. In Panel A, we examine changes in portfolio policies and we find that funds in $Large\Delta_d = 1$ deals become more active (column 1), more concentrated (column 2) and more differentiated (column 3) in their holdings in the post-merger periods relative to the control group. Importantly, we detect these changes only in the managers "Expertise Areas", there are no effects in the remaining "Non-Expertise Areas" (columns 4 to 6). We interpret this as evidence in favor of more specialized task assignment allowing managers to re-focus on what were historically their areas of investment expertise.

Under this interpretation, we would expect that the overall improvements in risk-adjusted returns documented in Table 6 are primarily driven by stronger performance in the manager's expertise areas. We directly test this in Panel B of the same table and the evidence confirms this conjecture: improvements in risk-adjusted returns are entirely concentrated in the managers expertise areas (columns 1 to 3) whereas there are no detectable effects in all other parts of the manager's portfolio. We therefore propose the following "channel" that links more specialized task assignment with improved fund performance: more specialized task assignment enables managers to better focus on their areas of investment expertise, possibly allowing for more specialized learning that manifests itself in portfolio policies that have long been associated with better fund performance.

6 Alternative Mechanisms and Robustness Tests

To this point, we have interpreted our results in the context of our main hypothesis. However, we recognize that our results may be open to alternative interpretations. In this section, we discuss and provide results to rule out several plausible mechanisms.

6.1 Buyer and Target Matching

Our difference-in-differences estimates that use control groups based on matching funds or funds from withdrawn deals suggest that the increase in managerial turnover and the related performance improvements are a direct consequence of the merger (and likely unattainable without it). These tests, however, do not address the potential issue of target selection as the matching between buyer and target is not random.

Our main hypothesis links value creation to greater room for human capital reallocation and specialized task assignment in a combined firm. If the ability to reassign managers to more specialized tasks is at the core of the value creation in mergers, we would expect buyers to select overall similar target firms, not just in terms of size but also in terms of other attributes such as pre-merger fund offerings. In other words, we expect that "like-buys-like" (Rhodes-Kropf and Robinson 2008).

A possible alternative is a "Q-theory of mergers", predicting that merging firms are different because the merger is a means to redeploy capital to a more productive use (e.g., Jovanovic and Rousseau 2002). Applied to our setting, we would expect differences in observable characteristics between buyer and target asset management firms. For example, we would expect differences in fund performance if a "high skill" buyer firm acquires a "low skill" target firm to improve fund performance in the post-merger period. A second possible alternative is that mergers are driven by a motive to acquire missing expertise (e.g., Ouimet and Zarutskie 2020). If so, we would also expect buyers and targets that are generally different from each other, as buyers would seek targets with different product offering and/or investment expertise.

To address these alternative explanations, we compare the actual buyer-target matches along specific deal characteristics against counterfactual matches between the buyers and hypothetical targets. This complements the descriptive statistics from Table 1, Panel B that already show similarities between buyer and target firms in $Large\Delta_d = 1$ deals along several observable characteristics, including size and performance measures. For every actual buyer-target pair, we select several hypothetical targets as follows: out of all asset management firms that are neither involved in mergers nor affiliated with our real targets under the same parent firms, we choose firms that are close in terms of the pre-merger AUM and that share the same conglomerate status as the given real target (i.e., if the given target is a parent firm or an affiliate under a parent firm, then we select a hypothetical target which is also a parent firm or an affiliate) one year prior to the merger. We then estimate linear probability regressions relating the actual target choice to understand to differences (or similarities) in observable characteristics between the buyer and possible target firms. We construct several "distance" measures between the actual buyer firm and all possible target candidates. The dimensions we include, in addition to firm size, are geography (km distance), culture (common language), skill (average fund performance), product offering (differences in investment objectives of funds), and distribution channels. The detailed definitions of all these dimensions are provided in the Appendix. We then estimate the following specification:

$$RealTarget_{dj} = \alpha_d + \beta' Distance_{d\leftrightarrow j} + \mu' x_j + \varepsilon_{dj}, \tag{4}$$

where the dependent variable is simply an indicator equal to 1 if firm j was selected as the real target in deal d and 0 if firm j is a hypothetical target. The vector $Distance_{d\leftrightarrow j}$ contains the various distance measures between the buyer firm in deal d and all possible target firms j and the vector x_j contains additional firm characteristics of all possible target firms for completeness. α_d indicates deal fixed effects. We include a list of 10 to 25 possible target firms for every deal.

Table 10 here

We present the results in Table 10 and find that actual targets are generally "closer" in terms of multiple deal characteristics compared to hypothetical targets. Specifically, we find actual targets to be more similar to the buyer firm compared to plausible alternative targets in terms of product offering ("style distance"), size ("size difference"), geography ("geographical distance"), culture ("different language"), and distribution network ("different distribution"). We find these effects to be robust to the inclusion of different numbers of possible candidate target firms. Interestingly, we find no evidence of performance differences between buyer and target to influence target choice which we interpret as evidence against the alternative interpretation that high-skill buyers seek to acquire low-skill targets, suggesting that differences in investment abilities are not a primary driver of mergers at least in our sample.

Instead, these results highlight possible drivers of asset management mergers. In fact, we interpret these results as difficult to reconcile with the two alternative merger motivations: similarity between buyer and observed target firms along many dimensions is inconsistent with a motive to acquire missing expertise.[15] Similarity in fund performance is also inconsistent with a Q-theory argument in which a firm with high performing funds acquires a firm with low performing funds in order to improve fund performance. In contrast, the observed matching of buyer and target firms is consistent with our hypothesis that predicts the most value creation for mergers where the two firms are similar not only in terms of size but also pre-existing product offering. From that perspective, expected synergies from human capital complementarities could play an important role for some asset management mergers, consistent with our estimates that show meaningful value creation in the post-merger periods.

6.2 Symmetry between Buyer and Target Funds

Another dimension that helps put our results into perspective relative to alternative interpretations is how the changes in managerial specialization and fund performance are distributed among buyer- and target-affiliated funds. Since our hypothesis is predicated on the notion of asset complementarities, it implies the extended prediction that both buyer- and target-affiliated funds should register these changes. In other words, under our hypothesis, we expect our results to be symmetric across funds from both buyer and target. In contrast, a Q-theory based alternative would not carry the same implication. In fact, under the alternative that high-skill buyers acquire low-skill targets, one might expect any changes to be concentrated in target funds.

We test this extended prediction and re-estimate our main specifications on changes in managerial specialization and changes in fund performance, testing for differences in these results for buyer- versus target-affiliated funds. We present the results in the Internet Appendix, Table IA.10. We indeed find that in

[15] This is also consistent with prior literature on sub-advising in asset management that has shown that asset management firms engage in sub-advisory relationship and hire unaffiliated portfolio managers in situations when the firm lacks specific investment expertise (Massa and Schumacher (2020)). Put simply, if lack of expertise is an issue for an asset management firm, there may be cheaper ways to obtain it than acquisitions: the firm can hire a sub-advisor or specific fund managers.

$Large\Delta_d = 1$ deals, changes in managerial specialization and improvements in fund performance are indeed symmetric across buyer- and target-funds with no statistical difference detectable between them. In the remaining sample of $Large\Delta_d = 0$ deals, we find that managers of neither fund type register a change in managerial specialization. However, when we examine changes in fund performance, we do observe that target fund performance improves in the post-merger periods. However, buyer fund performance marginally deteriorates, explaining the overall insignificant or marginally negative result for this part of the sample in Table 6. At the same time, this result does render support for a Q-theory based alternative for the sample of mergers that do not lead a large change in firm size (and for which Table 1, Panel B does document difference in pre-merger average fund performance between buyer and target funds).

6.3 Spillover Effects within Firms

Asset management mergers could also give rise to spillover effects. For example, managers of buyer and target funds will have new opportunities to engage with each other and disseminate ideas. This could result in, e.g., improved fund performance. While certainly plausible, such a channel is unlikely to explain our results for several reasons: First, this alternative does not share our predictions on managerial task allocations, changes in portfolio policies, and performance improvement in managers' expertise areas. Second, if spillover effects were at play, we should expect some degree of portfolio convergence as managers begin implementing similar investment ideas. To test this, we use two measures of portfolio similarity (portfolio distance and portfolio overlap) to examine whether buyer- and target-affiliated funds start holding similar stocks after mergers. The results, reported in the Internet Appendix Table IA.11, indicate no evidence of portfolio convergence in mergers that lead to a large increase in firm size. Since performance improvement is primarily driven by such deals, especially within managers' expertise areas, we do not think such spillover effects can be a mechanism to explain our findings.

6.4 Additional Robustness Tests

Finally, we present a number of robustness tests for our main results in the Internet Appendix. In Table IA.12, we examine if there are any differences in how fund performance improves in single- versus team-managed funds. We conduct this test because results in Chen, Xie, and Zhou (2020) indicate that families resort to team management to help managers mitigate the challenges that can arise from "multi-tasking". However, we find no difference along this dimension: in $Large\Delta_d = 1$ deals, both single- and team-managed funds improve performance relative to control funds in the post-merger period. Since the possibility to assign managers to teams is already available before the merger, we expect families to take advantage of this lever as much as possible, leaving it unclear that the benefits of the merger will benefit single-managed funds more than team-managed ones (or vice versa). In Table IA.13, we conduct sub-sample analysis by excluding specific deal types from the analysis: in Panel A, we exclude mergers between stand-alone firms from our sample to understand if our results hold among mergers that involve conglomerate-affiliated firms. One might speculate that such deals are prone to possible conflicts of interests that may interfere with the human capital synergies we seek to identify. Panel B of the same table presents a related test where we exclude deals that involve a bank-affiliated firm as Ferreira, Matos, and Pires (2018) show how funds managed by bank-affiliated families are subject to such conflicts of interest. We find that our results hold in both sub-samples. In Panel C, we exclude funds affected by a high-profile deal in our sample, the BlackRock-BGI merger, to understand if this large deal has a disproportionate impact on our results. We again find that our results hold. Finally, in Table IA.14, we present robustness tests using alternative definitions of our $Large\Delta_d$ indicator as discussed in Section 2.2 and again find our results to be robust to these alternative specifications.

6 Concluding Remarks

We test the hypothesis that asset management mergers create scale economies because the combined firm has a better ability to assign fund managers to more specialized tasks which improves productivity. We find that managerial turnover increases significantly following the merger of two asset management firms and that managerial turnover serves to assign more managers to more specialized tasks, especially following mergers that lead to a large increase in firm size. The reallocation of human capital creates additional value of $54 million per year for the average merger but $104 million per year following mergers that lead to a large increase in firm size. Our results highlight the important role asset management firms play in the assignment of employees to specialized tasks, the firm's contribution to value creation that is associated with this, and therefore an important source of firm level economies of scale in asset management.

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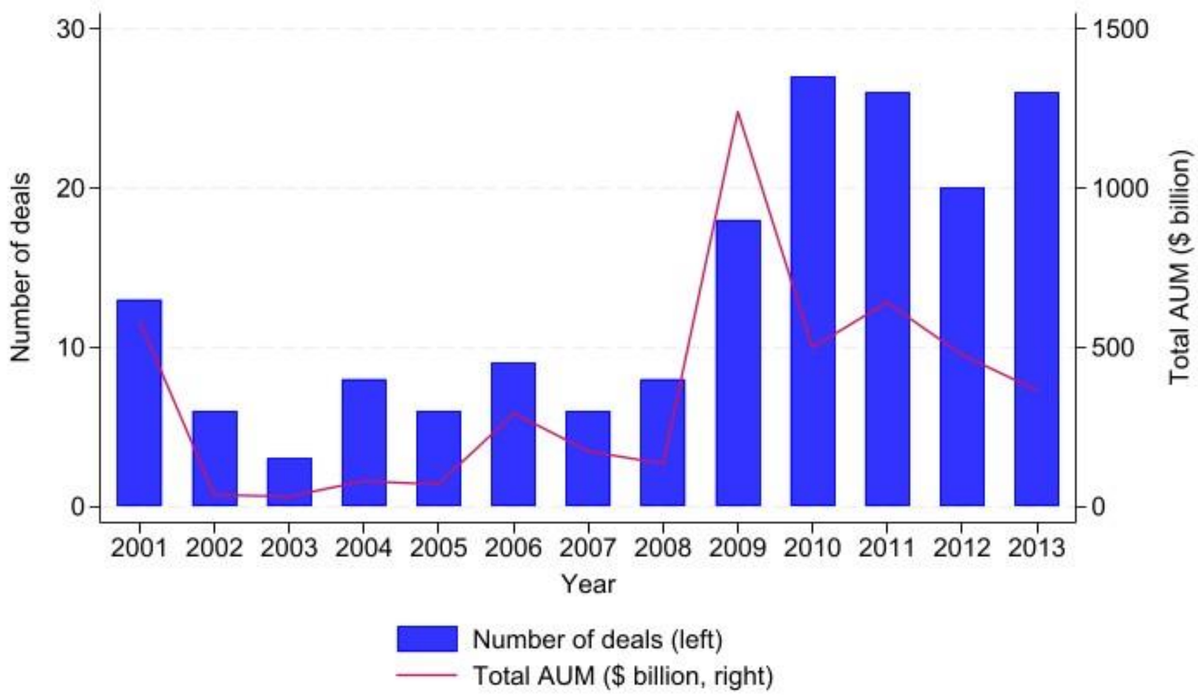
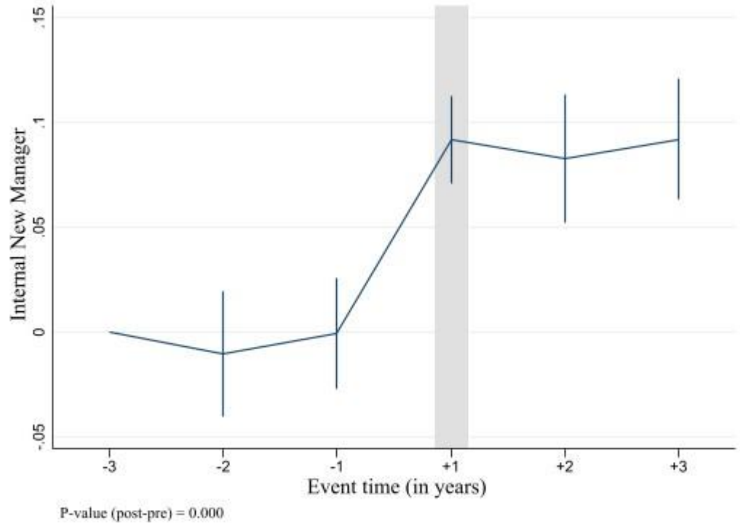
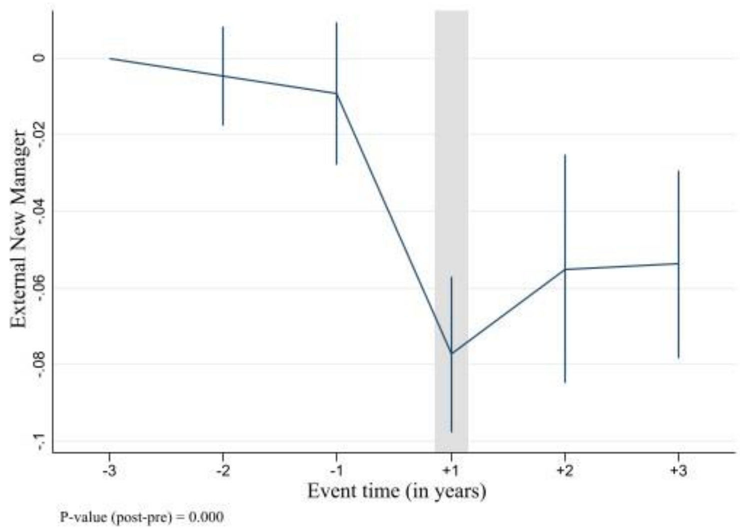


Figure 1: Deal volume over time

The figure reports the number of asset management merger deals in our sample, as well as total assets under management (in USD billion) across all deals for all sample years from 2001 to 2013.



Panel A: Managerial rotations – internal fund managers



Panel B: Managerial rotations – external fund managers

Figure 2: Managerial rotations of internal and external fund managers

The figure plots the differences in managerial rotations between treated and control funds around asset management mergers. In Panel A (Panel B), we regress $InternalNewManager$ ($ExternalNewManager$) on event year indicators, their interaction terms with the $Treat$ indicator, control variables, as well as deal $\times$ pair $\times$ fund and deal $\times$ pair $\times$ time fixed effects. The corresponding 95% confidence intervals are based on standard errors that are double clustered at the deal and time level. The grey bar indicates the first year after the deal completion date.

Table 1: Sample characteristics

Panels A and B report descriptive statistics at the firm level. In Panel A, the sample in column 1 includes the 135 mergers between asset management firms worldwide for which we have full holdings information. Columns 2 and 3 split the sample into mergers that lead to a large increase in firm size ($Large\Delta_d = 1$) and those that do not ($Large\Delta_d = 0$). We define $Large\Delta_d$ as an indicator equal to 1 for deals that lead to an above-average increase in the number of individual fund managers and 0 otherwise. Column 4 reports descriptive statistics for the overall FactSet sample for comparison. Panel B reports the firm level descriptive statistics reported in columns 2 and 3 of panel A separately for buyer and target firms in each merger including a t-test for the difference in each characteristic for buyer and target firms. Panel C reports descriptive statistics for fund level variables. All variables are defined in detail in the Appendix.

Panel A: Firm level characteristics

	Merger sample	$\boldsymbol{Large\Delta_d = 1}$	$\boldsymbol{Large\Delta_d = 0}$	**FactSet sample**
	(1)	(2)	(3)	(4)
Number of managers	16.63	11.11	19.11	13.21
Number of styles	6.08	4.94	6.60	4.96
Number of funds	14.50	10.29	16.38	10.81
Total net assets ($ billion)	7.86	4.02	9.58	8.48

Panel B: Firm level characteristics – decomposition into buyer and target firms

	$\boldsymbol{Large\Delta_d = 1}$				$\boldsymbol{Large\Delta_d = 0}$			
	Buyer	**Target**	**Diff.**	**t-stat**	**Buyer**	**Target**	**Diff.**	**t-stat**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of managers	10.70	11.48	-0.78	(-0.26)	27.40	5.39	22.01	(6.92)
Number of styles	5.04	4.86	0.18	(0.19)	8.86	2.85	6.01	(7.61)
Number of funds	10.44	10.16	0.29	(0.11)	23.40	4.78	18.61	(6.02)
Total net assets ($ billion)	4.85	3.26	1.59	(1.13)	14.26	1.83	12.43	(5.35)
Avg. Past return (annualized, %)	7.80	6.33	1.46	(0.85)	8.07	4.69	3.38	(2.53)
Cross-fund STD (%)	4.69	4.38	0.31	(0.58)	4.94	4.75	0.19	(0.49)

Panel C: Fund level characteristics

	Mean	**Std. dev.**	**5 pct.**	**25 pct.**	**Median**	**75 pct.**	**95 pct.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm size ($ billion)	15.96	19.78	0.19	2.00	8.11	21.82	59.65
Fund size ($ million)	500.16	1,353.01	5.95	36.96	121.42	397.56	2,044.01
Expenses (annualized, %)	1.54	0.49	0.79	1.24	1.50	1.79	2.42
Volatility (annualized, %)	19.40	9.13	7.55	12.41	17.99	24.41	36.88
Age (years)	13.11	10.73	2.25	6.00	10.75	16.67	33.00
Past return (annualized, %)	9.09	26.55	-42.62	-6.80	13.39	27.33	46.08
Number of managers	2.06	1.76	1.00	1.00	2.00	2.00	5.00

Table 2: Observable fund characteristics for treatment and control samples

The table reports the main fund level characteristics between the treated control samples 1 year prior to the merger completion date. Columns 1 to 4 report these statistics for sample where the control group is obtained from matching funds, columns 5 to 8 report the same statistics for the sample where control funds are drawn from withdrawn asset management merger. The table reports average characteristics of the sampled treated and control funds as well as the difference (including a t-test) between the two. All variables are defined in detail in the Appendix.

Control sample from:	**Matching funds**				**Withdrawn deals**			
	Treat	**Control**	**Diff.**	**t-stat**	**Treat**	**Control**	**Diff.**	**t-stat**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund performance measures								
Net-of-style returns (%)	0.07	0.02	0.05	(0.34)	-0.55	0.84	-1.40	(-1.97)
CAPM 1F alpha (%)	0.49	0.40	0.09	(0.24)	0.36	1.50	-1.14	(-1.88)
FFC 4F alpha (%)	0.42	0.43	-0.01	(-0.04)	-0.67	1.15	-1.81	(-3.09)
Market-bm Adj. returns (%)	0.81	0.62	0.19	(0.47)	1.46	1.59	-0.13	(-0.22)
DGTW-bm. Adj. returns (%)	0.63	0.54	0.10	(0.34)	0.51	0.84	-0.33	(-0.50)
ETF-bm. Adj. returns (%)	0.46	0.41	0.05	(0.19)	1.09	0.37	0.72	(1.36)
Value added based on ETF-bm. Adj. returns ($ million)	1.32	0.90	0.42	(0.56)	1.37	1.61	-0.25	(-0.22)
Fund controls								
Firm size (Log, $billion)	1.23	1.00	0.23	(1.27)	-0.62	0.48	-1.10	(-1.70)
Fund size (Log, $million)	4.56	4.48	0.09	(0.64)	4.52	4.57	-0.05	(-0.27)
Expenses (annualized, %)	1.54	1.47	0.07	(1.40)	1.46	1.59	-0.13	(-1.53)
Volatility (annualized, %)	22.02	21.91	0.11	(0.10)	20.39	26.35	-5.97	(-2.79)
Past return (annualized, %)	3.91	3.29	0.62	(0.45)	12.50	7.49	5.01	(1.82)

Table 3: Fund manager rotations

The table reports the estimates of Equation (1). The dependent variables include measures for different managerial rotation events for fund f in treatment-control pair p in merger deal d in the half-year t. In columns 1, the dependent variable is $NewManager_{dpft}$, an indicator equal to 1 if a new manager appears in the management team of the fund and 0 otherwise. In column 2, $ExternalNewManager_{dpft}$ is an indicator equal to 1 if a new manager that did not previously manage a fund in the buyer or target firm in deal d appears in the management team of the fund and 0 otherwise (i.e., if a new manager is an "external hire"). In columns 3 and 4, $InternalNewManager_{dpft}$ is an indicator equal to 1 if a new manager that previously managed a fund in the buyer or target firm in deal d appears in the management team of the fund and 0 otherwise (i.e., if a new manager is an "internal hire" of an existing fund manager). $Treat_{dpf}$ is an indicator equal to 1 if fund f in the treatment-control pair p in deal d is a treated fund (i.e., a fund of the buyer or target firm) and 0 if it is the sampled control fund. $Post_{dt}$ is an indicator equal to 1 for all half-year periods following (and including) the deal completion date and 0 otherwise. In columns 1 to 3, the treatment sample includes all funds in our merger sample, and the control sample includes the corresponding matching funds. In column 4, the control sample includes funds in withdrawn deals, and the treatment sample includes funds in matched completed deals. For each withdrawn deal, we select the closest completed deal in terms of relative size ratio which is completed within one year around the withdrawn date. In all specifications, x_{ft-1} is a vector of fund level control variables ($Firm\ size$, $Fund\ size$, $Expenses$, $Volatility$, and $Past\ return$). α_{dpt} and α_{dpf} denote deal × pair × time and deal × pair × fund fixed effects respectively. The estimation uses a 6-year event window, centered on the semi-annual period in which deal d completes. t-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Control funds from:		**Matching funds**		**Withdrawn deals**
Dep. Var.: $New\ Manager$	**All**	**External**	**Internal**	**Internal**
	(1)	(2)	(3)	(4)
$Treat \times Post$	0.034***	-0.062***	0.093***	0.144***
	(3.47)	(-7.60)	(11.91)	(8.65)
$Firm\ size$	-0.001	-0.001	0.001	0.007*
	(-0.35)	(-0.53)	(0.62)	(2.35)
$Fund\ size$	-0.010	-0.004	-0.009*	0.025*
	(-1.49)	(-0.86)	(-1.92)	(2.23)
$Expenses$	-0.006	0.019	-0.031	-0.013
	(-0.21)	(1.15)	(-1.42)	(-0.20)
$Volatility$	-0.118	-0.024	-0.142	-0.325
	(-0.80)	(-0.30)	(-1.34)	(-1.77)
$Past\ return$	-0.156**	-0.054	-0.082*	0.004
	(-2.28)	(-1.18)	(-1.79)	(0.04)
Deal × pair × fund F.E.	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y
R^2	0.589	0.598	0.582	0.236
N	33,848	33,848	33,848	1,791

Table 4: Fund manager rotations - across and within deal heterogeneity

The table reports augmented estimates from the specifications of Table 3. In column 1, we examine cross-sectional differences in managerial rotation volumes across merger types. We differentiate between mergers that lead to a large increase in the combined firm size and those that do not. We define $Large\Delta_d$ as an indicator equal to 1 for deals that lead to an above-average increase in the number of individual fund managers and 0 otherwise. The increase in the number of fund managers for the combined firm relative to the stand-alone buyer firm is simply the number of fund managers in the target firm prior to the merger divided by the sum of combined buyer and target fund managers. The estimates in column 1 augment the specification from Table 3 with a triple interaction term $Treat_{fpt} \times Post_{dt} \times Large\Delta_d$ (all other interaction and level terms are absorbed by the fixed effects). Columns 2 and 3 augment the same specification but focus on within-deal variation in managerial rotation volumes across funds in the same merger deal. We define an indicator $Generalist_{dp}$ equal to 1 if over the year prior to the deal, the management of treated funds in the pair p in the deal d includes only "generalist" fund managers who manage funds in more than 1 Morningstar investment objective and 0 otherwise. We examine these within-deals differences separately for mergers that lead to a large increase in firm size (column 2) and other mergers (column 3). In both columns, we augment the regression from Table 3 with the triple interaction term $Treat_{dpf} \times Post_{dt} \times Generalist_{dp}$ (all other interaction and level terms are again absorbed by the fixed effects). All the other specification are unchanged. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Sample:	**Full sample**	$\boldsymbol{Large\Delta = 1}$	$\boldsymbol{Large\Delta = 0}$
Dep. Var.:		$\boldsymbol{NewManager}$	
	(1)	(2)	(3)
$Treat \times Post \times Large\Delta$	-0.006		
	(-0.21)		
$Treat \times Post \times Generalist$		0.088**	-0.013
		(2.43)	(-0.80)
$Treat \times Post$	0.036***	-0.021	0.043***
	(4.08)	(-0.57)	(2.87)
Fund controls	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y
R^2	0.589	0.592	0.587
N	33,848	7,656	25,454

Table 5: Changes in managerial specialization

The table examines changes in task specialization at the individual fund manager level following Equation (2). The sample includes all fund managers of treated funds as well as the fund managers from the respective control funds and the sample window is defined analogously to Table 3, i.e., we include a 6-year sample window centered on the semi-annual period in which merger d completes. The dependent variable measures various dimensions of the overall task. Columns 1 to 4, the dependent variable measures the degree of task specialization for each manager. In column 1, it is Log($\# \; of \; styles$), the natural logarithm of the number of different investment objectives in which manager m is managing funds in period t. In column 2, $Concentration_{mt}$ is a Herfindahl-Hirschman-Index over the number of funds in a given investment objective divided by the total number of funds manager m manages in period t. Column 3 (4) uses the logarithm of one plus the number of added (removed) investment styles relative to the previous period. In columns 5 and 6, the dependent variable measures the overall workload for each manager. In column 5, it is the logarithm of total AUM overseen by manager m in period t. In column 5, we define the logarithm of total AUM per capita overseen by manager m in period t. The difference between the dependent variables in columns 5 and 6 is that in column 6, for team-managed funds, we pro-rate a fund's AUM to each manager whereas in column 5, we attribute the full fund AUM to every manager. x_{mt-1} is a vector of manager control variables, it contains the same set of control variables as in the fund level regressions but averaged across all funds managed by manager m (i.e., the manager level average of $Fund\ Size$, $Expenses$, $Volatility$, and $Past\ Return$ as well as $Firm\ Size$). All variables are defined in the Appendix. t-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Task Specialization				Workload	
Dep. Var.:	**Log (# of styles)**	**Conc.**	**Log (# of removed styles)**	**Log (# of added styles)**	**Log (AUM)**	**Log (AUM per capita)**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	-0.073***	0.036**	0.022*	0.002	-0.019	0.032
	(-2.79)	(2.35)	(1.79)	(0.17)	(-0.22)	(0.44)
$Treat \times Post$	-0.016	0.004	-0.001	0.012	0.020	-0.004
	(-0.95)	(0.43)	(-0.19)	(1.52)	(0.48)	(-0.10)
Manager controls	Y	Y	Y	Y	Y	Y
Deal × manager F.E.	Y	Y	Y	Y	Y	Y
Deal × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.915	0.890	0.246	0.266	0.941	0.929
N	58,691	58,691	58,691	56,493	58,691	58,691

Table 6: Changes in fund performance

The table examines changes in fund performance across merger types. The specification is as in Table 4, column 1 but the dependent variables include different measures of risk-adjusted fund performance. Columns 1 to 3 use style- or factor-adjusted fund returns whereas columns 4 to 6 use different holdings-based measures of fund performance. Specifically, column 1 uses net of style returns of fund f over half-year period t, columns 2 and 3 use semi-annual alpha from a CAPM regression or from an FFC-4F regression respectively, column 4 uses market-adjusted holding returns, column 5 uses characteristics-adjusted holding returns, and column 6 uses ETF benchmark-adjusted holding returns. All other specifications are unchanged. t-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Fund Returns			**Holding Returns**		
Dep. Var.:	**Net-of-style**	**CAPM 1F**	**FFC 4F**	**Market-adj**	**DGTW-adj.**	**ETF-adj.**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.008***	0.009***	0.008***	0.008**	0.007**	0.008**
	(3.59)	(3.72)	(3.33)	(2.71)	(2.45)	(2.43)
$Treat \times Post$	-0.003*	-0.003**	-0.002	-0.002	-0.001	-0.001
	(-1.78)	(-2.30)	(-1.32)	(-1.03)	(-0.90)	(-0.59)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.738	0.850	0.827	0.857	0.826	0.807
N	42,910	39,114	39,114	42,012	41,522	39,192

Table 7: Changes in fund performance – within-deal tests for "generalist" funds

The table augments the performance tests from Table 6 and examines within-deal heterogeneity in changes in fund performance. Specifically, we implement the same test as in Table 4, columns 2 and 3 to test for differential changes in fund performance for "generalist" funds that have only generalist managers on the management team during the 1-year pre-merger periods versus funds with "specialist" managers. Column 1 reports the estimates for the sample of mergers that lead to a large increase in firm size and column 2 for the rest of the sample. The dependent variable is the ETF benchmark-adjusted holding returns of fund f in period t. All other specifications are unchanged. t-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Sample:	$\boldsymbol{Large\Delta_d = 1}$	$\boldsymbol{Large\Delta_d = 0}$
Dep. Var.:	**ETF-adj. Holding Returns**	
	(1)	(2)
$Treat \times Post \times Generalist$	0.008**	0.002
	(2.74)	(0.86)
$Treat \times Post$	0.003	-0.002
	(0.98)	(-1.17)
Fund controls	Y	Y
Deal × pair × fund F.E.	Y	Y
Deal × pair × time F.E.	Y	Y
R^2	0.795	0.818
N	7,862	26,234

Table 8: Changes in value added around mergers

This table reports average deal-level and fund-level value added before fees (USD $million, per semi-annual period) around mergers. In every period, we aggregate the value added across all funds, divide by either the number of deals or the number of funds and report the average value added across all pre- or post-merger periods. *t*-statistics are reported in brackets. In rows 2 and 3, we perform these calculations separately for funds in $Large\Delta_d = 1$ and $Large\Delta_d = 0$ mergers. In rows 4 and 5, we perform these calculations separately for "generalist" and "specialist" funds. In columns 6 to 9, we perform these calculations for "generalist" and "specialist" funds in $Large\Delta_d = 1$ and $Large\Delta_d = 0$ mergers.

			Deal-level		**Fund-level**
		Pre-merger	**Post-merger**	**Post – Pre**	**Post – Pre**
		(1)	(2)	(3)	(4)
(1)	Full sample	8.880	35.996***	27.116*	0.979
		(0.93)	(3.29)	(1.87)	(1.76)
(2)	$Large\Delta = 1$	-7.301	44.953**	52.254**	2.241**
		(-0.95)	(2.55)	(2.72)	(2.75)
(3)	$Large\Delta = 0$	15.424	33.318***	17.894	0.622
		(1.21)	(3.27)	(1.10)	(1.07)
(4)	"Generalist" Funds	3.310	23.873***	20.563**	1.743**
		(0.50)	(4.06)	(2.32)	(2.46)
(5)	"Specialist" Funds	9.039	15.449**	6.410	0.790
		(1.49)	(2.85)	(0.79)	(0.94)
(6)	"Generalist" Funds in $Large\Delta = 1$	-6.641***	25.207***	31.848***	3.641***
		(-3.34)	(4.21)	(5.05)	(5.30)
(7)	"Generalist" Funds in $Large\Delta = 0$	7.817	23.683***	15.865	1.244
		(0.83)	(3.50)	(1.37)	(1.56)
(8)	"Specialist" Funds in $Large\Delta = 1$	2.736	15.442	12.706	1.522
		(0.27)	(1.58)	(0.91)	(0.90)
(9)	"Specialist" Funds in $Large\Delta = 0$	11.598*	15.490***	3.892	0.565
		(1.83)	(3.66)	(0.51)	(0.77)

Table 9: Fund portfolio policies and performance in manager expertise vs non-expertise areas

The table examines portfolio policies and performance in manager expertise areas and non-expertise areas. In Panel A, the dependent variables include measures of portfolio activeness (Active Share), concentration (ICI), or differentiation (Distance to Peers), computed separately for each managers expertise and non-expertise areas. Expertise areas are inferred from the full history of each manager's lifetime holdings and defined as the top 25% of country-industries in which the manager has generated the highest value added over her entire career path. Full definitions are provided in Section 5 and the Appendix. In Panel B, we decompose the results on overall performance improvements of Table 6, columns 4 to 6 into performance improvements in the same expertise versus non-expertise areas. All other specifications are unchanged. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Portfolio policies

Dep. Var.:	Expertise Areas			Non-Expertise Areas		
	Active share	**ICI**	**Distance to Peers**	**Active share**	**ICI**	**Distance to Peers**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.019*	0.024***	0.020***	-0.003	-0.000	0.000
	(1.94)	(4.08)	(3.19)	(-0.64)	(-0.08)	(0.14)
$Treat \times Post$	-0.008	-0.004	-0.005	-0.004	-0.002	-0.001
	(-1.60)	(-0.82)	(-1.15)	(-0.83)	(-0.71)	(-0.66)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.895	0.872	0.846	0.966	0.914	0.921
N	33,794	36,142	36,142	34,082	36,202	36,202

Panel B: Fund performance

Dep. Var.:	Expertise Areas			Non-Expertise Areas		
	Market-adj	**DGTW-adj.**	**ETF-adj.**	**Market-adj**	**DGTW-adj.**	**ETF-adj.**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.011***	0.010**	0.014***	0.005	0.005	0.006
	(2.93)	(2.12)	(3.51)	(1.36)	(1.46)	(1.59)
$Treat \times Post$	-0.005*	-0.004	-0.004	0.001	0.001	0.002
	(-1.78)	(-1.68)	(-1.60)	(0.61)	(0.49)	(0.91)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.838	0.814	0.819	0.824	0.791	0.793
N	33,814	33,548	32,252	35,000	34,840	33,286

Table 10: Target matching

This table examines the matching of buyer on target firms along observable characteristics. We report estimates of Equation (4). The dependent variable $RealTarget_{dj}$ is an indicator equal to 1 if the given asset management firm j is a real target involved in merger d, and 0 if it is a hypothetical target firm. For each real target firm, we include the closest 10, 15, 20 and 25 matching hypothetical targets in each column that are close in terms of the pre-merger AUM and that have the same conglomerate status as the real target in the year prior to the deal completion date. $Distance_{d\leftrightarrow j}$ is a set of pair-wise variables between firm j and the buyer firm in the given deal d calculated one year prior to the merger. All variables are defined in the Appendix. x_j is a vector of target firm characteristics, i.e., the average value of fund-level controls used throughout. α_d denotes deal fixed effects. In all specifications, t-statistics are based on standard errors clustered by deal and time. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Closest X matching targets	$\boldsymbol{X = 10}$	$\boldsymbol{X = 15}$	$\boldsymbol{X = 20}$	$\boldsymbol{X = 25}$
	(1)	(2)	(3)	(4)
$Different\ distribution$	-0.111***	-0.090***	-0.074***	-0.062***
	(-3.34)	(-4.06)	(-4.07)	(-4.21)
$Style\ distance$	-0.184***	-0.140***	-0.124***	-0.103***
	(-3.12)	(-3.31)	(-3.61)	(-3.79)
$Size\ difference$	-0.142	-0.120*	-0.090*	-0.080**
	(-1.37)	(-2.04)	(-1.90)	(-2.20)
$Geographical\ distance$	-0.021***	-0.015***	-0.013***	-0.011***
	(-4.58)	(-3.96)	(-3.99)	(-3.87)
$Different\ language$	-0.123***	-0.090***	-0.065***	-0.054***
	(-4.58)	(-4.02)	(-3.62)	(-3.73)
$Performance\ difference$	0.286	0.091	0.067	0.047
	(1.08)	(0.59)	(0.57)	(0.42)
Target controls	Y	Y	Y	Y
Deal F.E.	Y	Y	Y	Y
R^2	0.280	0.215	0.177	0.148
N	900	1,296	1,716	2,109

Appendix: Variable Description

Variable	Definition
Fund management characteristics	
$NewManager$	Indicator variable equal to 1 if at least 1 new manager joins the fund during the period, and 0 otherwise.
$InternalNewManager$	Indicator variable equal to 1 if at least 1 new manager who already managed at least 1 other fund in the buyer or target firm prior to the merger joins the fund during the period, and 0 otherwise
$ExternalNewManager$	Indicator variable equal to 1 if at least 1 new manager who did not already manage another fund in the buyer or target firm prior to the merger joins the fund during the period, and 0 otherwise
$Generalist$	Indicator equal to 1 if the management of the fund includes only generalist managers that manage funds in more than 1 Morningstar investment objective over the year prior to the deal and 0 otherwise.
Fund performance measures	
$Net\text{-}of\text{-}style\ returns$	Calculated as the fund's monthly gross return minus the average gross return of funds belonging to the same investment objective. We compound the monthly net-of-style returns to obtain semi-annual $Net\text{-}of\text{-}style\ returns$.
$CAPM\ alpha$	Market-adjusted excess fund returns. Returns are risk-adjusted with respect to a style-specific market factor which is a market capitalization weighted average of country-specific market factors. Country-specific market factors are based on the entire universe of firms in Worldscope for a particular country. The average is taken over all countries in the investment style set of fund j. The variable is then calculated by first regressing (-37 to -1)-month excess fund returns on the style-specific market-factor to estimate factor loadings and second by computing the difference between period t excess fund returns and predicted excess fund returns using the estimated loadings. At least 24 fund return observations are required. Monthly alphas are compounded to obtain semi-annual $CAPM\ alpha$.
$FFC4F\ alpha$	Same as $CAPM\ alpha$ but returns are risk-adjusted with respect to a style-specific four factor model that includes a market, size, value, and momentum factor. Each factor is a market capitalization weighted average of country-specific risk factors. Country-specific risk factors are constructed following the methodologies of Fama and French (1993) and Carhart (1997) and are based on the entire universe of firms in Worldscope. The average is taken over all countries in the investment opportunity set of the fund as defined by its investment style.
$Mkt\text{-}adj.return$	Defined as the raw holdings return minus the benchmark return where the benchmark portfolio includes all stocks from countries that form part of the Morningstar investment objective of the fund. The list of countries of each investment objective is inferred from the aggregate holdings of all funds with the same investment objective and includes all countries that cover at least 90% of the investment AUM of all funds with the same investment objective.
$DGTW\text{-}adj.return$	Defined as the raw holdings return minus the benchmark return where the benchmark portfolio is a size-value-momentum benchmark in the spirit of Daniel et al. (1997), constructed separately for each Morningstar investment objective (i.e., the benchmark portfolio is specific to the investment objective and constructed using the universe of stocks specific to each investment objective).
$ETF\text{-}benchmark\,adj.return$	Defined as the raw holdings return minus the benchmark return where the benchmark portfolio is constructed from the holdings of all physical-replication exchange traded funds (ETF) that track the same index to which fund f is benchmarked.
$Value\ added$	Calculated as the risk-adjusted holdings return multiplied by the fund's AUM (in USD million). The variable is winsorized at the 5% level (top and bottom 2.5%). To calculate after-fee value added, we subtract ½ of the annualized expenses from

	the risk-adjusted holdings return and then multiply by the fund's AUM (in USD million).
Fund characteristics	
$Fund\ size$	Natural logarithm of fund AUM (in USD million).
$Firm\ size$	Natural logarithm of the total AUM (in USD billion) of all funds managed by the fund's stand-alone management company, excluding fund f itself.
$Expenses$	Annual expense ratio as a percentage of AUM.
$Volatility$	Annualized standard deviation of fund returns over a trailing 12-month window.
$Past\ return$	Cumulative fund returns over a trailing 12-month window.
$Active\ Share$	The fund's active share as defined in Cremers and Petajisto (2009): stock-level benchmark weights for a fund in a given period are inferred from the aggregate portfolio of all physical replication ETFs in FactSet that track the same benchmark index as the fund.
ICI	The fund's industry concentration index from following Kacperczyk, Sialm, and Zheng (2005) computed as the Herfindahl-Hirschmann Index over country-industry portfolio weights.
$Distance\ to\ Peers$	A measure of portfolio "distance" between a given fund and its peers. It is calculated as: $\sum_c (w_{ict} - w_{ct})^2$ where w_{ict} is the portfolio weight in country-industry c of fund i that belongs to the investment style s, and w_{ct} is the value-weighted average portfolio weight in country-industry c of all active equity funds that belong to the same investment style at date t.
Deal characteristics	
$Large\Delta$	Indicator equal to 1 if the deal leads to an above-average increase in the number of fund managers, measured as the number of individual fund managers of the target firm over the sum of the number of fund managers of buyer and target firm combined, and 0 otherwise.
$Geographical\ distance$	Natural logarithm of the bilateral geographical distance between the country's capitals of the location countries of the buyer and target firms.
$Different\ distribution$	Indicator variable equal to 1 if the buyer and the target firms do not share countries in which their funds are available for sale and 0 otherwise.
$Different\ language$	Indicator variable equal to 1 if the countries where the buyer and the target firms are headquartered use different official languages, and 0 otherwise.
$Size\ difference$	Ratio of the absolute difference between the firm size of a target and buyer firm, over the total firm size of the two.
$Style\ distance$	A measure of investment style "distance" between the target and the buyer firm. It is calculated as: $\left[\sum_s (w_{ist} - w_{jst})^2\right]^{1/2}$, where w_{ist} and w_{jst} is the value-weighted average portfolio weight of all active equity funds in the investment style s of firm i and firm j at date t.
$Performance\ difference$	The absolute difference between the average market-adjusted holding returns of funds under a target and buyer firm.
$Headcount$	Natural logarithm of 1 plus the number of unique individual fund managers.
$Cross\text{-}fund\ STD$ (%)	The cross-fund standard deviation of 4-factor alphas of all active equity funds within a firm in the spirit of Nanda, Wang, and Zheng (2004).
Manager characteristics	
Log($\#\ of\ styles$)	Natural logarithm of the number of distinct Morningstar investment objectives in which manager m is managing in period t.
Log($\#\ of\ removed\ styles$)	Natural logarithm of one plus the number of removed Morningstar investment objectives for manager m in period t relative to period *t-1*.
Log($\#\ of\ added\ styles$)	Natural logarithm of one plus the number of newly added Morningstar investment objectives for manager m in period t relative to period *t-1*.
$Concentration$	Herfindahl-Hirschman-Index over share of funds of manager m in period t across different investment objectives.

Log(AUM)	Natural logarithm of total assets under management of manager m in period t.
Log(AUM per capita)	Same as Log (AUM) but in the case of team-managed funds, the AUM attributed to manager m is pro-rated equally across all managers.
Other variables	
$Post$	Indicator variable equal to 1 for the post-merger periods, and 0 otherwise.
$Treat$	Indicator variable equal to 1 for "treated funds", i.e., funds affected by a merger, and 0 for matched control funds.
$RealTarget$	Indicator variable equal to 1 if the given firm is a real target involved in mergers, and 0 if it is a matching firm.

Returns to Scale from Labor Specialization: Evidence from Asset Management Mergers

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Internet Appendix

(for online publication only)

This internet appendix presents additional tables to accompany the main manuscript.

- Table IA.1 presents additional summary statistics.
- Table IA.2 repeats Table 4 but decomposes the dependent variable into rotations of internal and external managers.
- Table IA.3 presents estimates of deal-level headcount changes.
- Table IA.4 presents estimates of the relationship between firm size and fund performance.
- Table IA.5 examines changes in benchmark timing around mergers.
- Table IA.6 presents multi-variate tests of changes in fund-level value added around mergers.
- Table IA.7 presents multi-variate tests of changes in deal-level value added around mergers.
- Table IA.8 tabulates changes in value-added after fees.
- Table IA.9 tabulates changes in risk adjusted returns.
- Table IA.10 examines changes in managerial specialization and fund performance for bidder versus target funds.
- Table IA.11 examines changes in portfolio distance between bidder and target funds.
- Table IA.12 examines changes in fund performance for single- versus team-managed funds.
- Table IA.13 presents sub-sample analysis by excluding certain deal types from the analysis.
- Table IA.14 presents robustness tests with alternative definitions of the $Large\Delta$ indicator.

Table IA.1: Summary statistics on sample distribution

Panel A reports the sample distribution by investment objectives and by fund countries. We aggregate the average fund TNA by each investment objective or by fund country and rank them in terms of the total fund TNA. We report the largest 25 investment objectives (columns 1 and 2) and the largest 25 fund countries (columns 3 and 4). Panel B reports the sample distribution by deal types as well as the percentage of $Large\Delta_d = 1$ deals by deal types.

Panel A: Sample distribution by investment objectives and fund countries

Top 25 investment objectives	Assets ($ bn)	Top 25 fund country	Assets ($ bn)
(1)	(2)	(3)	(4)
Global Equity Large Cap	163.03	United States	786.92
Emerging Markets Equity	139.87	United Kingdom	151.48
US Equity Large Cap Blend	135.68	Germany	100.75
US Equity Large Cap Growth	118.11	Canada	72.34
US Equity Large Cap Value	108.96	France	36.84
US Equity Mid Cap	99.34	Belgium	33.67
UK Equity Large Cap	66.53	Sweden	26.47
US Equity Small Cap	56.31	Australia	13.72
Europe Equity Large Cap	56.31	Italy	13.69
Global Equity	55.45	China	10.24
Other Europe Equity	47.30	Spain	9.27
Real Estate Sector Equity	18.94	Switzerland	7.05
Global Equity Mid/Small Cap	17.97	Singapore	3.59
UK Equity Mid/Small Cap	16.95	South Africa	2.24
Asia Ex-Japan Equity	15.91	Taiwan	1.71
Latin America Equity	15.28	Malaysia	1.12
Technology Sector Equity	10.81	Hong Kong	1.05
Greater China Equity	10.66	Finland	0.80
Utilities Sector Equity	8.65	Netherlands	0.67
Europe Equity Mid/Small Cap	7.92	Indonesia	0.59
Healthcare Sector Equity	7.68	Japan	0.57
Precious Metals Sector Equity	7.36	Denmark	0.55
Japan Equity	6.83	Thailand	0.21
Natural Resources Sector Equity	6.78	Ireland	0.09
Asia Equity	6.09	Andorra	0.06
Total	1,204.75		1,275.70

Table IA.1: Summary statistics on sample distribution – continued

Panel B: Sample distribution by deal type

Deal type	**Number of deals**	**% of deals**	**% of which are $Large\Delta_d = 1$ deals**
	(1)	(2)	(3)
Deals between stand-alone firms only	19	14%	26%
All other deals	116	86%	29%
Total	135	100%	28%

Table IA.2: Fund manager rotations - across and within deal heterogeneity: internal vs. external new managers

This table repeats Table 4 but uses $InternalNewManager$ and $ExternalNewManager$ as the dependent variables. All other specifications are unchanged. Standard errors are double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Sample:	**Full sample**	$\boldsymbol{Large\Delta = 1}$	$\boldsymbol{Large\Delta = 0}$	**Full sample**	$\boldsymbol{Large\Delta = 1}$	$\boldsymbol{Large\Delta = 0}$
Dep. Var.:	$\boldsymbol{InternalNewManager_{dfpt}}$			$\boldsymbol{ExternalNewManager_{dfpt}}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta_d$	0.000			-0.004		
	(0.01)			(-0.18)		
$Treat \times Post \times Generalist$		0.036**	-0.018**		0.053	0.011
		(2.52)	(-2.60)		(1.69)	(0.79)
$Treat \times Post$	0.093***	0.073***	0.104***	-0.061***	-0.096***	-0.068***
	(9.95)	(4.49)	(9.43)	(-9.27)	(-3.21)	(-6.67)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.582	0.572	0.584	0.598	0.598	0.596
N	33,848	7,656	25,454	33,848	7,656	25,454

Table IA.3: Deal level headcount changes around mergers

The table reports the estimates of Equation (3). The regression is performed at the deal level. In column 1, the dependent variable is the natural logarithm of 1 plus the number of unique fund managers in the buyer and target firm. In columns 2 and 3, it is the natural logarithm of 1 plus the number of unique internal or external fund managers in the buyer and target. The specifications include average fund controls across all funds of the buyer and target firms as well as deal and time fixed effects. Standard errors are double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Dep. Var.: Log(1 + # of Managers)	**All Managers**	**Internal Managers**	**External Managers**
	(1)	(2)	(3)
$Large\Delta_d \times Post$	-0.017	-0.015	0.042
	(-0.20)	(-0.19)	(0.32)
$Post$	-0.001	0.024	-0.019
	(-0.01)	(0.64)	(-0.25)
Average fund controls, deal and time F.E.	Y	Y	Y
R^2	0.926	0.926	0.867
N	1,304	1,304	1,304

Table IA.4: Relationship between firm size and fund performance

The table reports the estimates of:

$$R_{ft} = \alpha_t + \alpha_s + \beta_1 Firm\ size_{ft-1} + \beta_2 Fund\ size_{ft-1} + \mu' x_{ft-1} + \varepsilon_{ft}.$$

The dependent variable R_{ft} is the fund performance measure. It is the compounded net of style returns in column 1, compounded monthly CAPM alpha in column 2, compounded monthly Fama-French-Carhart 4 factor alpha in column 3, market-adjusted holdings return in column 4, the characteristics-adjusted holdings return in column 5, and the ETF benchmark-adjusted holdings return in column 6. x_{ft-1} includes other fund control variables ($Volatility$, $Expenses$ and $Past\ return$). The regressions are run at the semi-annual frequency for actively managed open-ended Equity funds. α_t and α_s denote time and investment style fixed effects respectively. t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Dep. Var.:	**Fund Returns**			**Holding Returns**		
	Net-of-style	**CAPM 1F**	**FFC 4F**	**Market-adj**	**DGTW-adj.**	**ETF-adj.**
	(1)	(2)	(3)	(4)	(5)	(6)
$Firm\ size$	0.075***	0.085***	0.074***	0.035***	0.021**	0.018
	(8.68)	(8.08)	(8.39)	(3.17)	(2.35)	(1.51)
$Fund\ size$	-0.040***	-0.052***	-0.021*	-0.097***	-0.056***	-0.126***
	(-3.97)	(-4.06)	(-1.89)	(-7.45)	(-5.34)	(-8.84)
$Expenses$	-0.137***	-0.180***	-0.121***	-0.182***	-0.085**	-0.147***
	(-3.91)	(-4.05)	(-3.12)	(-3.81)	(-2.10)	(-2.99)
$Volatility$	-3.045***	-8.262***	-4.493***	-3.269***	2.977***	-7.145***
	(-5.60)	(-14.86)	(-8.98)	(-4.58)	(5.44)	(-10.02)
$Past\ return$	1.465***	2.293***	0.357*	3.408***	2.406***	0.235
	(8.42)	(10.24)	(1.85)	(13.96)	(11.13)	(1.03)
Investment style and time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.010	0.091	0.063	0.071	0.051	0.080
N	108,639	97,455	97,455	100,015	98,411	100,015

Table IA.5: Changes in timing ability around mergers

The table repeats Table 4 but uses as dependent variable the fund-level benchmark timing measure of Daniel et al. (1997) with ETF benchmark returns. All other specifications are unchanged. Standard errors are double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Sample:	**Full Sample**	$\boldsymbol{Large\Delta_d = 1}$	$\boldsymbol{Large\Delta_d = 0}$
Dep. Var.:		**Benchmark Timing**	
	(1)	(2)	(3)
$Treat \times Post \times Large\Delta_d$	0.012		
	(0.62)		
$Treat \times Post \times Generalist$		-0.068	-0.014
		(-1.32)	(-0.67)
$Treat \times Post$	-0.006	0.047	0.001
	(-0.41)	(1.34)	(0.05)
Fund controls	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y
R^2	0.938	0.931	0.948
N	39,348	6,636	27,662

Table IA.6: Fund-level value added around mergers

The table repeats Table 6 but uses measures of fund-level value added as dependent variables. Value added is constructed by multiplying fund TNA with the corresponding fund benchmark-adjusted returns. All other specifications are unchanged. Standard errors are double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Dep. Var.: Value Added using	Fund Returns			Holding Returns		
	Net-of-style	CAPM 1F	FFC 4F	Market-adj	DGTW-adj.	ETF-adj.
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	1.643	3.083**	2.711**	2.904**	2.241**	1.569
	(1.62)	(2.39)	(2.26)	(2.58)	(2.77)	(1.47)
$Treat \times Post$	-0.253	-0.759	-0.351	-0.645	-0.483	0.407
	(-0.41)	(-1.00)	(-0.58)	(-0.80)	(-0.83)	(0.65)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.656	0.769	0.731	0.767	0.729	0.737
N	42,910	39,114	39,114	42,012	41,522	39,192

Table IA.7: Deal-level value added around mergers

The table reports the estimates of:

$$
\begin{aligned}
Value\ added_{dit} = {} & \alpha_{dt} + \alpha_{di} + \beta_1 Post_{dt} + \beta_2 Large\Delta_d + \beta_3 Treat_{di} + \beta_4 Treat_{di} \times Post_{dt} \\
& + \beta_5 Large\Delta_d \times Post_{dt} + \beta_6 + Large\Delta_d \times Treat_{di} + \beta_7 Treat_{di} \times Post_{dt} \times Large\Delta_d \\
& + \mu' x_{dit-1} + \varepsilon_{dit}
\end{aligned}
$$

The regression is estimated at the deal level. $Value\ added$ is the total value added of treatment group or control group $\boldsymbol{i}$ in deal $\boldsymbol{d}$ at time $\boldsymbol{t}$, i.e., the sum of fund-level value added of all treated or control funds. In all specifications, $\boldsymbol{x_{dit-1}}$ includes average control variables of treated and control funds. $\boldsymbol{\alpha_{dt}}$ denotes deal × time fixed effects and $\boldsymbol{\alpha_{di}}$ denotes deal × group fixed effects. t-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Dep. Var.: Value Added using	**Fund Returns**			**Holding Returns**		
	Net-of-style	**CAPM 1F**	**FFC 4F**	**Market-adj**	**DGTW-adj.**	**ETF-adj.**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	29.745**	28.930	31.264**	73.311***	44.933***	37.828*
	(2.13)	(1.52)	(2.46)	(3.43)	(5.37)	(1.76)
$Treat \times Post$	-8.716	-17.150	-13.721	-16.501	-12.435	11.626
	(-0.82)	(-1.08)	(-1.35)	(-1.22)	(-1.48)	(0.83)
Average fund controls	Y	Y	Y	Y	Y	Y
Deal × group F.E.	Y	Y	Y	Y	Y	Y
Deal × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.682	0.842	0.818	0.859	0.828	0.797
N	2,610	2,610	2,610	2,610	2,610	2,610

Table IA.8: Changes in after-fee value added around mergers

The table repeats Table 8 with after-fee value added.

			Deal-level		Fund-level
		Pre-merger	**Post-merger**	**Post – Pre**	**Post – Pre**
		(1)	(2)	(3)	(4)
(1)	Full sample	-44.969***	-25.541**	19.429	0.880
		(-3.97)	(-2.62)	(1.30)	(1.37)
(2)	$Large\Delta_d = 1$	-39.808***	-8.896	30.912*	1.714*
		(-5.03)	(-0.60)	(1.84)	(1.98)
(3)	$Large\Delta_d = 0$	-46.876***	-31.472***	15.404	0.632
		(-3.24)	(-3.56)	(0.91)	(0.92)
(4)	"Generalist" Funds	-31.075***	-13.940*	17.134*	1.340
		(-4.58)	(-2.16)	(1.83)	(1.74)
(5)	"Specialist" Funds	-16.839**	-9.255	7.584	0.665
		(-2.39)	(-1.76)	(0.86)	(0.72)
(6)	"Generalist" Funds in $Large\Delta_d = 1$	-25.275***	1.103	26.379***	2.967***
		(-9.47)	(0.22)	(4.61)	(4.63)
(7)	"Generalist" Funds in $Large\Delta_d = 0$	-33.393***	-20.082**	13.311	0.886
		(-3.62)	(-2.70)	(1.12)	(1.00)
(8)	"Specialist" Funds in $Large\Delta_d = 1$	-17.402	-8.273	9.129	0.864
		(-1.76)	(-0.84)	(0.65)	(0.51)
(9)	"Specialist" Funds in $Large\Delta_d = 0$	-16.468**	-9.649**	6.819	0.602
		(-2.20)	(-2.36)	(0.80)	(0.71)

Table IA.9: Changes in risk-adjusted returns around mergers

The table repeats Table 8 but reports average fund-level ETF-adjusted returns before fees per semi-annual period instead of value-added.

		Fund-level		
		Pre-merger	**Post-merger**	**Post – Pre**
		(1)	(2)	(3)
(1)	Full sample	0.001	0.002	0.001
		(0.73)	(1.57)	(0.67)
(2)	$Large\Delta = 1$	-0.001	0.005***	0.006**
		(-1.02)	(3.14)	(3.07)
(3)	$Large\Delta = 0$	0.002	0.002	0.000
		(0.92)	(0.97)	(0.00)
(4)	"Generalist" Funds	0.002	0.006***	0.004**
		(1.38)	(4.62)	(2.26)
(5)	"Specialist" Funds	0.002	0.003	0.001
		(0.92)	(1.57)	(0.42)
(6)	"Generalist" Funds in $Large\Delta = 1$	-0.000	0.011***	0.011***
		(-0.01)	(8.22)	(4.31)
(7)	"Generalist" Funds in $Large\Delta = 0$	0.002	0.005**	0.003
		(1.34)	(2.80)	(1.02)
(8)	"Specialist" Funds in $Large\Delta = 1$	-0.001	0.004	0.005
		(-0.41)	(1.53)	(1.20)
(9)	"Specialist" Funds in $Large\Delta = 0$	0.003	0.003	0.000
		(1.12)	(1.48)	(0.00)

Table IA.10: Changes in managerial specialization and fund performance: bidder vs target funds

The table examines changes in managerial specialization in Panel A and fund performance in Panel B for bidder versus target funds. The specifications are as in Tables 5 and 7 respectively but with an indicator for target funds instead of an indicator for "Generalist" funds. All other specifications are unchanged. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Changes in managerial specialization

Sample:	$\boldsymbol{Large\Delta_d = 1}$	$\boldsymbol{Large\Delta_d = 0}$
Dep. Var.:	**Log(# of styles)**	
	(1)	(2)
$Treat \times Post \times Target$	-0.017	-0.073
	(-0.56)	(-1.42)
$Treat \times Post$	-0.078***	-0.010
	(-3.00)	(-0.56)
Manager controls	Y	Y
Deal × manager F.E.	Y	Y
Deal × time F.E.	Y	Y
R^2	0.903	0.912
N	10,614	40,774

Panel B: Changes in fund performance

Sample:	$\boldsymbol{Large\Delta_d = 1}$	$\boldsymbol{Large\Delta_d = 0}$
Dep. Var.:	**ETF-adj. Holding Returns**	
	(1)	(2)
$Treat \times Post \times Target$	-0.001	0.015***
	(-0.25)	(3.62)
$Treat \times Post$	0.008**	-0.002
	(2.62)	(-1.52)
Fund controls	Y	Y
Deal × pair × fund F.E.	Y	Y
Deal × pair × time F.E.	Y	Y
R^2	0.796	0.810
N	8,830	30,362

Table IA.11: Fund portfolio similarity

The table examines portfolio distance and portfolio overlap to the average counterparty fund. All other specifications are unchanged. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Dep. Var.:	Portfolio Distance			Portfolio Overlap		
	All Areas	Expertise Area	Non-Expertise Area	All Areas	Expertise Area	Non-Expertise Area
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.005*	0.001	0.003	-0.004	-0.001	-0.002
	(1.71)	(0.41)	(1.54)	(-0.77)	(-0.47)	(-0.54)
$Treat \times Post$	-0.005**	-0.000	-0.003**	0.004**	0.001	0.002
	(-2.13)	(-0.20)	(-2.33)	(2.24)	(0.51)	(1.46)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.967	0.971	0.955	0.990	0.989	0.987
N	39,108	39,108	39,108	39,108	39,108	39,108

Table IA.12: Changes in fund performance: team-managed vs single-managed funds

The table examines changes in fund performance for team- versus single-managed funds. The specifications are as in Table 7 but with an indicator for single-managed funds instead of an indicator for "Generalist" funds. All other specifications are unchanged. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Sample:	$\boldsymbol{Large\Delta_d = 1}$	$\boldsymbol{Large\Delta_d = 0}$
Dep. Var.:	**ETF-adj. Holding Returns**	
	(1)	(2)
$Treat \times Post \times Single\ Managed$	-0.001	-0.000
	(-0.18)	(-0.11)
$Treat \times Post$	0.008**	-0.001
	(2.36)	(-0.30)
Fund controls	Y	Y
Deal × pair × fund F.E.	Y	Y
Deal × pair × time F.E.	Y	Y
R^2	0.796	0.810
N	8,830	30,362

Table IA.13: Changes in fund performance: sub-sample analysis

The table repeats Table 6 but focusses on subsamples. Panel A exclude deals between stand-alone firms. Panel B exclude deals in which either the target or the acquiror is affiliated with banks. Panel C excludes BlackRock-BGI merger. All other specifications are unchanged. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Exclude deals between stand-alone firms

Dep. Var.:	Fund Returns			Holding Returns		
	Net-of-style	CAPM 1F	FFC 4F	Market-adj	DGTW-adj.	ETF-adj.
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.008***	0.009***	0.008***	0.007**	0.006*	0.007*
	(3.11)	(3.30)	(2.95)	(2.23)	(2.04)	(1.97)
$Treat \times Post$	-0.002	-0.002*	-0.002	-0.001	-0.001	-0.000
	(-1.52)	(-1.87)	(-1.26)	(-0.66)	(-0.67)	(-0.24)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.740	0.851	0.828	0.860	0.826	0.808
N	39,182	35,690	35,690	38,434	38,038	35,774

Panel B: Exclude bank-affiliated deals

Dep. Var.:	Fund Returns			Holding Returns		
	Net-of-style	CAPM 1F	FFC 4F	Market-adj	DGTW-adj.	ETF-adj.
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.009**	0.009**	0.007	0.009**	0.008***	0.012***
	(2.48)	(2.32)	(1.67)	(2.39)	(2.80)	(3.01)
$Treat \times Post$	-0.002	-0.002	-0.001	-0.001	0.000	-0.000
	(-0.95)	(-0.73)	(-0.40)	(-0.22)	(0.17)	(-0.10)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.731	0.847	0.812	0.839	0.794	0.820
N	17,904	16,180	16,180	17,836	17,548	16,626

Table IA.13: Changes in fund performance: sub-sample analysis – continued

Panel C: Exclude Blackrock-BGI deal

Dep. Var.:	**Fund Returns**			**Holding Returns**		
	Net-of-style	**CAPM 1F**	**FFC 4F**	**Market-adj**	**DGTW-adj.**	**ETF-adj.**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.008***	0.008***	0.007***	0.007**	0.006**	0.008**
	(3.31)	(3.52)	(3.07)	(2.46)	(2.15)	(2.26)
$Treat \times Post$	-0.002	-0.002*	-0.001	-0.001	-0.001	-0.000
	(-1.49)	(-2.05)	(-0.96)	(-0.66)	(-0.55)	(-0.30)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.739	0.850	0.826	0.857	0.825	0.807
N	41,774	38,080	38,080	40,840	40,350	38,158

Table IA.14: Robustness Tests: Alternative definitions of $Large\Delta_d$

The table repeats our main results with alternative definitions of the $Large\Delta$ indicator: across panels, in columns 1 and 2, $Large\Delta$ is based on the absolute increase in firm size as measured by the size of the target firm alone, in columns 3 and 4, the indicator is defined on the relative increase in firm size as measured by both the number of individual fund managers and funds in the target firm relative to the total combined entity, and in column 5 and 6, the indicator is defined on the relative increase in firm size as measured by both the number of individual fund managers and styles in the target firm relative to the total combined entity. The different panels then repeat the main specifications of Tables 5, 6, and 7 respectively. *t*-statistics are based on standard errors double clustered by deal and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Changes in managerial specialization

$Large\Delta$ defined based on:	**Absolute target size only**		**Relative size based on # of managers and # of funds**		**Relative size based on # of managers and # of styles**	
Dep. Var.:	**Log (# of styles)**	**Conc.**	**Log (# of styles)**	**Conc.**	**Log (# of styles)**	**Conc.**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	-0.076***	0.033**	-0.063**	0.032**	-0.083***	0.043***
	(-2.97)	(2.28)	(-2.41)	(2.11)	(-3.33)	(2.87)
$Treat \times Post$	-0.003	-0.001	-0.021	0.006	-0.015	0.003
	(-0.16)	(-0.12)	(-1.18)	(0.66)	(-0.89)	(0.33)
Manager controls	Y	Y	Y	Y	Y	Y
Deal × manager F.E.	Y	Y	Y	Y	Y	Y
Deal × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.915	0.890	0.915	0.890	0.915	0.890
N	58,691	58,691	58,691	58,691	58,691	58,691

Panel B: Changes in fund performance

$Large\Delta$ defined based on:	**Absolute target size only**		**Relative size based on # of managers and # of funds**		**Relative size based on # of managers and # of styles**	
Dep. Var.:	**FFC 4F**	**ETF-adj. HR**	**FFC 4F**	**ETF-adj. HR**	**FFC 4F**	**ETF-adj. HR**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Large\Delta$	0.009***	0.009***	0.008***	0.007*	0.008***	0.007*
	(3.63)	(3.68)	(3.30)	(1.85)	(2.89)	(2.01)
$Treat \times Post$	-0.003**	-0.002	-0.001	-0.000	-0.001	-0.000
	(-2.20)	(-1.56)	(-1.33)	(-0.15)	(-1.16)	(-0.23)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.827	0.807	0.827	0.807	0.827	0.807
N	39,114	39,192	39,114	39,192	39,114	39,192

Table IA.14: Robustness Tests: Alternative definitions of $Large\Delta_d$ – continued

Panel C: Changes in fund performance – within-deal tests for "generalist" funds

$Large\Delta$ defined based on:	**Absolute target size only**		**Relative size based on # of managers and # of funds**		**Relative size based on # of managers and # of styles**	
Sample			**$Large\Delta_d = 1$**			
Dep. Var.:	**New Manager**	**ETF-adj. HR**	**New Manager**	**ETF-adj. HR**	**New Manager**	**ETF-adj. HR**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post \times Generalist$	0.044	0.004	0.087**	0.009**	0.091**	0.007**
	(1.56)	(1.63)	(2.25)	(2.70)	(2.29)	(2.32)
$Treat \times Post$	0.015	0.005*	-0.013	0.002	-0.018	0.002
	(0.47)	(1.91)	(-0.33)	(0.47)	(-0.48)	(0.71)
Fund controls	Y	Y	Y	Y	Y	Y
Deal × pair × fund F.E.	Y	Y	Y	Y	Y	Y
Deal × pair × time F.E.	Y	Y	Y	Y	Y	Y
R^2	0.583	0.814	0.585	0.814	0.588	0.803
N	12,976	13,282	6,658	6,644	7,148	7,252