The Value of Human Capital Synergies in M&A: Evidence from Global Asset Management

Mancy Luo
Erasmus University

Alberto Manconi
Bocconi University

David Schumacher*
McGill University

We use mergers in the global asset management industry to study the value of human capital synergies and to shed new light on the relationship between firm size and fund performance. We document significant changes in managerial turnover, portfolio differentiation, and fund performance in the post-merger period. The re-allocation of human capital following a merger creates $4.2 million additional value per year per fund. These synergies are strongest in mergers that increase the size and complementarity of human capital expertise, which leads to a better matching of human to investment capital. The added flexibility to create value via discretionary increases in the size and quality of internal labor markets appears to be a central benefit of asset management mergers.

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* Mancy Luo, Rotterdam School of Management, Erasmus University, Email: mancy.luo@rsm.nl, Alberto Manconi, Bocconi University, Email: alberto.manconi@unibocconi.it, corresponding author: David Schumacher, Desautels Faculty of Management, McGill University, Email: david.schumacher@mcgill.ca.

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The relationship between scale and performance is of central interest to our understanding of money management at least since the theoretical work of Berk and Green (2004) and the empirical study of Chen et al. (2004) who document a negative relationship between fund size and performance. So far, attention has focused primarily on the relationship between performance and *fund* size (e.g., Pollet and Wilson (2008), Elton, Gruber, and Blake (2012), Berk and van Binsbergen (2015), Reuter and Zitzewitz (2015) among others). However, the relationship between average performance and asset management *firm* size has received less attention.[1]

This is surprising not least because Chen et al. (2004) also document a positive relationship between family size and fund performance. This and two empirical observations motivate us to turn our attention to the role of firm size: First, a few large firms increasingly dominate the global asset management industry. Figure 1.A shows a large increase in the industry concentration at the firm level; the largest 1% firms manage 55% of the industry's total AUM by 2012, up from around 30% in the early 2000s. Second, the global asset management industry has been consolidating over the last years. Figure 1.B displays strong growth in the volume of M&A transactions between global asset management companies.

Therefore, we set out to shed new light on the possible economies of scale at the firm level by investigating mergers between asset management companies. We assemble what is to date, to the best of our knowledge, the most comprehensive sample of asset management mergers worldwide. Our sample spans mergers in the global asset management industry between 2001 and 2013. We identify 176 mergers between asset management firms across 50 different bidder and target countries, affecting a total of 8,524 distinct funds, or 4.6 trillion USD in assets under management (AUM).

Mergers between asset management companies offer a useful environment to learn more about potential economies of scale at the firm level as these mergers typically increase the size of the firm in a large and discrete manner. Indeed, our first results not only confirm a strong positive relationship between average

[1] Instead, the literature on fund families has focused more on performance differences within families (e.g., Gaspar, Massa, and Matos (2003), Kempf and Ruenzi (2008), Bhattacharya, Lee, and Pool (2013), Gonçalves-Pinto and Schmidt (2014), Chuprinin, Massa, and Schumacher (2015) among others). Recently, Pastor, Stambaugh, and Taylor (2015) have documented diseconomies of scale at the industry level.

fund performance and firm size in the global asset management industry overall but also show that average fund performance increases in the 3-year period following a merger – but only in mergers where the size of the firm increases significantly. In mergers where the target is small relative to the acquirer, we detect no changes in average fund performance.

We readily acknowledge that asset management mergers are not exogenous events. This complicates the attribution of these performance changes to the merger events. We confront this challenge and focus the analysis on the mechanisms and channels by which these performance improvements come about. Specifically, we use asset management mergers as a laboratory to perform a micro-level analysis of merger-related operating changes in mutual funds. In doing so, we follow the perspective of Berk, van Binsbergen, and Liu (2017, BBL hereafter), and view an asset management company as a collection of mutual funds that form the "establishments" of the firm.[2] For each establishment, we analyze the "production process" (i.e., portfolio holdings) throughout the merger, and how changes in the production process impact operating performance (i.e., returns on portfolio holdings).

Throughout the analysis, we take advantage of a central feature of the global asset management industry: its reliance on human capital as by far its most important production input. BBL argue that fund families add significant value by allocating the human to the investment capital of the firm. Indeed, asset management firms are unique in that they generally do not own the capital they manage. Instead, their key production input is the human capital they employ to invest the financial capital entrusted to them by outside investors. BBL argue that this makes the asset management industry an ideal setting to study the firm's role in human capital allocation.

Translating this reasoning to our setting suggests that the performance improvements following a merger relate to changes in human capital and / or the ability to better allocate human capital in a larger firm. Consistent with this view, when we replace the standard measure of firm size (defined by AUM) with the

[2] In other words, we think of the asset management company as a collection of establishments. Each establishment produces one "product" (the specific mutual fund). As such, depending on the context, we use the words "establishment" and "product" interchangeably.

number of individual fund managers, we find that fund performance improves the most after mergers where the number of individual fund managers grows the most. Indeed, the change in individual fund managers wins a horse race against the change in AUM in a joint specification, suggesting that changes in fund performance relate more directly to changes in human capital.

To substantiate this claim, we examine the impact of the merger on the internal labor markets by investigating managerial turnover in the post-merger period. We find that fund manager rotations increase by almost 20% following the merger. The increase in managerial rotation intensity is driven primarily by an increase in the reallocation of “internal managers”, i.e., managers that used to work for the bidder or target prior to the merger. Further, rotation intensity is much higher among “generalist” fund managers, which we define as fund managers that have managed funds in different investment objectives in their career. In those cases, managerial rotations increase by over 30% in the post-merger period. In fact, while generalists are more likely to leave a given fund, they do not necessarily join another fund in the new entity. Instead, they are more likely to leave the firm, suggesting that the combined entity gravitates towards more specialization and differentiation, at least in terms of human capital.

Why would the combined entity gravitate towards more specialization and / or differentiation? First, prior literature on mutual fund performance indicates that various dimensions of product differentiation and specialization are associated with superior fund performance (e.g., Kacperczyck, Sialm, and Zheng (2004), Brands, Brown, and Gallagher (2004), Cremers and Petajisto (2009), Amihud and Goyenko (2013), Schumacher (2018), among others). Second, the results in Pollet and Wilson (2008) indicate that family growth is associated with product differentiation. Third, prior literature on mergers and acquisitions emphasizes the importance of asset complementarities for the creation of merger synergies (Rhodes-Kropf and Robinson (2008)) and empirical evidence links asset complementarities to product improvements and differentiation in the post-merger period (Hoberg and Phillips (2010)).[3] As such, we hypothesize that asset

[3] We confirm in additional results that the average merger in our sample likely exhibits asset complementarities and that the “like-buys-like” argument of Rhodes-Kropf and Robinson (2008) provides a good description of the matching between bidder and target asset managers.

management mergers create additional value via discretionary increases in the size and quality of internal labor markets that allow for a better matching of human to investment capital. As a result, fund managers can afford (or are encouraged to engage in) a higher level of portfolio differentiation, which leads to better performance. Our remaining tests aim to evaluate this hypothesis.

First, we find that mergers have a significant impact on the production processes (i.e., portfolio holdings) of affected funds. Following the merger, funds scale down their portfolio holdings in their "core" areas (i.e., investment areas where funds of the firm used to invest heavily prior to the merger) in order to increase holdings in "non-core" areas. While bidder funds start investing in the core areas of the target and vice versa to some extent, we find the quantitatively strongest portfolio reallocations towards investment areas that are completely new to both bidder and target funds. For example, within three years following the completion of the merger, the average fund allocates about 14% of its portfolio away from core and towards new investment areas.[4] We also find that funds shift their active share (Cremers and Petajisto (2009)) from previously core investment areas, where they become more "passive," to non-core investment areas, where they become more "active." Finally, funds realize the highest risk-adjusted performance in those non-core areas: while funds deliver similar performance in core and non-core areas prior to the merger, investments in non-core areas outperform those in core areas after the merger by up to 2% per year in risk-adjusted terms.

Second, we document positive relationships between managerial turnover, portfolio rebalancing, and performance in non-core investment areas: funds with a new manager allocate substantially more AUM to those areas compared to funds that do not experience a managerial rotation in the post-merger period. Even more striking, the outperformance in completely new investment areas is almost 3 times as large (5.2% versus 1.6% per year in risk-adjusted terms) for funds with a new manager compared to funds with no change in the management team. This suggests that value creation is associated with human capital reallocation, consistent with the arguments of BBL.

[4] We provide precise definitions of the labels for different investment areas shortly.

Third, to clarify if these results reflect merger-related synergies, we perform a series of tests. We investigate if these operating changes are unique to funds affected by mergers, or if funds in general (regardless of their involvement in a deal) experience higher managerial turnover and rebalance their portfolios into specific areas around the times when mergers happen to occur. We compare the funds in our sample to matching funds that are not affected by mergers and find that (i) matching funds experience no changes in managerial turnover and (ii) the rebalancing of affected funds is an order of magnitude more aggressive than for the matching funds. For example, funds affected by mergers reallocate, on average, 2 to 3 times as much AUM to non-core investment areas in the post-merger period. Furthermore, conditional on the matching funds also rebalancing towards these areas, the funds affected by mergers marginally outperform matching funds in those investments. This suggests that mergers are associated with increased product differentiation because management of affected funds engages in portfolio rebalancing that is different compared to the rebalancing of comparable funds (i.e., competitors).

Putting these pieces together, given the more aggressive re-allocation of AUM in the post-merger period by new fund managers and the strong returns on those investment, we find that managerial rotations are associated with additional value-added of $2.6 million ($4.2 million) per year relative to matching funds on a before (after) fee basis. When we decompose this additional value-added, we find that non-core areas contribute 76% (57%) to the overall change on a before (after) fee basis.

Fourth, in light of this evidence, we ask which deal characteristics are associated with stronger or weaker synergy effects. We find no differences in the quantity of managerial turnover across different deal characteristics (i.e., managerial turnover tends to increase after all mergers). However, we do find significant quality differences in the observed matches of human to investment capital, in particular along dimensions that capture the changes in the overall pool of human capital and the complementarity in human capital expertise between the bidder and the target. In mergers with a large degree of complementarity in the investment expertise or that lead to a large increase in the overall pool of human capital, new managers bring relatively more investment expertise in non-core investment areas (and less expertise in core areas) to the funds they manage compared to new managers in other mergers. We also find significantly stronger portfolio rebalancing in those particular mergers. All this suggests that mergers are associated with improvements in internal labor markets, especially following mergers that grow these markets in terms of size and human capital complementarity. Combining this observation with the result that the synergies are associated with the creation of new investment ideas (rather than improvements in already existing core expertise) suggests that they derive from the specific match of bidder and target, and are difficult to realize without a merger.

As a final step and in an effort to test for alternative interpretations of our results, we analyze if there are differences between bidder and target funds in the extent to which these synergies are realized. One alternative would posit that the synergies we document simply reflect "extraction of resources" from one merger party. In our context, one might speculate that the bidder extracts investment ideas and talent from the target funds in order to allocate them to bidder funds. Given that bidders tend to have larger AUM than targets in our sample, such value transfers could explain our results. Prior research on the behavior of mutual fund families has documented performance allocation of this kind (e.g., Gaspar, Massa, and Matos (2003), Bhattacharya, Lee, and Pool, (2013), Gonçalves-Pinto and Schmidt (2014), Chuprinin, Massa, and Schumacher (2015) among others). Our evidence, however, does not support these alternatives because the additional value added that we document is primarily generated in non-core investment areas and because we find that our main results are symmetric across bidder and target funds. As such, it appears that mergers benefit both bidder and target funds.

Our paper makes two main contributions to the literature. First, we contribute to the debate on (dis-) economies of scale in the mutual fund industry. We shed new light on the economies of scale at the fund family level and highlight key drivers behind the positive relationship between firm size and average fund performance: the benefits of a large internal labor market, the flexibility to better allocate specialized human capital, and the improved ability to engage in product differentiation. This allows us to add to the growing literature on the consequences of the industrial organization of the global asset management industry for financial markets. Recent studies have raised concerns on multiple dimensions, such as the impact of large asset managers on product market competition (He and Huang (2017), Azar, Tecu, and Schmalz (2017)), their interaction with other large financial conglomerates in the banking industry (Ferreira, Matos, and Pires (2015)), or their impact on financial stability (Massa, Schumacher, and Wang (2016)). We highlight that consolidation allows for the realization of scale economies which lead to improved fund performance.

Second, we contribute to the literature on mergers and acquisitions. This literature indicates that mergers, on average, create net positive valuation changes and operating improvements.[5] However, the literature has struggled to identify the exact channels and mechanisms by which merger-related synergies come about. A small number of studies try to open up the "black box" of value creation in the post-merger period. Sheen (2014) analyzes how product quality and pricing change in mergers of (largely) consumer-product firms to illuminate how operational efficiencies are achieved in the post-merger period. Hoberg and Phillips (2010) use textual analysis to analyze how merging firms use product development and differentiation to improve operating performance after a merger. Our empirical setting, which takes advantage of the unique level of data granularity in the asset management industry, allows us to document the micro-level channels and mechanisms that are behind these synergies, and to quantify the improvements in internal labor markets and operational outcomes that these synergies have. More broadly, we contribute to the literature on the value of human capital in mergers (e.g., Tate and Yang (2016), Ouimet and Zarutskie (2016), and Lee, Mauer, and Xu (2017) among others), on internal labor markets (e.g., Jovanovic (1979), Baker, Gibbs, and Holmstrom (1994), Giroud and Mueller (2015), Tate and Yang (2015), Cestone et al. (2016), Silva (2017) among others), and in general on the optimal allocation of resources internal to the firm (e.g., Stein (1997)). BBL find that at least 30% of the value added by mutual funds is due to the firm's ability to match human capital to investment capital. Our results indicate that this ability is particularly valuable around mergers and corporate reorganization.

[5] For overviews of the literature on mergers and acquisitions, see Bradley, Desai, and Kim (1988), Andrade, Mitchell, and Stafford (2001), or Betton, Eckbo, and Thornburn (2008) among others.

I. Data

We combine information from a range of sources: the SDC Platinum and Zephyr Mergers and Acquisitions databases, FactSet Ownership institutional holdings, the Morningstar Global database, section Global open-end funds, as well as international stock return data from Thomson Datastream and balance sheet information from 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. Both databases cover domestic and cross-border M&A deals, and provide information on acquiror and target identity, deal announcement date and structure, and source of the information. SDC and Zephyr are complementary: SDC has a longer history and broader coverage for U.S. deals, Zephyr for non-U.S. deals. Due to constraints on the availability of institutional investors stock holdings data from the FactSet Ownership database (see below), we consider deals completed from 2001 up to and including 2013.

We restrict the attention to completed deals in which both the acquiror and the target belong to the financial industry,[6] and in which the acquiror controls less than 50% of the target's shares before and more than 50% after the deal.

We merge the M&A deals with the FactSet ownership database by manually screening acquiror 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 acquiror or target in the M&A deals data directly to a management company in FactSet. In a number of 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

[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 Zephus classification ("Banking, insurance & financial service").

Corp. are treated as acquirors, and their funds as acquiror funds (and likewise, reversing roles, when the target is in turn a parent company). In addition, we require available holdings data for both acquiror and target prior to the merger. These filters result in a final sample of 176 mergers.

To obtain data on fund characteristics, such as fund investment style, monthly returns, fees, and information on share classes etc., we match FactSet to the Morningstar Direct mutual fund database.[7] From the Global Open-End funds section of Morningstar, we also obtain the information on the fund's individual managers.[8]

In our main analysis, where we examine portfolio holdings and holdings-based performance, we impose additional filters to our sample, which result in a smaller subset of deals (i.e., 135 deals). First, we require that portfolio holdings information is available in the FactSet database for both the merging asset managers at least one year prior to the acquisition completion date. The holdings data are reported at the semi-annual frequency for about 50% of the entities in FactSet, and at the quarterly frequency for about 40%. The remaining 10% report mostly at a higher frequency, e.g., monthly, with a few entities only reporting annually. Following Chuprinin, Massa, and Schumacher (2015), we focus on semi-annual holdings information throughout the analysis, to maximize coverage. Second, we restrict attention to open-ended, actively managed mutual funds.[9] 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.

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 standard screens to detect data errors, as outlined in Ince and Porter (2006) and performed in e.g., Schumacher (2018).

[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 are able to obtain a match in the Morningstar database for 90% of the FactSet funds in our sample.
[8] We retrieve the individual manager names from Morningstar Direct. In addition, Morningstar provides us with a separate data file that contains unique manager identifiers linked to the manager names which ensures the accuracy of our manager-fund mappings.
[9] We rule out the index funds based on the "Index" flag provided by Morningstar.

The resulting full data set comprises 8,524 funds that are affiliated with 507 management companies (or their parent companies). Out of 8,524 funds overall, 7,383 are acquiror funds, and 1,741 target funds. 600 funds appear as acquiror funds in one deal and target funds in a separate deal. Similarly, out of 507 management companies, 397 are acquirors, and 162 targets, and 52 management companies appear as acquirors 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 3,127 funds (2,655 acquiror funds and 747 target funds), affiliated with 390 management companies (301 acquirors and 123 targets). In our analysis in the Internet Appendix, where we investigate other types of synergies such as fund distribution strategy and flows (Table IA.4 and Table IA.5), we analyze the full sample of 176 deals, including non-equity funds as well as passive funds.

These data highlight the ongoing consolidation wave in the global asset management industry, as shown in Figure 1. Over the sample period, the M&A deals covered by our analysis are associated with a cumulative $4.6 trillion of AUM. In total, our sample includes bidder and target firms from 50 countries.

Table 1 reports descriptive statistics for our main sample, i.e., the active equity funds from the 135 deals, at the deal level in Panel A, at the manager level in Panel B, and at the fund level in Panel C. The average deal affects 24 funds and 27 individual managers (affiliated to the acquiror or the target, Panel A). Panel C shows that the average fund in our sample has $495 million in AUM, is managed in a family with $15.8 billion AUM and counts 2 managers in its management team. Over the pre-merger period, about 14% of funds experience some form of managerial rotation, and 10% of funds receive a new manager in a given period. The panels contain additional descriptive statistics that we will discuss and refer back to in later section (for example, statistics on core and non-core investment areas in Panel A, manager characteristics and estimates of individual manager lifetime expertise in Panel B, or measures of trading behavior and performance in different investment areas in Panel C).

II. Firm size, human capital, and fund performance

We begin and establish three results that form the basis of the subsequent analysis. First, we verify a positive relationship between firm size and performance in the global asset management industry. Second, we examine if fund performance improves after mergers that lead to a large change in firm AUM. Third, in light of the arguments in BBL, we investigate if and how changes in human capital impact fund performance in the periods following a merger.

A. Preliminary result: Firm size and performance in the global asset management industry

Next to their main result on the negative relationship between fund size and performance, Chen et al. (2004) document a positive relationship between family size and performance. As a starting point, we verify this relationship in the global asset management industry. We construct a panel of all actively-managed equity mutual funds from Morningstar over the period 2001 to 2013 (to match our merger sample),[10] regress fund performance on different fund characteristics (including $Fund\ size$ and $Firm\ size$) and fixed effects, and present the results in the Appendix, Table IA.1. We present specifications at the monthly frequency using fund returns from Morningstar in Columns 1 to 3. To match our later analysis on holdings-based performance, we include holdings-based performance measures at the semi-annual frequency in Columns 4 to 6. Across the specifications, we confirm a positive relationship between firm size and fund performance. Consistent with Chen et al. (2004) and others, we also find a negative relationship between fund size and performance.

B. Changes in fund performance around mergers

Mergers are typically associated with large and discrete increases in firm size. If firm size is associated with better fund performance, we would expect fund performance to improve after asset management mergers. Our first tests examine changes in fund performance around mergers by running the following regression:

$$R_{ft+1} = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 \Delta AUM_d + \beta_3 PostM\&A_{dt} \times \Delta AUM_d + \mu' x_{ft} + \varepsilon_{fst}, \quad (1)$$

[10] We only apply minimum filters: all actively-managed equity mutual funds with AUM greater than US$ 5 million and a performance history of at least 2 years are included.

where R_{ft+1} measures semi-annual holding returns (in excess of various benchmark portfolios) of fund f, $PostM\&A_{dt}$ is an indicator equal to 1 for all periods t following the completion date of deal d and 0 otherwise, ΔAUM is an indicator equal to 1 for deals with above median increase in the AUM of the combined entity (i.e., where the ratio $\frac{TargetAUM}{Target+BidderAUM}$ is above the sample median) and 0 otherwise, and the interaction between the two. The specification further includes fund-level control variables, fund and time fixed effects. Standard errors are clustered at the fund level.

We present the results in Table 2. Column 1 shows that fund performance is significantly higher in the post-merger period compared to the pre-merger period, but only following mergers with above-median increase in firm-level AUM: the coefficient on the interaction term is highly significant and suggests that market-adjusted holding returns are about 1.2% per year higher (t-statistic 2.61) in the post-merger period for those deals. In contrast, the coefficient on $PostM\&A$ is insignificant suggesting that in mergers that lead to a small increase in AUM, fund performance does not change following the completion of the deal.

Next, we examine how performance improvements relate to changes in human capital. BBL argue that asset management firms add value through their ability to better allocate human to investment capital. Given that mergers are not only associated with increases in AUM but also with increases in human capital, we ask if more human capital is associated with better fund performance. We measure the increase in human capital via the number of individual fund managers and define the variable $\Delta Managers_d$ analogously to ΔAUM_d, just in terms of individual fund managers. We re-estimate Eq. (1), replace the variable ΔAUM_d with $\Delta Managers_d$ and find the same result in Column 2 of the same table: in mergers that increase the number of fund manager a lot, fund performance is about 1.6% per year higher (t-statistic 3.74) in the post- compared to the pre-merger period.

In Column 3, we run a horse race between these two variables and find that the full economic and statistical significance concentrates on the interaction term with $\Delta Managers_d$. Columns 4 and 5 confirm this result for alternative risk corrections, which are described in the data appendix. Column 4 replaces the market benchmark with a benchmark portfolio constructed from the holdings of physical-replication exchange traded funds (ETFs) that track the same index as fund f. We construct this alternative benchmark following Berk and van Binsbergen (2015) who use returns from ETFs to adjust fund performance. In Column 5, we use a size-value-momentum matched benchmark portfolio as a third alternative (in the spirit of Daniel, Grinblatt, Titman, and Wermers (1997)). All these results suggest that increases in fund performance are more directly associated with changes in human capital, a claim we substantiate in the next section.

III. Managerial rotations and portfolio changes following mergers

A. Managerial rotations following mergers

To understand why fund performance increases following mergers that lead to a large increase in the human capital of the firm, we first investigate how the managerial turnover changes around mergers: are fund managers re-allocated in the combined firm? If so, what types of managers are more likely to experience a rotation? To answer these questions, we estimate linear probability models of the following form:

$$ManagerialRotation_{ft} = \beta_1 PostM\&A_{dt} + \mu' x_{ft} + \alpha_t + \alpha_f + \varepsilon_{fst}, \tag{2}$$

where the dependent variable includes different indicators for a change in the management team of fund f in period t: $Rotation_{ft}$ is an indicator equal to 1 if the fund experiences any changes in its management team in the period and 0 otherwise, $NewManager_{ft}$ is an indicator equal to 1 if a new manager appears in the management team of the fund in the period and 0 otherwise, $InternalNewManager_{ft}$ is an indicator equal to 1 if a new manager appears in the management team of the fund who has already worked as a fund manager for another fund in the bidder or the target before and 0 otherwise, $ExternalNewManager_{ft}$ is the counterpart to that and indicates a new manager that has not worked as a fund manager in the bidder or target before, and $ManagerLeave_{ft}$ is an indicator equal to 1 if the fund experiences a departure in its management team in the period and 0 otherwise. All other specifications are as before.

Panel A of Table 3 presents the results. They show that the intensity of managerial rotations increases significantly in the post-merger period (Columns 1 and 2). The estimates imply that the probability of a fund experiencing a managerial rotation in any given half-year period following the deal completion date increases by 1.7%, significant at the 1% level. Compared to the unconditional probability of a change in the management team of about 10% in the pre-merger period, this corresponds to a nearly 20% increase in the intensity of managerial rotation following a merger. Column 3 shows that these increases in managerial rotation are mostly driven by new managers joining the funds, and especially "internal" managers being rotated within the new entity, i.e., managers that were already employees of the firm prior to the merger (Column 4). The rate at which external new managers are hired increases only about half as much and the statistical significance for this effect is borderline (Column 5). In Column 6, we only find economically modest (and statistically insignificant) evidence of an increased chance of dismissal for existing managers.

In Panel B of the same table, we augment Eq. (2) and include a measure that captures if the fund is managed by a specialist or a generalist manager. For each manager, we track his / her entire career in Morningstar up to 1 year prior to the merger and count the number of different Morningstar investment objectives in which s/he has ever managed funds before. We then take the average of this count across all managers of fund f in period t and set the variable $Generalist_{ft}$ equal to 1 if this average is above median in sample. Panel B shows that funds managed by generalist managers are far more likely to experience a managerial rotation (Columns 1 and 2) and, specifically, to receive a new manager in the post-merger period. The estimate in Column 3 suggest that this probability increase by 3.1%, almost twice the effect documented on the full sample in Panel A. Column 4 shows that funds managed by generalist managers are also more likely to experience a departure in the management team in the post-merger period. Interestingly, the level-effect of $Generalist$ is insignificant in all specifications, suggesting that managerial turnover was no different from funds with generalist versus specialist managers before the merger.[11]

[11] To preserve space, we do not show the estimates on all the other interacted fund attributes here but relegate them to the Appendix, Table IA.2 where we display all coefficient estimates. We find them to be mostly unrelated to managerial turnover.

The concentration of managerial rotations among funds with generalist managers raises the question if these generalists are re-allocated in the combined entity or if they leave the firm, which would suggest an overall tendency towards more specialized human capital. We test this logic by taking the analysis to the individual manager level and estimating linear probability models in the post-merger period of the following form:

$$Turnover_{mt} = \beta_1 \#Styles_{mt} + \beta_2 PastPerformance_{mt} + \beta_3 Tenure_{mt} + \mu' x_{mt} + \alpha_t + \alpha_d + \varepsilon_{fst}, \tag{3}$$

where $Turnover_{mt}$ measures various career events for manager m in period t: $Turnover_{mt}$ is an indicator equal to 1 if the manager experiences any rotation in the period and 0 otherwise, $LeaveFund_{mt}$ is an indicator equal to 1 if the manager leaves a fund s/he was managing during the previous period and 0 otherwise, $JoinFund_{mt}$ is an indicator equal to 1 if the manager joins at least one fund in the combined entity that s/he was not managing during the previous period and 0 otherwise, and $LeaveSample_{mt}$ is an indicator equal to 1 if the manager was managing at least one fund in the combined entity in the previous period but no longer appears on the team of any fund in the combined entity and 0 otherwise. The main explanatory variables mirror the ones from the previous panel, now defined manager-by-manager: $\#Styles_{mt}$ is a count of the different investment objectives in which the manager has managed funds in the entire Morningstar database (up to 1 year prior to the merger), $PastPerformance_{mt}$ measures average fund returns in excess of the investment objective across all funds the manager is managing over the previous 1 year period, $Tenure_{mt}$ is the number of years the manager is traceable in the Morningstar database up to 1 year prior to mergers. The regressions include further controls in the vector x_{mt} that measure additional average fund characteristics of all at the funds the manager is currently managing, time and deal fixed effects.

Panel C of Table 3 present the results. Controlling for past performance and the overall experience / tenure of the manager, Column 1 confirms that generalist managers are more likely to experience a promotion / demotion in the post-merger period. The estimate suggests that for every investment objective in which the manager has managed funds in the past, the probability of experience a rotation increases by 1.3% in any given semi-annual period (t-statistic 4.28). Columns 2 and 3 decompose and show that generalists are more likely to leave a fund (Column 2) but no more likely to join a new fund (Column 3). Instead, Column 4 shows that generalist managers are more likely to leave the sample.

In summary, we not only find that managerial rotations increase significantly following a merger but that the overall human capital of the combined entity gravitates towards more specialization as generalist managers are more likely to leave a given fund and the combined entity altogether.

B. Portfolio rebalancing following mergers

We now examine if similar changes take place in portfolio holdings in the post-merger period to understand if the post-merger periods are characterized by increased product differentiation. Past literature has shown increased product differentiation (and operating performance) following mergers (Hoberg and Phillips (2010)) and Pollet and Wilson (2008) link family growth to fund differentiation.

We decompose fund portfolios into several sub-portfolios by categorizing each portfolio position into one of three mutually exclusive investment areas. We first seek to measure the "core" areas of investment expertise of all bidder and target firms. We aggregate the holdings of all funds of a given bidder or target in the pre-merger period and identify the top quartile of country-industries (e.g. "U.S. Automobiles") in terms of allocated AUM. We label these country-industries $Core$ investment areas: these country-industries have attracted the most AUM of all funds in a given bidder or target prior to the merger. In total, these country-industries attract on average almost 85% of fund AUM in the pre-merger period (Table 1, Panel A). Portfolio holdings in all other country-industries that we observe at any moment in the 3-year pre-merger period are labeled investments in $Peripheral$ areas. They account on average for the remaining 15% of allocated pre-merger AUM. All other country-industries that have not attracted any AUM from any fund in the given bidder or target in the 3 years prior to the merger are potential New investment areas. Taken together, $Peripheral$ and New investment areas are the counterpart to $Core$ areas and we refer to them as $NonCore$ area. We then examine how funds change their portfolio allocations to these investment areas after the merger by estimating a time-series regression similar to Eq. (2):

$$NP_{ft} = \beta PostM\&A_{dt} + \alpha_t + \alpha_f + \mu' x_{ft} + \varepsilon_{ft}, \tag{4}$$

where the dependent variable measures the net purchases (NP) of fund f over period t. The regression is estimated separately for every investment area. In particular, we first calculate the net purchase NP_{jt} for every stock j at time t and then aggregate over all stocks that fall into a particular investment area (for a given deal). NP_{jt} is defined as the change in the portfolio weight w_{jt}, net of price appreciation (Kacperczyk, Sialm, and Zheng (2005)):

$$NP_{jt} = w_{jt} - \frac{w_{jt-1}(1+r_{jt})}{\sum_j w_{jt-1}(1+r_{jt})}. \tag{5}$$

Table 4, Panel A presents the results. In Column 1, we find that, on average, funds reduce their $Core$ holdings by almost 1% per half-year over the three-year period following the deal. The average fund has a size of $495 million on the eve of the merger (Table 1, Panel A), implying that the average fund reallocates about $30 million away from $Core$ areas over the 3-year period following the merger (not counting the additional impact performance differences in these investment areas can have on portfolio weights).

The corresponding increase in the $NonCore$ allocations (Column 2) is driven by investments in country-industries labelled as New. The estimates of Column 3 indicate that funds increase their holdings in New areas by 0.7% of their AUM per half-year over the three-year period following the deal. This implies a reallocation of about $21 million towards these areas for the average fund. The remaining portfolio shares are allocated to $Peripheral$ investment areas.

In a variation of this test, we investigate if these portfolio reallocations indicate a shift in the investment focus and the degree of "activeness" of the fund. We exchange the dependent variable in Eq. (4) and replace it with the fund's active share in the various investment areas, which we compute following Cremers and Petajisto (2009) and Cremers et al. (2016). In Table 4, Panel B, we find that the active share falls in $Core$ but increases in $NonCore$ areas. We attribute the increase in non-core $Activeshare$ almost equally to changes in New and $Peripheral$ areas. This suggests an overall shift in the investment strategy and the degree of portfolio differentiation for funds in the post-merger period.

C. Managerial rotations, portfolio rebalancing, and performance

We now link the reallocation of human capital and the portfolio rebalancing documented in the previous two sections to understand if (i) they go together and (ii) they have an impact on fund performance. The reorganization of human and investment capital both point towards more specialization and differentiation. Past mutual fund literature has linked specialization to better fund performance (e.g., Kacperczyck, Sialm, and Zheng (2004), Brands, Brown, and Gallagher (2004), Cremers and Petajisto (2009), Amihud and Goyenko (2013), Schumacher (2018), among others). Our main hypothesis states that larger asset management firms can accomplish a better match of human to investment capital and afford more product specialization / differentiation. If so, we would expect positive relationships between managerial rotations, portfolio rebalancing, and performance across those various investment areas, supporting our earlier findings that show improved fund performance after mergers that lead to a large increase in the overall human capital of the firm.

We test these conjectures by directly comparing the rebalancing activities of funds in the pre- and post-merger periods for funds that experience a change in the management team relative to those that do not. We stack the rebalancing behavior in the different investment areas on top of each other and estimate the following regression:

$$NP_{fst} = \beta_1 NonCore_{fs} + (\beta_2 NewManager_{ft} + \beta_3 NonCore_{fs} \times NewManager_{ft}) + \alpha_t + \alpha_f + \mu' x_{ft} + \varepsilon_{fst}, \tag{6}$$

where s indicates the sub-portfolio of a particular investment area (i.e., $Core$, $NonCore$, $Peripheral$, or New) and all other variables are defined as before. The regression compares the net purchase behavior in the different investment areas and we estimate Eq. (6) separately for the pre- and post-merger period.

We present the results in Table 5, Panel A. Column 1 shows that there is only minimal rebalancing towards $NonCore$ areas in the pre-merger period: net purchases in $NonCore$ areas are about 0.2% higher per semi-annual period prior to the merger. We add the interaction with $NewManager$ in Column 2 and find it to be insignificant. In other words, new fund managers do not engage in significantly different portfolio rebalancing compared to other funds prior to the merger.

The remaining columns show that net purchases are significantly higher in New and $Peripheral$ investment areas in the post merger period relative to $Core$ areas (Column 3) and that these differences in trading behavior are particularly pronounced when a new manager joins the fund (Column 4). In those instances, net purchases in, for example, New areas are about 50% larger compared to net purchases in New areas of funds that do not experience a change in the management team. For $Peripheral$ areas, that difference is even larger, suggesting that new fund managers enter all non-core areas more aggressively than other funds during those periods.

We make the direct link to operating performance and examine the performance in those different investment areas. We augment Eq. (6) by replacing the dependent variables with semi-annual benchmark-adjusted holding returns. Specifically, we estimate:

$$R_{fst+1} = \beta_1 NonCore_{fs} + (\beta_2 NewManager_{ft} + \beta_3 NonCore_{fs} \times NewManager_{ft}) + \alpha_t + \alpha_f + \mu' x_{ft} + \varepsilon_{fst}, \tag{7}$$

where R_{fst+1} is the risk-adjusted holding return of sub-portfolio s over the next semi-annual period.

Column 1 of Table 5, Panel B shows that funds delivered similar performance in core and non-core areas in the pre-merger period: the coefficient on $NonCore$ is insignificant and small (about 10 bps per period). In Column 2, we add the interaction with $NewManager$ and find again no performance differences in the different investment areas following the appearance of a new manager in the pre-merger period.

From Column 3 onwards, we estimate the regression in the post-merger period and find strong and significant performance differences between portfolio positions in the different investment areas. Column 3 shows that holdings in new and peripheral investment areas perform better in the post-merger period: holdings in new (peripheral) areas perform about 2% (1.2%) better per year, both estimates significant at the 1% level. In Column 4, we again include interaction terms with $NewManager$ and find them positive, large, and significant for holdings in new investment areas: following the appearance of a new manager, holdings in new investment areas outperform by another 3.6% per year relative to holdings in core areas. In total, this suggests that holdings in new areas outperform holdings in core areas by 5.2% per year for funds that have just received a new manager. For holdings in peripheral areas, we find no additional performance spread following the appointment of a new manager. Columns 5 and 6 show virtually identical results for alternative benchmark portfolios.

D. Matching fund analysis

The results thus far suggest that mergers have a significant impact on the management and portfolio activities of affected funds with positive consequences for fund performance. However, an immediate concern with this interpretation is the possibility that mergers happen to coincide with time periods when funds in general enter specific investment areas that are new territory to all funds, not just those affected by mergers. In this case, the results of the previous sub-sections may overestimate the impact of the mergers on fund behavior. In this section, we address this concern via a matching-fund analysis.

For each fund in our sample, we identify a matching fund as follows: 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, we select the one that shares the same investment objective, is managed in the same country, and is closest in terms of pre-merger AUM and pre-merger portfolio holdings to the fund in question. Following this algorithm, we are able to identify matching funds for 82% of the funds affected by mergers that are present one year prior to mergers in our sample. We then re-estimate the main results of the previous sections, now comparing managerial turnover, rebalancing, and performance across the different areas of funds affected to merger to the same attributes of their matching counterparts in the pre- versus post-merger period.

Table 6 presents the results. In Panel A, we document that matching funds experience no changes in managerial turnover in the post-merger period. The regression mirror the specification in Table 3, Panel A, now with additional observations for the matching fund and an interaction term if a given fund is affected by a merger or a matching fund. Across the columns, the interaction terms take the opposite sign compared to the $PostM\&A$ indicator and are almost of the same absolute value, showing that managerial turnover is generally constant for matching funds around the periods when asset management mergers tend to occur.

In Panel B of the same table, we present the counterpart to Table 4, Panel A, now again augmented with the observations from the matching funds. The results show that matching funds are far less aggressive in their rebalancing activities towards non-core investment areas (and away from core areas). The estimate in Column 1 suggests that net sales of matching funds in core areas are only about half as big compared to those of funds affected by mergers. Correspondingly, their net purchase in new and peripheral areas are only about half as big compared to those of funds affected by mergers. As such, while some investments in e.g., new areas are likely due to time-specific investment opportunities that many funds engaged in, it remains that funds affected by mergers pursue those opportunities more aggressively and on a larger scale.

To illustrate the magnitude of these results, we plot the portfolio weights of sample and matching funds in the different investment areas in Figure 2. They show that (i) the evolution of portfolio weights for sample versus matching funds follows parallel trends in the pre-merger periods (i.e., all periods prior to period 0) and that (ii) sample funds allocate about 18% of their AUM away from $Core$ areas over the 3-years following the completion of the merger. For matching funds, the corresponding portfolio re-allocation only amounts to about 4% of AUM. The figure then highlights that the lion-share of this portfolio re-balancing goes towards New areas (about 14% for sample funds). In contrast, matching funds allocate only about 5% of their AUM to those same areas over the same period. Sample funds allocate the remaining 4% of AUM to $Peripheral$ areas while the allocation of matching funds to those same areas declines slightly.

In Panel C of Table 6, we tabulate the average risk-adjusted performance for funds affected by mergers and their matching counterparts in the post-merger period in the different investment areas. The results show that funds affected by merger in general perform marginally better compared to their matching counterparts. While some of these differences are economically meaningful (for example, funds affected by mergers perform 80 bps better per year in new areas compared to matching funds), they are statistically weak. Nevertheless, these results potentially understate the true magnitude of the performance differences for two reasons. First, funds affected by mergers allocate about twice as much AUM away from core areas and towards non-core investment areas yet are able to maintain the same (or slightly better) levels of performance. In other words, despite previously documented dis-economies of scale at the fund level, funds affected by mergers at least match the performance of matching funds in specific areas while allocating twice as much AUM to those investment opportunities. Second, we highlight that this performance test is conditional on the matching fund actually entering, for example, a specific New area. If the matching fund has no holdings in the New areas (which is the case for about 46% of observations), we are unable to make this comparison. In other words, this test potentially understates the impact of the merger, because it limits the sample to those matching funds that were able to generate an investment idea in the New areas for alternative and unobservable reasons.

E. Value added

Taken together, the results presented in this section suggest that managerial rotations following mergers create additional value in the sense of BBL. In fact, the results so far have examined the two components of value added – AUM and excess returns – both of which move in the direction of additional added value.

We now put the pieces together and formally document that this is indeed the case. Our measure of value-added is the holdings-based equivalent to the measure proposed in Berk and van Binsbergen (2015). 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.

We report the average value-added before and after managerial rotations in the post-merger period in Figure 3. The two panels report average value-added relative to matching funds across the different investment areas as well as the grand total. The left panel reports value-added before fees, the right panel after fees. We find that before fees, total value-added is about $2.6 million higher per year following a managerial rotation in the post-merger period. After fees, the change in total value-added is even larger, amounting to $4.2 million per year. When we decompose the change in total value-added, we find that both core and non-core investments contribute to it. Investments in core areas contribute in the sense that funds lose less on those positions: value-added in core areas is less negative following a managerial rotation compared to before. The quantitatively bigger contribution, however, comes from non-core areas, and especially investments in peripheral areas. These patterns are very similar on a before- or after-fee basis: before fees (after fees), non-core areas contribute about 76% (57%) to the incremental value-added that funds realize around managerial turnover events.

F. Symmetry between bidder and target funds

We perform a final test to clarify if the results we document can indeed be understood as synergies in the conventional sense (that is, value improvements that require the specific combination of bidder and target) as opposed to a simple reallocation of existing resources from e.g., the target to the bidder. To do so, we investigate the extent to which the results we find are symmetric between bidder and target funds. For example, an alternative interpretation of our results might postulate that the bidder "poaches" the resources of the target (e.g., investment ideas and talent) to apply them to bidder funds on a larger scale. Prior literature on performance allocation in mutual fund families has documented such instances (e.g., Gaspar, Massa, and Matos (2003), Bhattacharya, Lee, and Pool (2013), Gonçalves-Pinto and Schmidt (2014), Chuprinin, Massa, and Schumacher (2015) among others). If this was the case, one would still associate asset management mergers with an overall improvement in value added for affected funds, but the interpretation of the synergies would have to take this into account.

We reproduce the main results separately for bidder and target funds and present them in Table 7. In summary, we find that all our main results are symmetric across bidder and target funds, which speaks in favor of the interpretation that asset management mergers create synergies that are beneficial to all funds (and not just to one group of funds). In Panel A, we show that managerial rotation increase for both bidder and target funds (though target fund do seem to show more managerial turnover than bidder funds in the post-merger period). In Panel B, we show that that portfolio re-balancing away from core areas and towards non-core areas is almost identical across the two groups, as are the performance spreads between the various investment areas, which we document separately for bidder and target funds in Panel C. As such, given the symmetry of the results across bidder and target funds coupled with the observation that new value creation is concentrated in non-core investment areas, resource extraction by the acquirer is unlikely to explain our findings. Instead, we conclude that asset management mergers lead to synergies that benefit all funds.

IV. Human capital synergies across deal characteristics

In this section, we examine if there are specific deal characteristics that are conducive of larger or smaller merger synergies. Given the focus on human capital and the documented tendency to gravitate towards more specialization and differentiation (in terms of both human capital and portfolio policies), we analyze how deal characteristics that are related to the size and complementarity in human capital between the bidder and the target firm interact with the operating changes documented in the previous section. Specifically, we ask how differences in deal characteristics impact the matching of human to investment capital in the combined firm and subsequently, portfolio rebalancing and performance.

The characteristics we are interested in measure the (ex-ante) complementarity and size of the human capital pool that the merger brings together. We gauge complementarity in investment expertise via two measures. The first one is $PortfolioDistance$, defined as the distance in the aggregated pre-merger portfolios of bidder and target:

$$PortfolioDistance_d = \left[\sum_c \left(w_{ci} - w_{cj}\right)^2\right]^{1/2}, \tag{8}$$

where w_{ci} and w_{cj} are the value-weighted average portfolio weights of all funds belonging to target i and to acquiror j allocated to the country-sector c. A high $PortfolioDistance$ means that the bidder and target have a different investment focus, hence a greater scope to potentially transfer and exchange expertise.

The second measure is $ManagerDistance_d$, the distance in average lifetime investment expertise of all individual fund managers in the bidder and target. For every individual fund manager, we trace all the funds s/he was ever associated with in our data, potentially stretching back years prior to the actual merger date. We then aggregate the holdings of all these manager-fund observations to create the manager's "lifetime portfolio".[12] The expertise of a given manager in a given country-sector is then the portfolio weight of this country-sector in the lifetime portfolio of the manager.[13] We aggregate these measures of individual investment expertise to the deal-level measure of $ManagerDistance$ in the same way as in Eq. (8). As before, we expect a high $ManagerDistance$ to measure the complementarity in investment expertise between fund managers that gain an affiliation via the merger. Both measures focus on the scope for complementarities between the investment know-how of bidder and target.

In addition to this, value creation around the merger will depend on the change in size of the human capital pool. To measure this change, we use again the variable $\Delta Managers_d$, introduced in Section II.B, that measures the increase in the overall human capital of the combined firm (in terms of number of individual managers). We expect that the ability to optimally allocate human capital grows more in mergers that lead to a relatively larger increase in the pool of fund managers.

Finally, we investigate if there are any differences between domestic and cross-border deals. On the one hand, we can expect a greater degree of complementarity in cross-border mergers simply because the expertise of many asset managers may concentrate on domestic investment areas. On the other hand, geographic distance in itself could limit the realization of synergies, because the transfer and distribution of expertise is more difficult across geographic (and / or cultural) boundaries.

We begin with a modification of Eq. (2) and test if those deal characteristics are related to the intensity of managerial turnover in the post-merger period. We complement the specification with interaction terms between the indicator $PostM\&A$ and the different deal characteristics and present the results in Table 8. In Panel A, we find no significant differences in the quantity of managerial rotations across the different mergers. If anything, we find a slightly lower propensity to assign a new merger to a fund in mergers with

[12] We exclude the portfolio holdings in the 1-year period (in unreported robustness tests, the 3-year period) immediately preceding the merger, to minimize the overlap between the two measures.

[13] A number of mechanisms, rational or otherwise, suggest using past exposure to a given sector or asset class as a proxy for the fund manager's expertise in that sector. We are agnostic regarding the precise mechanism for the accumulation of expertise and/or information by fund managers, which is the topic of a growing literature (e.g. Cici, Gehde-Trapp, Goericke, and Kempf (2015), Kacperczyk, van Nieuwerburgh, and Veldkamp (2014), Kempf, Manconi, and Spalt (2016), Schumacher (2018)).

high $ManagerDistance$. However, the estimates generally fall short of conventional levels of statistical significance, or are at best borderline.

Given comparable *quantities* of managerial rotations, we examine if the *quality* of rotations is different across deals. In other words, we ask if the matching of human to investment capital differs along deal characteristics. We use our measures of individual manager expertise which we tabulate in Panel B of Table 1. The typical new manager still has most of his / her lifetime expertise in $Core$ areas (about 77%), followed by expertise in $Peripheral$ areas (20%), and New areas (3%). We then test if the distribution of new manager expertise is significantly different across the different deal characteristics. For every new manager that is assigned to a fund in the post-merger, we measure his / her lifetime expertise the different investment areas and relate the differences in investment expertise to deal characteristics.

We present the results in Panel B of Table 8. We tabulate the average manager expertise across newly assigned managers. We find that overall, new managers have earned about 22.5% of their lifetime expertise in non-core areas (out of which about 19.5% come from peripheral and 3% from new areas; see Table IA.7 for this decomposition). Tabulating these expertise measures across deal characteristics, we find that new managers bring significantly more lifetime expertise in non-core areas to their new funds in mergers with a high degree of human capital complementarity and mergers that lead to a large increase in the overall pool of human capital. For example, in mergers with above-median values of $\Delta Managers_d$, new managers have almost twice as much investment expertise in non-core areas compared to new managers that are assigned in the remaining mergers. Similar results obtain for our measures that capture the overall complementarity in investment expertise between bidder and target.

We confirm these insights in a multi-variate regression in the Appendix, Table IA.6. These regressions confirm that these differences in the allocation of human to investment capital are significant and robust in a joint specification. In other words, mergers with a large complementarity in human capital lead to managerial rotations that assign more non-core investment expertise across the funds of the combined entity, suggesting that value creation in non-core areas is related to the improved allocation of human to investment capital.

If managerial rotations in these mergers assign more non-core expertise to funds, we should observe stronger portfolio rebalancing to those investment areas along exactly those deal characteristics. We implement this final tests by the revisiting Eq. (4), and adding interaction terms for these deal characteristics to the regression specification. We focus on net purchases in New areas as our main dependent variable. The results in Table 9 show that funds rebalance into New areas much more aggressively in mergers with a high degree of complementarity in the investment expertise of the bidder and the target. For example, the estimates in Column 3 suggest that net purchases in New areas of funds in mergers with above-median $\Delta Managers$ are almost 50% larger compared to funds in mergers with below-median $\Delta Managers$ in the post-merger period. Similar results obtain for mergers with high manager or portfolio distance.

Column 4 shows no significant differences in the rebalancing behavior between domestic and cross-border mergers. We speculate that geographic distance limits the extent to which synergies are realized in such deals, as we generally observe higher $PortfolioDistance$ and $ManagerDistance$ in cross-border mergers. Column 5 shows that (i) all these effects are robust in a joint specification and (ii) a negative effect of $CrossBorder$ now that we explicitly control for differences in portfolio or manager distance, confirming the interpretation that distance in itself limits the realization of human capital synergies.

In Internet Appendix Table IA.8, we estimate the same regressions using as dependent variables net purchases in $Core$ or $Peripheral$ areas. The results complement the ones here in that the additional allocations to New investment areas come at the expense of marginally lower allocations to both $Core$ and $Peripheral$ areas.

In summary, our investigation of deal characteristics establishes a direct link between the ability to re-allocate human capital, the observed matching of human to investment capital, and portfolio rebalancing in the post-merger period. In mergers with a high degree of complementarity in investment expertise between the bidder and target, while we observe no differences in the quantity of managerial turnover, we find significant differences in the re-assignment of human capital and in portfolio re-allocations. Taken together, these findings show that the added value that we attribute to the mergers in Section III is in no small part due to improvements in internal labor markets that seem hard to accomplish without the merger.

V. Discussion

A. Bidder and target matching

Mergers between asset management companies – just like any other merger – are unlikely to happen by chance. Our results that human capital synergies vary across specific deal characteristics (in particular characteristics that measure the complementarity in human capital expertise between bidder and target) would suggest that bidders select targets that show the greatest potential to complement the quality of human capital of the combined firm. After all, the property rights theory of the firm (e.g., Grossman and Hart (1986), Hart and Moore (1990), Hart (1995)) indicates that complementary assets should be managed under common ownership to minimize incomplete contracting problems. And complementarities in terms of human capital seem like a good example that would justify common ownership. If this is the case, we would expect larger complementarity between bidders and selected targets compared to bidders and alternative target candidates in order to maximize human capital synergies.

In contrast, as pointed out in Rhodes-Kropf and Robinson (2008), mergers require a negotiation process in which the bargaining power increases in the scarcity of the resources or complementarities that would lead to synergies if the merger succeeded. If particular human capital is in high demand by potential bidders, a lot of bargaining power may end up in the hands of the target candidates. This could prevent an actual paring of bidders with highly complementary targets, and lead to mergers between "similar" firms.

We argue that neither effect would impact the validity of our conclusions; after all, we include fund and deal fixed effects to study the realization of synergies conditional on the merger between the actual bidder and target happening. However, an investigation of determinants that increase the chance of an actual target being chosen over plausible alternatives is helpful to put the magnitudes of our synergy estimates into perspective.

We carry out this test by comparing the actual bidder-target matches along specific deal characteristics against counterfactual matches between the bidders and pseudo-targets in the Internet Appendix, Table IA.3. For every actual bidder-target pair, we select alternative pseudo-targets,[14] and we estimate linear probability regressions to understand how the specific characteristics that we associate with human capital synergies impact the choice of target. We find that size differences in terms of human capital lower the probability that a firm is selected as a target (the coefficient on $\Delta Managers$ is negative in all specifications). However, this may simply reflect the observation that most target firms are smaller than their acquirors. For our other measures of investment expertise, we find that actual targets are generally "closer" in terms of human capital expertise compared to alternative pseudo-targets: the coefficients on $PortfolioDistance$ and $ManagerDistance$ are negative throughout, though statistically insignificant. Also, geographic distance or barrier in languages decrease the probability of being selected as a target.

These results suggest that matching based on these specific characteristics is unlikely behind our results. In fact, these results indicate that the "like buys like" argument of Rhodes-Kropf and Robinson (2008) provides a better description of these asset management mergers, suggesting that differences in bargaining power may limit the extent of human capital synergies in our sample.

B. Additional merger synergies

The focus of our paper is on human capital synergies, but asset management mergers can generate value via alternative channels too. A prominent one is distribution: Acquiring an asset management company based in, say, the U.K. provides access to British investors because the bidder can access the target's existing distribution channels and brand name. We examine this argument in tests reported in the Internet Appendix, Tables IA.4 and IA.5. In Table IA.4, we find that the intensity of new fund launches shifts towards new markets (i.e., countries part of the distribution network of the target that were previously

[14] We select pseudo targets based on the following criteria: 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 the firm that is closest in the pre-merger AUM and shares 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 pseudo target which is also a parent firm (or an affiliate).

inaccessible to the bidder and vice versa) in the post-merger period and Table IA.5 shows that new funds that are launched in these new markets generate higher flows compared to funds launched in "old markets".

A second alternative, often emphasized in related papers that examine post-merger synergies, are cost synergies. As indicated above, the human capital synergies we document appear different from cost synergies (e.g., we do not find strong evidence of large-scale dismissals to reduce duplication of human capital expertise). An alternative source of cost synergies could be the streamlining of the overall fund menu (e.g., the closing of funds with the same investment objective in order to avoid duplication of fund administration costs). In unreported results, we do find some evidence of individual fund mergers (i.e., a target fund is merged into an equivalent bidder fund or vice versa) in the post-merger period; but we also find the extent of these fund mergers to be overall small. While the average merger affects 48 funds, we only find 2 fund mergers on average in the post-merger period.

VI. Concluding remarks

Exploiting the central features of the global asset management industry (its reliance on human capital as the foremost input in the production function of the firm, and an unmatched level of data granularity), we implement a micro-level approach to examine the channels and mechanisms by which human capital synergies are realized following mergers between two asset managers.

We find significant increases in managerial turnover and portfolio rebalancing away from core investment areas and towards non-core areas that are associated with improved fund performance. In combination, these re-allocations of human capital create $4.2 million in additional value per year per fund.

These synergies are closely related to improvements in internal labor markets: the matching of human to investment capital improves, especially in mergers that strongly grow the size and the complementarity of expertise of the internal labor market.

We conclude that the added flexibility to create value via discretionary increases in the size and quality of internal labor markets is a central benefit of these mergers. Interestingly, the synergies we document are realized primarily via the creation of new investment ideas in non-core areas (rather than improvements of already existing expertise) which suggests that the improved ability to match human to investment capital acts as a catalyst to improved labor productivity.

VII. References

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Figure 1.A: Industry concentration over time

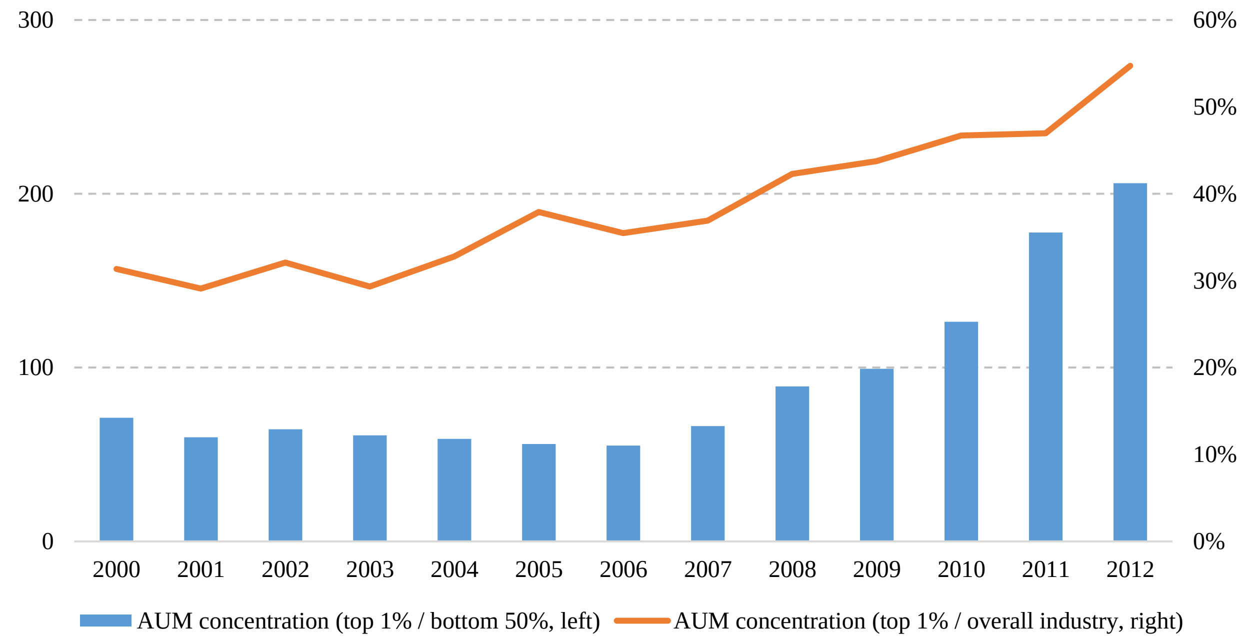

Figure 1.B: Deal volume over time

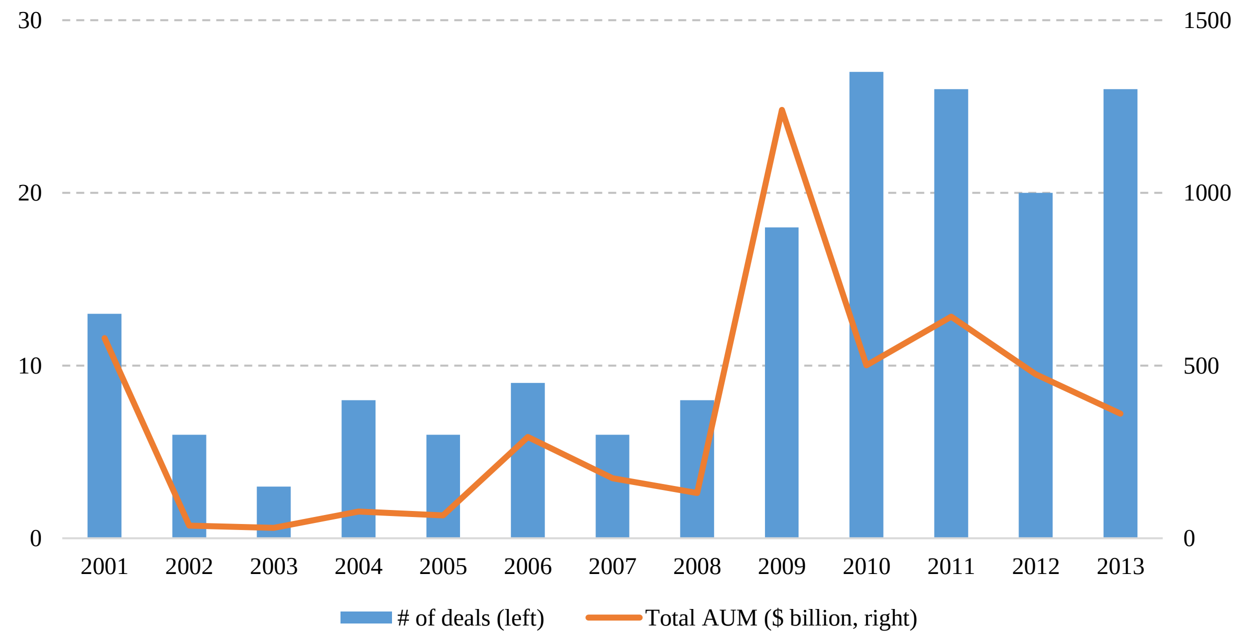

Figure 1: industry concentration globally over time

The figure 1.A plots the ratio of the total assets under management (AUM) of the top 1% and the bottom 50% asset management companies, as well as the ratio of the total AUM of the top 1% and the overall industry from 2001 to 2012. Figure 1.B reports the number of merger deals in our sample, as well as the total assets under management (in USD billion) by deal year from 2001 to 2013.

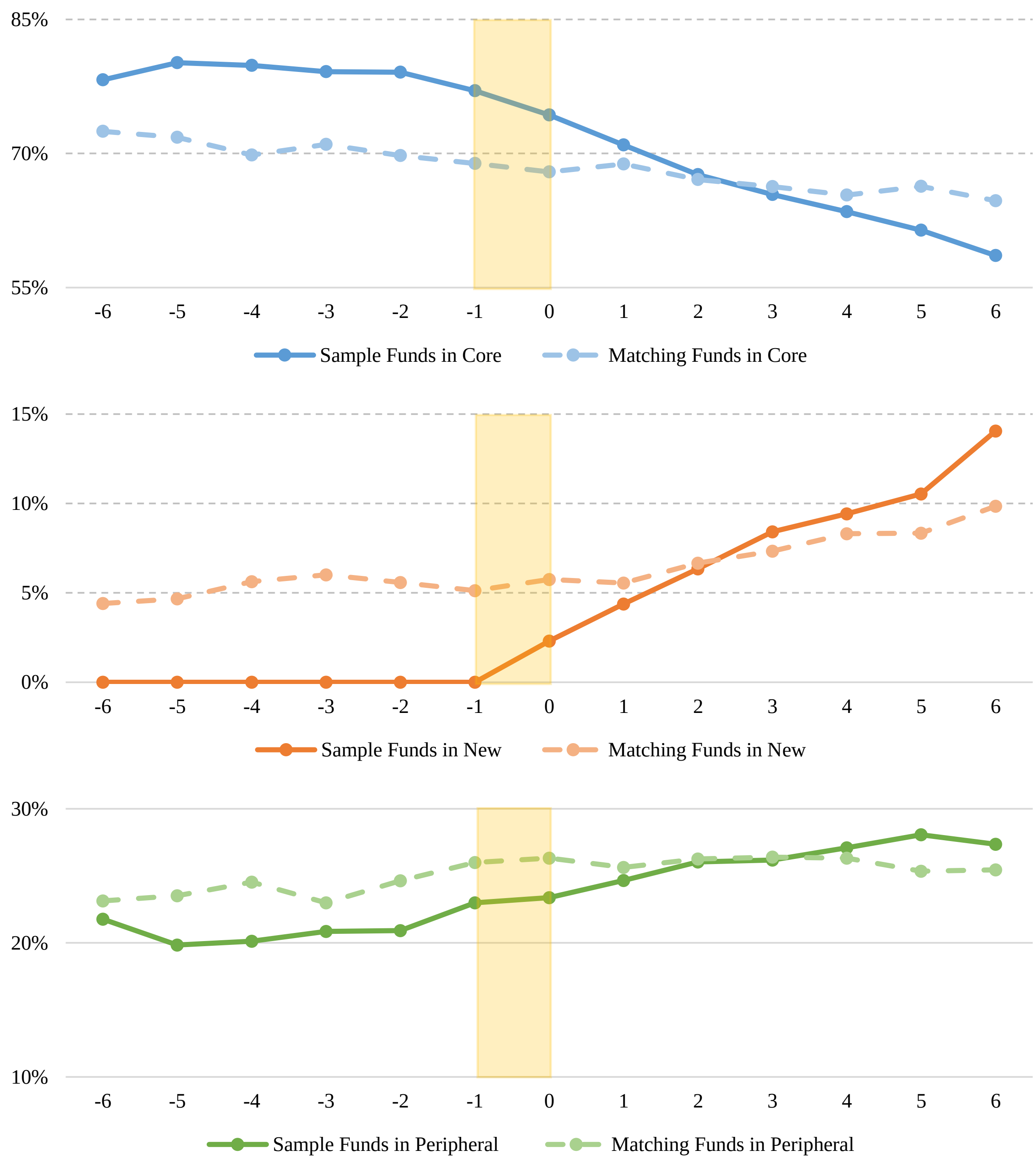

Figure 2: Portfolio weights for sample funds and matching funds in sub-portfolios over time

The figure reports the portfolio weights of sample funds (involved in an asset management company merger) and matching funds in *Core*, *New* and *Peripheral* investment areas, at half-year intervals relative to the deal completion date, over the period from 3 years before to 3 years after the deal completion date. The shaded area denotes the half-year period during which the deal is completed.

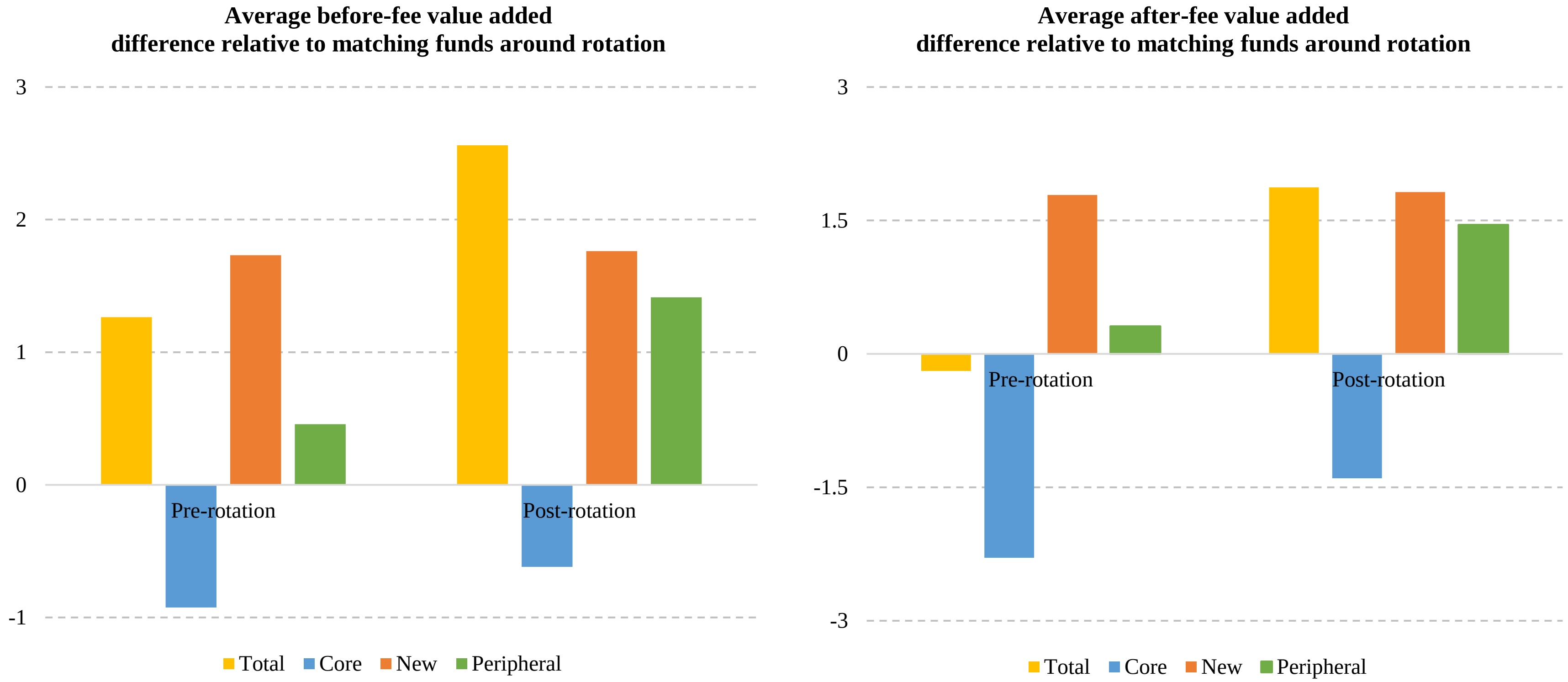

Figure 3: Value added around managerial rotations in the post-merger period

The left panel reports the fund level average value added (i.e., AUM multiplied by ETF benchmark-adjusted returns) before fees around managerial rotation events in the post-merger periods of sample funds relative to matching funds including the decomposition into value added in the $Core$, New, and $Peripheral$ investment areas. The right panel reports the same statistics after fees. Value added is expressed in USD million per semi-annual period per fund.

Table 1: Sample characteristics

The table reports descriptive statistics at the deal level in Panel A. Panel B reports descriptive statistics for manager level variables. Panel C reports descriptive statistics for fund level variables. The sample consists of active equity funds involved in 135 merger deals between asset management companies world-wide. All variables are defined in detail in the Appendix.

Panel A: Deal level characteristics

	Mean	**Std. dev.**	**5 pct.**	**25 pct.**	**Median**	**75 pct.**	**95 pct.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deal level characteristics one year prior to merger							
Number of funds	24.32	28.85	1.00	6.00	14.00	29.00	94.00
Number of managers	27.35	29.70	2.00	6.00	15.00	46.00	100.00
Total net assets ($ billion)	10.69	17.66	0.01	0.56	2.54	14.62	53.96
Deal level portfolio characteristics over the pre-merger period							
Portfolio weight w_C (%)	84.63	13.51	57.29	78.05	89.22	94.53	98.65
Portfolio weight w_P (%)	15.37	13.51	1.35	5.47	10.78	21.95	42.71

Panel B: Manager level characteristics

	Mean	**Std. dev.**	**5 pct.**	**25 pct.**	**Median**	**75 pct.**	**95 pct.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Manager characteristics one year prior to merger							
$\#Styles$	2.31	1.66	1.00	1.00	2.00	3.00	5.00
Past performance (monthly, %)	0.04	0.60	-0.90	-0.26	0.02	0.31	1.10
Manager tenure (years)	7.49	4.83	1.17	3.58	6.67	10.58	17.00
New manager expertise distribution (*excluding holdings 1-year prior to mergers*)							
Expertise in $Core$	0.77	0.28	0.07	0.60	0.91	0.99	1.00
Expertise in New	0.03	0.11	0.00	0.00	0.00	0.01	0.19
Expertise in $Peripheral$	0.20	0.25	0.00	0.01	0.08	0.34	0.74

Table 1: Sample characteristics – continued

Panel C: Fund level characteristics

	Mean	**Std. dev.**	**5 pct.**	**25 pct.**	**Median**	**75 pct.**	**95 pct.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fund level characteristics							
Fund firm size ($ billion)	15.76	19.74	0.16	1.83	7.89	21.57	59.18
Fund size ($ million)	494.82	1,345.02	5.80	36.21	119.27	393.30	2,017.15
Expenses (annualized, %)	1.54	0.49	0.79	1.24	1.50	1.79	2.42
Volatility (annualized, %)	19.39	9.13	7.54	12.41	17.99	24.40	36.84
Age (years)	13.05	10.69	2.25	6.00	10.67	16.58	32.83
Past return (annualized, %)	9.13	26.55	-42.55	-6.76	13.39	27.35	46.13
Number of managers	2.06	1.75	1.00	1.00	2.00	2.00	5.00
Managerial rotation intensity over the pre-merger period							
$Rotation$ (dummy)	0.14	0.35	0.00	0.00	0.00	0.00	1.00
$NewManager$ (dummy)	0.10	0.30	0.00	0.00	0.00	0.00	1.00
$InternalNewManager$ (dummy)	0.05	0.22	0.00	0.00	0.00	0.00	1.00
$ExternalNewManager$ (dummy)	0.06	0.23	0.00	0.00	0.00	0.00	1.00
$ManagerLeave$ (dummy)	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Fund sub-portfolio characteristics over the pre-merger period							
Net purchase NP_C (half-year, %)	-0.12	5.96	-7.10	-1.26	0.00	1.11	6.90
Net purchase NP_P (half-year, %)	0.12	5.96	-6.90	-1.11	0.00	1.26	7.10
Market-adj. return R_C (half-year, %)	0.62	8.18	-10.82	-3.27	0.12	3.79	13.85
Market-adj. return R_P (half-year, %)	0.72	14.56	-22.01	-6.37	0.34	7.19	23.82
ETF-adj. return R_C (half-year, %)	0.04	7.23	-11.02	-3.11	0.05	3.18	10.69
ETF-adj. return R_P (half-year, %)	0.04	14.67	-23.29	-6.96	-0.14	6.62	23.00
DGTW-adj. return R_C (half-year, %)	0.36	7.28	-9.96	-2.84	0.09	3.23	11.39
DGTW -adj. return R_P (half-year, %)	0.54	13.93	-21.11	-6.20	0.18	6.69	23.04
Active share in $Core$ (%)	38.24	18.49	10.33	24.90	36.50	49.41	73.85
Active share in $Peripheral$ (%)	12.97	13.32	0.06	1.59	8.94	21.26	39.03

Table 2: Fund performance following mergers

The table reports the estimates of:

$$R_{ft+1} = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 \Delta Deal_d + \beta_3 PostM\&A_{dt} \times \Delta Deal_d + \mu' x_{ft} + \varepsilon_{ft}$$

The dependent variables include market-adjusted holding returns of fund f at time $t+1$ in Columns 1 to 3, ETF benchmark-adjusted holding returns in Column 4, or characteristics-adjusted holding returns in Column 5. $PostM\&A$ is an indicator equal to 1 for the post-merger period and 0 otherwise. $\Delta Deal_d$ includes indicator variables equal to 1 for mergers that lead to an above median change in firm size, measured either by assets under management (ΔAUM) or number of managers ($\Delta Managers$). x is a vector of fund characteristics ($Fund\ size$, $Firm\ size$, $Expenses$, $Volatility$, and $Past\ return$). α_t and α_f denote time and fund fixed effects respectively. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Market-adjusted			**ETF benchmark-adjusted**	**DGTW-adjusted**
	(1)	(2)	(3)	(4)	(5)
$PostM\&A$	-0.001	-0.002	-0.002	-0.001	-0.002**
	(-1.11)	(-1.28)	(-1.52)	(-0.73)	(-2.29)
ΔAUM	-0.001		0.001	0.000	0.001
	(-0.69)		(0.36)	(0.10)	(0.50)
$\Delta Managers$		-0.002	-0.003	-0.002	-0.003
		(-1.24)	(-1.19)	(-1.01)	(-1.62)
$PostM\&A \times \Delta AUM$	0.006***		0.001	-0.001	0.001
	(2.61)		(0.26)	(-0.22)	(0.50)
$PostM\&A \times \Delta Managers$		0.008***	0.007**	0.007***	0.007***
		(3.74)	(2.56)	(2.63)	(2.59)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y
R^2	0.193	0.203	0.200	0.198	0.182
N	29,643	27,186	25,801	24,549	25,578

Table 3: Managerial rotations following mergers

Panel A reports the estimates of:

$$ManagerialRotation_{ft} = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \mu' x_{ft} + \varepsilon_{ft}$$

The dependent variables include measures for managerial rotation for fund f in period t. In Columns 1 and 2, $Rotation$ is an indicator equal to 1 if the fund experiences any managerial rotation over the period and 0 otherwise. In Columns 3 to 6, we decompose this variable: $NewManager$ is an indicator equal to 1 if a new manager appears in the management of the fund and 0 otherwise, $InternalNewManager$ indicates new managers that are already affiliated with the bidder or target, $ExternalNewManager$ indicates new manager that join the combined firm from outside, and $ManagerLeave$ is an indicator equal to 1 if a manager leaves the fund and 0 otherwise. In all specifications, x is the vector of control variables used throughout. α_t and α_f denote time and fund fixed effects respectively.

Panel B reports the estimates of:

$$\begin{aligned} ManagerialRotation_{ft} &= \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 Generalist_{ft} + \beta_3 PostM\&A_{dt} \times Generalist_{ft} \\ &+ \beta_4 Characteristics_f + \beta_5 PostM\&A_{dt} \times Characteristics_f + \mu' x_{ft} + \varepsilon_{ft} \end{aligned}$$

$Generalist_{ft}$ is and indicator equal to 1 if the average number of investment objectives in which managers of fund f managed funds in the past is above the median, and 0 otherwise. $Characteristics_f$ is a set of indicator variables for fund-level characteristics in the pre-merger period, including $HighFundSize$, $HighFamilySize$, $HighFundVolatility$, $HighFundFee$, $HighFundPastReturn$, $HighFundActiveShare$, and $Acquiror$. x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. All other specifications are as before.

Panel C reports the estimates of:

$$Turnover_{mt} = \alpha_t + \alpha_d + \beta_1 \#Styles_{mt} + \beta_2 PastPerformance_{mt} + \beta_3 Tenure_{mt} + \mu' x_{mt} + \varepsilon_{mt}$$

The dependent variable measures managerial rotation for manager m in period t in the post-merger period. In Column 1, $Turnover$ is an indicator equal to 1 if a given manager experiences any type of rotation over the period and 0 otherwise. In Column 2, $LeaveFund$ is an indicator equal to 1 if the given manager leaves at least one fund (s)he managed over the period and 0 otherwise. In Column 3, $JoinFund$ is an indicator equal to 1 if a given manager joins at least one fund over the period and 0 otherwise. In Column 4, $LeaveSample$ is an indicator equal to 1 if the given manager leaves the sample over the period and 0 otherwise. $\#Styles$ is the total number of investment styles a given manager used to manage during his (her) entire career path up to one year prior to the merger. $PastPerformance$ is the average fund returns in excess of the investment objective across all funds the manager is managing over the previous one year. $Tenure$ is the number of years the manager is traceable in the Morningstar database up to one year prior to mergers. α_t and α_d denote time and deal fixed effects respectively. x is the vector of control variables used throughout, average at the manager level. All variables are defined in the Appendix. The t-statistics are based on standard errors clustered by fund in Panels A and B, and by deal in Panel C. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Table 3: Managerial rotations following mergers – continued

Panel A: Managerial rotations following mergers

	$\boldsymbol{Rotation}$		$\boldsymbol{NewManager}$			$\boldsymbol{ManagerLeave}$
			All new managers	**Internal new managers**	**External new managers**	
	(1)	(2)	(3)	(4)	(5)	(6)
$PostM\&A$	0.018***	0.017***	0.017***	0.013***	0.007*	0.005
	(3.25)	(3.19)	(3.54)	(3.71)	(1.83)	(1.20)
Fund controls, fund and time f.e.	N	Y	Y	Y	Y	Y
R^2	0.200	0.200	0.166	0.143	0.175	0.165
N	28,894	28,894	28,894	28,894	28,894	28,894

Table 3: Managerial rotations following mergers – continued

Panel B: Managerial rotations following mergers and fund characteristics

	$\boldsymbol{Rotation}$		$\boldsymbol{NewManager}$	$\boldsymbol{ManagerLeave}$
	(1)	(2)	(3)	(4)
$PostM\&A$	-0.007	0.010	0.015	-0.001
	(-0.82)	(0.52)	(0.97)	(-0.07)
$Generalist$	-0.008	-0.010	-0.009	-0.012
	(-0.81)	(-1.03)	(-1.15)	(-1.48)
$PostM\&A \times Generalist$	0.034***	0.035***	0.031***	0.022***
	(3.26)	(3.45)	(3.61)	(2.77)
$Characteristics$	N	Y	Y	Y
$PostM\&A \times Characteristics$	N	Y	Y	Y
Fund controls, fund and time f.e.	Y	Y	Y	Y
R^2	0.180	0.181	0.146	0.150
N	24,398	24,398	24,398	24,398

Panel C: Managerial rotations following mergers and manager characteristics

	$\boldsymbol{Turnover}$	$\boldsymbol{LeaveFund}$	$\boldsymbol{JoinFund}$	$\boldsymbol{LeaveSample}$
	(1)	(2)	(3)	(4)
$\#Styles$	0.013***	0.014***	0.002	0.006***
	(4.28)	(6.12)	(0.78)	(3.17)
$PastPerformance$	-0.054***	-0.076***	0.016**	-0.059***
	(-5.51)	(-8.17)	(2.38)	(-6.00)
$Tenure$	-0.002*	-0.000	-0.002***	-0.000
	(-1.84)	(-0.02)	(-2.62)	(-0.69)
Fund controls, deal and time f.e.	Y	Y	Y	Y
R^2	0.049	0.040	0.036	0.030
N	15,629	15,629	14,725	15,629

Table 4: Portfolio rebalancing following mergers

Panel A (B) reports the estimates of:

$$NP_{fst}(ActiveShare_{fst}) = \alpha_t + \alpha_f + \beta PostM\&A_{dt} + \mu' x_{ft} + \varepsilon_{ft}$$

In Panel A, the dependent variable measures the net purchases (NP) of sub-portfolio s of a particular investment area for fund f in period t. The regression is estimated separately for every investment area (i.e., $Core$, $NonCore$, New, and $Peripheral$). In Panel B, the dependent variable is the active share of fund f in these investment areas in period t. x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Portfolio rebalancing following mergers

	$\boldsymbol{Core}$	$\boldsymbol{NonCore}$	$\boldsymbol{New}$	$\boldsymbol{Peripheral}$
	(1)	(2)	(3)	(4)
$PostM\&A$	-0.009***	0.009***	0.007***	0.002***
	(-10.82)	(10.82)	(12.07)	(2.64)
Fund controls, fund and time f.e.	Y	Y	Y	Y
R^2	0.093	0.095	0.096	0.079
N	31,878	31,878	31,878	31,878

Panel B: Changes in active share change following mergers

	$\boldsymbol{Core}$	$\boldsymbol{NonCore}$	$\boldsymbol{New}$	$\boldsymbol{Peripheral}$
	(1)	(2)	(3)	(4)
$PostM\&A$	-0.053***	0.050***	0.028***	0.024***
	(-15.78)	(15.68)	(7.82)	(11.02)
Fund controls, fund and time f.e.	Y	Y	Y	Y
R^2	0.851	0.888	0.769	0.866
N	31,792	31,769	30,197	31,726

Table 5: Managerial rotation, portfolio rebalancing, and performance

The table reports the estimates of:

$$NP_{fst}(R_{fst+1}) = \alpha_t + \alpha_f + \beta_1 NonCore_{fs} + (\beta_2 NewManager_{ft} + \beta_3 NonCore_{fs} \times NewManager_{ft}) + \mu' x_{ft} + \varepsilon_{fst}$$

In Panel A, the dependent variable is the net purchase NP of sub-portfolio s of fund f at time t. We run the regressions for the pre-merger periods in Columns 1 to 2 and for the post-merger periods in Columns 3 to 4. In Columns 3 to 4, we decompose the $NonCore$ areas into "new" and "peripheral" areas and we use New and $Peripheral$ indicators instead. In Columns 2 and 4, we augment the specification by including $NewManager$ indicator and its interaction term with $NonCore$, or with $Peripheral$ and New. $NewManager_{ft}$ is the indicator variable used in Table 2 Panel A. The number of observations in each regression is reported in the bottom row. In Columns 1 to 2 (3 to 4), these correspond to 13,325 (14,204) deal-fund-time observations (i.e., prior to the decomposition into fund sub-portfolios). In Panel B, the dependent variable is the risk-adjusted holdings return of sub-portfolio s of fund f at time $t+1$. In particular, it is the market-adjusted holdings return in Columns 1 to 4, the ETF benchmark-adjusted holdings return in Column 5, and the characteristics-adjusted holdings return in Column 6. We run the regressions for the pre-merger periods in Columns 1 to 2 and for the post-merger periods in Columns 3 to 6. The number of observations correspond to 13,395 deal-fund-time observations in Columns 1 to 2, 13,683 deal-fund-time observations in Columns 3 to 4, 13,166 deal-fund-time observations in Column 5 and 13,646 deal-fund-time observations in Column 6. x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Portfolio rebalancing and managerial rotations

	Pre-merger period		**Post-merger period**	
	(1)	(2)	(3)	(4)
$NonCore$	0.002***	0.002*		
	(2.74)	(1.79)		
New			0.015***	0.014***
			(18.40)	(16.12)
$Peripheral$			0.013***	0.012***
			(15.64)	(13.50)
$HasNewManager$		-0.003		-0.006***
		(-1.54)		(-3.08)
$NonCore \times NewManager$		0.006		
		(1.54)		
$New \times NewManager$				0.007**
				(2.56)
$Peripheral \times NewManager$				0.011***
				(3.21)
Fund controls, fund and time f.e.	Y	Y	Y	Y
R^2	0.000	0.001	0.015	0.015
N	26,650	26,650	42,612	42,612

Table 5: Managerial rotation, portfolio rebalancing, and performance – continued

Panel B: Performance and managerial rotation

	Pre-merger period			**Post-merger period**		
			Market-adjusted		**ETF benchmark-adjusted**	**DGTW-adjusted**
	(1)	(2)	(3)	(4)	(5)	(6)
$NonCore$	-0.001	-0.001				
	(-0.36)	(-0.47)				
New			0.010***	0.008***	0.009***	0.006**
			(3.77)	(2.83)	(3.30)	(1.97)
$Peripheral$			0.006***	0.006***	0.007***	0.008***
			(4.68)	(4.52)	(4.58)	(5.55)
$NewManager$		-0.001		0.000	0.006**	-0.001
		(-0.45)		(0.01)	(2.51)	(-0.60)
$NonCore \times NewManager$		0.002				
		(0.44)				
$New \times NewManager$				0.018**	0.018**	0.016**
				(2.30)	(2.27)	(1.97)
$Peripheral \times NewManager$				-0.001	-0.001	-0.003
				(-0.24)	(-0.37)	(-0.79)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y	Y
R^2	0.191	0.191	0.149	0.150	0.139	0.128
N	24,022	24,022	31,410	31,410	30,207	29,883

Table 6: Matching fund analysis

Panel A (B) of the table report the estimates of:

$$ManagerialRotation_{ft}(NP_{fst}) = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 MatchingFund_{ft} + \beta_3 PostM\&A_{dt} \times MatchingFund_{ft} + \mu' x_{ft} + \varepsilon_{ft}$$

In Panel A, the dependent variables include measures for managerial rotation for fund f in period t, which are also used in Table 3, Panel A. $MatchingFund$ is an indicator equal to 1 if the fund is a matching fund and 0 otherwise. In Panel B, the dependent variable is the net purchase NP in the sub-portfolio s of fund f at time t. In both panels, x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. Panel C reports the average sub-portfolio risk-adjusted holdings return of fund f at period $t+1$ in $Core$, New, and $Peripheral$ areas in the post-merger periods. $SampleFund$ is an indicator equal to 1 if the fund is a sample fund, and 0 otherwise, i.e., $SampleFund = 1 - MatchingFund$. It also reports t-statistics for differences between the sub-portfolio returns of sample funds and matching funds. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Managerial rotations following mergers

	$\boldsymbol{Rotation}$		$\boldsymbol{NewManager}$			$\boldsymbol{ManagerLeave}$
			All new managers	**Internal new managers**	**External new managers**	
	(1)	(2)	(3)	(4)	(5)	(6)
$PostM\&A$	0.017***	0.017***	0.017***	0.012***	0.009**	0.006
	(3.34)	(3.25)	(3.88)	(3.84)	(2.39)	(1.46)
$PostM\&A \times MatchingFund$	-0.017**	-0.017**	-0.022***	-0.009*	-0.018***	-0.010
	(-2.11)	(-2.13)	(-3.19)	(-1.86)	(-3.37)	(-1.62)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y	Y
R^2	0.193	0.194	0.158	0.136	0.167	0.157
N	48,242	48,242	48,242	48,242	48,242	48,242

Table 6: Matching fund analysis – continued

Panel B: Portfolio rebalancing following mergers

	$Core$	$NonCore$	New	$Peripheral$
	(1)	(2)	(3)	(4)
$PostM\&A$	-0.011***	0.011***	0.007***	0.003***
	(-13.17)	(13.10)	(15.61)	(4.19)
$PostM\&A \times MatchingFund$	0.005***	-0.005***	-0.003***	-0.002**
	(4.80)	(-5.04)	(-5.23)	(-2.39)
Fund controls, fund and time f.e.	Y	Y	Y	Y
R^2	0.075	0.075	0.081	0.065
N	58,443	58,443	58,443	58,443

Panel C: Average performance across investment areas

	Market-adjusted			**ETF benchmark-adjusted**	**DGTW-adjusted**
	$Core$	New	$Peripheral$	New	New
	(1)	(2)	(3)	(4)	(5)
$SampleFund$	0.003***	0.013***	0.011***	0.008***	0.008***
	(4.42)	(5.85)	(10.10)	(3.50)	(2.99)
$MatchingFund$	0.002***	0.009***	0.010***	0.008***	0.004
	(2.78)	(3.66)	(7.23)	(2.88)	(1.53)
t-stat ($SampleFund - MatchingFund$)	(0.79)	(1.14)	(0.43)	(0.12)	(0.85)

Table 7: Symmetry across acquirer and target funds

The table reports our main estimates in Table 3 Panel A, Table 4 Panel A, and Table 5 Panel B for acquiror and targets funds separately.

Panel A: Managerial rotations following mergers

	Acquiror funds			Target funds		
		$NewManager$			$NewManager$	
	$Rotation$	All New Managers	Internal New Managers	$Rotation$	All New Managers	Internal New Managers
	(1)	(2)	(3)	(4)	(5)	(6)
$PostM\&A$	0.011*	0.010**	0.010***	0.033*	0.028*	0.035***
	(1.90)	(2.06)	(2.58)	(1.73)	(1.67)	(3.27)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y	Y
R^2	0.200	0.165	0.144	0.236	0.211	0.183
N	23,768	23,768	23,768	5,126	5,126	5,126

Panel B: Portfolio rebalancing following mergers

	Acquiror funds			Target funds		
	$Core$	New	$Peripheral$	$Core$	New	$Peripheral$
	(1)	(2)	(3)	(4)	(5)	(6)
$PostM\&A$	-0.009***	0.007***	0.002***	-0.008**	0.011***	-0.004
	(-9.74)	(12.37)	(2.81)	(-2.14)	(6.39)	(-0.91)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y	Y
R^2	0.103	0.117	0.089	0.099	0.116	0.088
N	25,971	25,971	25,971	5,907	5907	5,907

Table 7: Symmetry across acquirer and target funds – continued

Panel C: Performance across investment areas

	Acquiror funds			**Target funds**		
	Market-adjusted	**ETF benchmark-adjusted**	**DGTW-adjusted**	**Market-adjusted**	**ETF benchmark-adjusted**	**DGTW-adjusted**
	(1)	(2)	(3)	(4)	(5)	(6)
New	0.009***	0.010***	0.009***	0.012**	0.014**	-0.001
	(3.17)	(3.57)	(2.99)	(2.18)	(2.48)	(-0.13)
$Peripheral$	0.006***	0.006***	0.007***	0.008***	0.009***	0.008***
	(3.72)	(3.71)	(4.69)	(3.48)	(3.51)	(3.21)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y	Y
R^2	0.149	0.136	0.130	0.186	0.208	0.149
N	26,116	25,092	24,801	5,294	5,115	5,082

Table 8: Managerial turnover, expertise, and deal characteristics

Panel A reports the estimates of:

$$NewManager_{ft} = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 Characteristics_d + \beta_3 PostM\&A_{dt} \times Characteristics_d + \mu' x_{ft} + \varepsilon_{ft}$$

The dependent variable is the $NewManager$ indicator, equal to 1 if a new manager appears in the management team of the fund and 0 otherwise. $Characteristics_d$ includes indicator variables for various deal-level characteristics including $HighPortfolioDistance$ in Column 1, $HighManagerDistance$ in Column 2, $\Delta Managers$ in Column 3, and $CrossBorder$ in Column 4, all of which are defined in the Appendix. x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. Panel B reports the average lifetime expertise of new managers in $NonCore$ areas in the post-merger period for the overall sample, and for sub-samples with high or low deal characteristics, as well as the t-statistics for the differences between the two. Manager lifetime expertise takes into account all portfolio holdings the given manager was ever associated with throughout her career, excluding the holdings in the 1-year period immediately preceding the merger, and is defined in greater detail in the Appendix. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Managerial rotations following mergers and deal characteristics

	(1)	(2)	(3)	(4)	(5)
$PostM\&A$	0.020***	0.017***	0.014***	0.017***	0.018**
	(3.33)	(3.20)	(2.64)	(2.89)	(2.37)
$HighPortfolioDistance$	0.001				-0.023*
	(0.15)				(-1.84)
$HighManagerDistance$		0.009			0.024**
		(1.17)			(2.14)
$\Delta Managers$			-0.008		-0.007
			(-1.07)		(-0.80)
$CrossBorder$				0.004	0.010
				(0.48)	(1.21)
$PostM\&A \times HighPortfolioDistance$	-0.015				-0.021
	(-1.57)				(-1.45)
$PostM\&A \times HighManagerDistance$		-0.016*			-0.005
		(-1.75)			(-0.35)
$PostM\&A \times \Delta Managers$			-0.010		-0.012
			(-1.05)		(-1.28)
$PostM\&A \times CrossBorder$				-0.003	0.006
				(-0.33)	(0.57)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y
R^2	0.167	0.167	0.165	0.166	0.164
N	26,960	28,461	24,945	28,894	23,568

Table 8: Managerial turnover, expertise, and deal characteristics – continued

Panel B: Manager expertise in $NonCore$ areas following mergers and deal characteristics

	Overall sample	$\Delta Managers$	$HighPortfolioDistance$	$HighManagerDistance$	$CrossBorder$
	(1)	(2)	(3)	(4)	(5)
Characteristics = 0 (low)		0.154***	0.205***	0.187***	0.231***
		(13.55)	(15.11)	(16.86)	(15.04)
Characteristics = 1 (high)	0.225***	0.286***	0.290***	0.310***	0.216***
	(15.20)	(14.97)	(9.00)	(9.18)	(7.59)
t-stat (high – low)		0.132***	0.085**	0.123***	-0.015
		(6.15)	(2.46)	(3.49)	(-0.48)

Table 9: Fund net purchase in "new" areas and deal-level characteristics

The table reports the estimates of:

$$NP_{ftNew} = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 Characteristics_d + \beta_3 PostM\&A_{dt} \times Characteristics_d + \mu' x_{ft} + \varepsilon_{ft}$$

The dependent variable is the net purchase in New investment areas for fund f in period t and $Characteristics_d$ contains the same deal-level characteristics as in Table 8. x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Fund net purchase NP in the New sub-portfolio				
	(1)	(2)	(3)	(4)	(5)
$PostM\&A$	0.006***	0.007***	0.006***	0.007***	0.005***
	(9.58)	(10.54)	(11.42)	(10.12)	(7.91)
$HighPortfolioDistance$	-0.004***				-0.002*
	(-4.00)				(-1.75)
$HighManagerDistance$		-0.003***			-0.001
		(-3.67)			(-1.14)
$\Delta Managers$			-0.000		0.000
			(-0.16)		(0.11)
$CrossBorder$				-0.001	-0.000
				(-1.20)	(-0.07)
$PostM\&A \times HighPortfolioDistance$	0.004***				0.004***
	(4.53)				(3.19)
$PostM\&A \times HighManagerDistance$		0.002***			0.001
		(3.05)			(0.60)
$PostM\&A \times \Delta Managers$			0.003***		0.003***
			(3.71)		(3.75)
$PostM\&A \times CrossBorder$				-0.000	-0.001*
				(-0.37)	(-1.89)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y
R^2	0.109	0.102	0.091	0.103	0.097
N	29,851	31,216	26,880	31,878	25,401

Appendix I: Variable Description

Variable	Definition
Fund characteristics	
$Fund\ size$	Natural logarithm of fund AUM (in US $ million).
$Firm\ size$	For a given fund f, it is computed as the natural logarithm of the total AUM (USD $ million) of all funds managed by the fund's management company, excluding the fund f itself.
$Expenses$	Annual expense ratio as a percentage of AUM.
$Volatility$	Annualized standard deviation of fund returns computed over a trailing 12 months window.
$Past\ return$	The cumulative fund return computed over a trailing 12 months window.
Fund-level managerial rotation variables	
$Rotation$	Indicator variable equal to 1 if there is any managerial rotation, i.e., the number of managers that are rotated is positive for a given fund at a given time period relative to the previous period, and 0 otherwise.
$NewManager$	Indicator variable equal to 1 if there are managers joining in the given fund, and 0 otherwise.
$InternalNewManager$	Indicator variable equal to 1 if the new manager has already worked for the target or the bidder prior to mergers, and 0 otherwise.
$ExternalNewManager$	The counterpart to $InternalNewManager$. Indicate variable equal to 1 if the new manager that has not worked as a fund manager in the bidder or target prior to mergers, and 0 otherwise.
$ManagerLeave$	Indicator variable equal to 1 if there are managers leaving the given fund, and 0 otherwise.
Fund performance variables	
$Mkt\text{-}adj.return$	Market-adjusted return. It is defined as the raw holdings return minus the benchmark return. The benchmark portfolio comprises all the stocks in the fund's investment objective.
ETF-benchmark $adj.return$	The benchmark portfolio is constructed from the holdings of physical-replication exchange traded funds (ETFs) that track the same index as fund *f*.
$DGTW\text{-}adj.return$	Characteristic-adjusted return in the spirit of Daniel, Grinblatt, Titman, and Wermers (1997). It is a value-weighted average of the characteristic-adjusted return on each stock in the fund's portfolio. For a given stock, the characteristic-adjusted return is defined as the raw return minus the benchmark return. The benchmark portfolio is a value-weighted average of all stocks in the same size/book-to-market/momentum portfolio and belonging to the fund's investment objective. Investment objectives are retrieved from Morningstar.
$Value\ added$	It is calculated as the before-fee (or after-fee) ETF benchmark-adjusted holdings return multiplied by the fund's AUM (USD $million).
Sub-portfolio variables	
$Core$	Indicator variable equal to 1 if the sub-portfolio comprises a given fund's "core" areas, and 0 otherwise. The "core" areas are defined as follows: First, we sort all country-sectors in the portfolio of a given fund's family by their average weight over the pre-merger period. Second, we select the country-sectors that fall in the top 25 percentile, and label them as "core".
$NonCore$	Indicator variable equal to 1 if the sub-portfolio is not a given fund's "core", and 0 otherwise, i.e., $NonCore + Core = 100\%$.
New	Indicator variable equal to 1 if the sub-portfolio is defined as a given fund's "new" areas, and 0 otherwise. "New" areas include country-sectors that neither fund's family nor the counterparty family have held over the pre-merger period.

$Peripheral$	Indicator variable equal to 1 if the sub-portfolio is a given fund's "peripheral" areas, and 0 otherwise. The "peripheral" areas are all remaining country-sectors that are neither $Core$ nor New, i.e., $New + Peripheral = NonCore$.
NP (net purchase)	Change in portfolio weight net of price changes as in Kacperczyk, Sialm and Zheng (2005). Formally: $$NP_{jt} = w_{jt} - \frac{w_{jt-1}(1 + r_{jt})}{\sum_j w_{jt-1}(1 + r_{jt})}$$ where w_{jt} is the percentage of fund's portfolio invested in stock j at time t, and r_{jt} denotes the return of stock j from time $t - 1$ to time t. Portfolio net purchase NP_C, NP_{NC}, NP_N and NP_P are the aggregate net purchase of stocks forming in "core", "noncore", "new" and "peripheral" country-sectors.
$ActiveShare$	Calculated following Cremers and Petajisto (2009) and especially Cremers et al. (2016) using benchmark holdings information from all (physical replication) ETFs in FactSet that track a particular fund benchmark. For every sub-portfolio, the active share is constructed as: $$ActiveShare = \frac{1}{2}\sum_{i=1}^{N}\lvert w_{ct} - \overline{w}_{ct}\rvert$$ where w_{ct} is the portfolio weight of a given fund in country-sector c at time t, and $\overline{w}_{ct}$ is the corresponding average portfolio weight of the benchmark index. The sum is taken over the universe of all country-sectors in a given sub-portfolio.
Deal characteristics	
$PortfolioDistance$	A measure of portfolio "distance" between a target firm (or a matching target) and the corresponding acquiror firm. It is calculated as: $\left[\sum_c\left(w_{ict} - w_{jct}\right)^2\right]^{1/2}$, where w_{ict} and w_{jct} is the value-weighted average portfolio weight of all active equity funds in the country-sector c of firm i and firm j at date t.
$ManagerDistance$	A measure of manager expertise "distance" between a target firm (or a matching target) and the corresponding acquiror firm. It is calculated as $\left[\sum_c\left(w_{ict} - w_{jct}\right)^2\right]^{1/2}$, where w_{ict} and w_{jct} are the average portfolio weight of all managers in their expertise country-sector c of the given firm i and the acquiror firm j respectively.
$\Delta Managers$	A measure of the number of managers added to the combined entity. It is calculated as the number of managers of the target firm (or a matching target) over the sum of the number of managers of the acquiror firm and the number of managers of the target (or a matching target).
$GeographicalDistance$	The natural logarithm of the bilateral geographical distance between a target firm (or a matching target) and the corresponding acquiror firm in kilometers.
$CrossBorder$	Indicator variable equal to 1 if the acquiror and the target are headquartered in different countries, and 0 otherwise.
$DifferentLanguage$	Indicator variable equal to 1 if the countries where the acquirer and the target are headquartered use different languages, and 0 otherwise.
Manager-level characteristics	
$LeaveFund$	Indicator variable equal to 1 if the manager leaves a fund he / she was managing during the previous period, and 0 otherwise.
$LeaveSample$	Indicator variable equal to 1 if the manager was managing at least one fund in the combined entity in the previous period but no longer appears on the team of any fund in the combined entity, and 0 otherwise.

$JoinFund$	Indicator variable equal to 1 if the manager joins at least one fund that he / she was not managing during the previous period, and 0 otherwise.
$\#Styles$	The number of unique investment objectives in which the manager has managed funds in the entire Morningstar database (up to 1 year prior to the merger).
$PastPerformance$	The average fund returns in excess of the investment objective across all funds the manager is managing over the previous 1 year period.
$Tenure$	The number of years the manager is traceable in the Morningstar database up to 1 year prior to mergers.
$Expertise$	We measure the lifetime investment expertise for a given manager as the average portfolio weight in a given country-sector the manager overlooked across all portfolio snapshots we have in our data (excluding the holdings in the 3-year or alternatively 1-year period prior to the merger the manager is affected by). Per manager, the portfolio weights are equally-weighted across time. If a manager manages more than one fund in a given time period, we aggregate the holdings of all his/her funds. If a fund is team-managed, we assign equal expertise to all its managers.
Other variables	
$PostM\&A$	Indicator variable equal to 1 for the post-merger period, and 0 otherwise.
$MatchingFund$	Indicator variable equal to 1 if the fund is a matching fund, and 0 otherwise.
$RealTarget$	Indicator variable equal to 1 if the given firm is a real target involved in mergers, and 0 if it is a matching firm.
$NewMarket$	An indicator equal to 1 for countries where the counterparty family has sold funds to prior to the merger, excluding the countries which fall in the top decile of its own market in terms of fund TNA.
$OldMarket$	An indicator for the countries where the own family has sold funds to prior to mergers. It is calculated as $1 - NewMarket$.
$FundCreation$	An indicator that is equal to 1 if the number of funds of a given firm (either acquiror or target) launched in the given time t is larger than zero, and 0 otherwise.

Internet Appendix

This internet appendix presents additional tables to accompany the paper "The Value of Human Capital Synergies in M&A: Evidence from Global Asset Management". The contents are as follows:

Table IA.1 examines the relationship between firm size and fund performance.

Table IA.2 presents all coefficient estimates for Table 3, Panel B.

Table IA.3 examines the likelihood of being selected as a target.

Table IA.4 examines the likelihood of fund launching.

Table IA.5 presents the results on fund flows following mergers.

Table IA.6 presents additional results on manager expertise distribution and deal characteristics.

Table IA.7 presents the results in Panel B, Table 8 for "new" and "peripheral" areas.

Table IA.8 presents the results in Table 9 with the net purchase in "core" and "peripheral" areas as dependent variables.

Table IA.1: Relationship between firm size and fund performance

The table reports the estimates of:

$$R_{ft+1} = \alpha_t + \alpha_s + \beta FirmSize_{ft} + \mu' x_{ft} + \varepsilon_{dt}$$

The dependent variable R_{ft+1} is the fund performance measure. It is the net of style returns of fund f at time $t+1$ in Columns 1 to 3, the market-adjusted holdings return in Column 4, the ETF benchmark-adjusted holdings return in Column 5, or characteristics-adjusted holdings return in Column 6. x is a vector of fund characteristics, including $Fund\ size$, $Expenses$, $Volatility$, $Fund\ age$, $Past\ return$, $Number\ of\ share\ classes$, $Institutional\ share\ classes$. α_t and α_s denote time and investment style fixed effects respectively. In all specifications, the t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

	Net of style returns			**Market-adjusted**	**ETF benchmark-adjusted**	**DGTW-adjusted**
	(1)	(2)	(3)	(4)	(5)	(6)
$Firm\ size$	0.0082***	0.0061***	0.0069***	0.0199***	0.0138	0.0206**
	(8.06)	(5.30)	(6.25)	(2.75)	(1.28)	(2.55)
Fund controls	N	Y	Y	Y	Y	Y
Investment style and time f.e.	N	N	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.04	0.07	0.06
N	1,179,820	1,178,450	1,178,450	142,820	104,598	141,537

Table IA.2: Full menu of coefficient estimates for Table 3 Panel B

This table reports all coefficient estimates of Panel B in Table 3.

	$Rotation$		$NewManager$	$ManagerLeave$
	(1)	(2)	(3)	(4)
$PostM\&A$	-0.007	0.010	0.015	-0.001
	(-0.82)	(0.52)	(0.97)	(-0.07)
$Generalist$	-0.008	-0.010	-0.009	-0.012
	(-0.81)	(-1.03)	(-1.15)	(-1.48)
$PostM\&A \times Generalist$	0.034***	0.035***	0.031***	0.022***
	(3.26)	(3.45)	(3.61)	(2.77)
$HighFundSize$		0.001	0.003	-0.004
		(0.07)	(0.30)	(-0.47)
$HighFamilySize$		0.001	0.015*	-0.003
		(0.10)	(1.69)	(-0.37)
$HighFundVolatility$		0.004	0.006	-0.001
		(0.36)	(0.68)	(-0.08)
$HighFundFee$		0.018	0.018	0.011
		(1.28)	(1.55)	(1.07)
$HighFundPastReturn$		-0.001	0.000	-0.002
		(-0.09)	(0.05)	(-0.32)
$HighFundActiveshare$		0.004	-0.000	0.001
		(0.30)	(-0.02)	(0.06)
$Acquiror$		0.027**	0.017	0.026**
		(2.00)	(1.64)	(2.27)
$PostM\&A \times HighFundSize$		0.021*	0.011	0.016**
		(1.94)	(1.24)	(2.02)
$PostM\&A \times HighFamilySize$		-0.007	-0.008	0.002
		(-0.67)	(-1.01)	(0.26)
$PostM\&A \times HighFundVolatility$		0.019*	0.011	0.014*
		(1.83)	(1.32)	(1.75)
$PostM\&A \times HighFundFee$		-0.015	-0.005	-0.005
		(-1.40)	(-0.62)	(-0.61)
$PostM\&A \times HighFundPastReturn$		-0.014	-0.006	-0.008
		(-1.34)	(-0.70)	(-0.94)
$PostM\&A \times HighFundActiveShare$		-0.011	-0.010	-0.004
		(-1.06)	(-1.13)	(-0.44)
$PostM\&A \times Acquiror$		-0.019	-0.020*	-0.017
		(-1.31)	(-1.74)	(-1.52)
Fund controls, fund and time f.e.	Y	Y	Y	Y
R^2	0.180	0.181	0.146	0.150
N	24,398	24,398	24,398	24,398

Table IA.3: Likelihood of being selected as a target

The table reports the estimates of:

$$RealTarget_{dj} = \alpha_t + \alpha_d + \beta Characteristics_d + \mu' x_{ft} + \varepsilon_{dt}$$

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 corresponding matching target. We include the closest 10, 15, 20 and 25 matching targets in each column. $Characteristic_d$ is a set of pair-wise variables between the given firm j and the acquiror firm in the given deal d calculated at one year prior to mergers. All variables are defined in the Appendix. x is a vector of target firm characteristics, i.e., the average value of $Fund\ size$, $Firm\ size$, $Expenses$, $Volatility$, and $Past\ return$. α_t and α_d denote time and deal fixed effects respectively. In all specifications, the t-statistics are based on standard errors clustered by deal. *, **, 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)
$PortfolioDistance$	-0.133	-0.096	-0.121	-0.108
	(-0.74)	(-0.81)	(-1.40)	(-1.65)
$ManagerDistance$	-0.075	-0.095	-0.029	-0.020
	(-0.41)	(-0.74)	(-0.32)	(-0.29)
$\Delta Managers$	-0.213**	-0.187***	-0.155***	-0.119***
	(-2.09)	(-2.63)	(-2.89)	(-2.81)
$GeographicalDistance$	-0.263***	-0.215***	-0.182***	-0.151***
	(-5.01)	(-5.37)	(-5.62)	(-5.66)
$DifferentLanguage$	-0.157***	-0.104***	-0.077***	-0.065***
	(-4.79)	(-4.84)	(-4.79)	(-5.13)
Target controls, deal and time f.e.	Y	Y	Y	Y
R^2	0.269	0.210	0.171	0.143
N	818	1,184	1,578	1,945

Table IA.4: Likelihood of launching new funds

The table reports the estimates of:

$$FundCreation_{mt} = \alpha_d + \alpha_{ct} + \beta PostM\&A_{dt} + \gamma NewMarket_{mt} + \delta PostM\&A_{dt} \times NewMarket_{mt} + \mu' x_{ft} + \varepsilon_{ct}$$

The dependent variable is a new fund creation indicator, equal to 1 if the number of funds of a given firm (acquiror or target) launched at a given time t is larger than 0, and 0 otherwise. $NewMarket$ is an indicator equal to 1 for countries where the counterparty family has sold funds to prior to the merger, excluding the countries which fall in the top decile of its own market in terms of fund TNA. In all specifications, each observation is a given country c, for either the acquiror or the target at a given time. x is a vector of the average acquiror- (target-) family characteristics ($Fund\ size$, $Firm\ size$, $Volatility$, $Expenses$ and $Past\ return$). α_d and α_{ct} denote deal and country × date fixed effects respectively. The t-statistics are based on standard errors clustered by deal. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
$PostM\&A$	-0.083***	-0.085***	-0.102***	-0.031**
	(-4.82)	(-4.83)	(-5.97)	(-2.20)
$NewMarket$	-0.126***	-0.119***	-0.118***	-0.118***
	(-7.28)	(-7.07)	(-6.14)	(-5.82)
$PostM\&A \times NewMarket$	0.070***	0.068***	0.069***	0.071***
	(4.24)	(4.05)	(4.09)	(4.11)
Family controls	N	Y	Y	Y
Deal f.e.	N	N	Y	Y
Country × date f.e.	N	N	N	Y
R^2	0.040	0.047	0.112	0.221
N	20,221	20,221	20,221	20,136

Table IA.5: Fund flows following the mergers

The table reports the estimates of:

$$Flow_{ft} = \alpha_d + \alpha_s + \beta NewFund_{ft} + \mu' x_{ft} + \varepsilon_{ft}$$

The dependent variable is the semi-annual investment flow into fund f at time t. x is a vector of fund characteristics ($Fund\ size$, $Firm\ size$, $Volatility$, $Expenses$ and $Past\ return$), α_d and α_s denote deal and investment style fixed effects respectively. The sample is restricted to the post-merger completion period (when $PostM\&A$ is equal to one). The newly-created fund indicator $NewFund$ is equal to one if the inception date of a given fund is later than the deal's completion date, and zero otherwise. In Columns 3 and 4, we split the indicator $NewFund$ in two parts by the new market indicator $NewMarket$, and the $OldMarket$ indicator (equal to $1 - NewMarket$), suggesting new funds that are launched in the new market and in the old market. In all specifications, the t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
$NewFund$	0.265***	0.193***		
	(8.95)	(6.75)		
$NewMarket \times NewFund$			0.304***	0.200***
			(6.33)	(4.11)
$OldMarket \times NewFund$			0.243***	0.189***
			(6.81)	(5.66)
Fund controls	Y	Y	Y	Y
Deal and style f.e.	N	Y	N	Y
R^2	0.028	0.060	0.028	0.060
N	33,223	33,220	33,218	33,215

Table IA.6: New managers' expertise distribution following the mergers

The table reports the estimates of:

$$Expertise_{fms} = \alpha_f + \beta_1 New_{fs} + \beta_2 Peripheral_{fs} + \beta_3 Characteristics_d + \beta_4 New_{fs} \times Characteristics_d + \beta_5 Peripheral_{fs} \times Characteristics_d + \mu' x_f + \varepsilon_f$$

The dependent variable is the lifetime expertise of new manager m of fund f in sub-portfolio area s (i.e., $Core$, New, or $Peripheral$) in the post-merger period. Manager lifetime expertise takes into account all portfolio holdings the new manager was ever associated throughout her career, excluding the holdings in the 1-year period immediately preceding the merger, and is defined in greater detail in the Appendix. $Characteristics_d$ contains the same deal-level characteristics as in Table 8. x is the vector of control variables used throughout, and α_t and α_f denote time and fund fixed effects respectively. The t-statistics are based on standard errors clustered by fund. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
New	-0.772***	-0.791***	-0.827***	-0.743***	-0.785***
	(-46.24)	(-56.98)	(-58.25)	(-39.16)	(-33.05)
$Peripheral$	-0.614***	-0.647***	-0.710***	-0.563***	-0.630***
	(-21.99)	(-28.55)	(-30.31)	(-17.84)	(-16.84)
$HighPortfolioDistance$	-0.085**				-0.030
	(-2.27)				(-1.07)
$HighManagerDistance$		-0.122***			0.008
		(-3.22)			(0.30)
$\Delta Managers$			-0.132***		-0.110***
			(-5.66)		(-4.40)
$CrossBorder$				0.015	0.078***
				(0.44)	(3.58)
$New \times HighPortfolioDistance$	0.114**				0.041
	(2.24)				(1.26)
$New \times HighManagerDistance$		0.155***			-0.009
		(2.96)			(-0.29)
$New \times \Delta Managers$			0.150***		0.125***
			(5.32)		(4.11)
$New \times CrossBorder$				-0.000	-0.083***
				(-0.01)	(-3.14)
$Peripheral \times HighPortfolioDistance$	0.141**				0.048
	(2.20)				(0.93)
$Peripheral \times HighManagerDistance$		0.212***			-0.015
		(3.29)			(-0.30)
$Peripheral \times \Delta Managers$			0.245***		0.205***
			(5.71)		(4.47)
$Peripheral \times CrossBorder$				-0.045	-0.151***
				(-0.78)	(-3.75)
R^2	0.660	0.685	0.769	0.674	0.759
N	4,995	5,430	4,689	5,460	4,254

Table IA.7: New managers' expertise distribution following the mergers – based on expertise defined excluding one year prior to mergers

The table presents the average new managers' expertise in New and $Peripheral$ areas as complimenting Panel B in Table 8.

Panel A: New manager's expertise in New areas (excluding holdings 1-year prior to the merger)

	Overall sample	$\Delta Managers$	$HighPortfolioDistance$	$HighManagerDistance$	$CrossBorder$
	(1)	(2)	(3)	(4)	(5)
Characteristics = 0 (low)		0.018***	0.023***	0.021***	0.026***
		(6.10)	(6.98)	(7.38)	(6.64)
Characteristics = 1 (high)	0.031***	0.036***	0.053***	0.054***	0.040***
	(5.22)	(5.19)	(3.38)	(3.23)	(2.95)
t-stat (high – low)		0.018***	0.030*	0.033*	0.014
		(2.59)	(1.87)	(1.95)	(1.05)

Panel B: New manager's expertise in $Peripheral$ areas (excluding holdings 1-year prior to the merger)

	Overall sample	$\Delta Managers$	$HighPortfolioDistance$	$HighManagerDistance$	$CrossBorder$
	(1)	(2)	(3)	(4)	(5)
Characteristics = 0 (low)		0.136***	0.181***	0.166***	0.206***
		(13.18)	(14.66)	(16.63)	(14.72)
Characteristics = 1 (high)	0.194***	0.250***	0.237***	0.256***	0.176***
	(16.93)	(15.51)	(10.29)	(10.43)	(9.44)
t-stat (high – low)		0.114***	0.056**	0.090***	-0.030
		(6.11)	(2.15)	(3.44)	(-1.32)

Table IA.8: Fund net purchase in "core" and "peripheral" areas and deal-level characteristics

The table reports the estimates of:

$$NP_{fCt}(NP_{fPt}) = \alpha_t + \alpha_f + \beta_1 PostM\&A_{dt} + \beta_2 Characteristics_d + \beta_3 PostM\&A_{dt} \times Characteristics_d + \mu' x_{ft} + \varepsilon_{ft}$$

The dependent variable is the net purchase in "core" areas (in Panel A) or the net purchase in "peripheral" areas (in Panel B) for fund f in period t. All other specifications are as in Table 9.

Panel A: Net purchase in "core" areas and deal-level characteristics

	Fund net purchase NP in the $Core$ sub-portfolio				
	(1)	(2)	(3)	(4)	(5)
$PostM\&A$	-0.008***	-0.009***	-0.008***	-0.009***	-0.007***
	(-7.71)	(-9.23)	(-8.85)	(-8.40)	(-5.88)
$HighPortfolioDistance$	-0.001				-0.002
	(-0.38)				(-0.40)
$HighManagerDistance$		0.000			0.004
		(0.30)			(1.19)
$\Delta Managers$			0.002		0.003*
			(1.07)		(1.78)
$CrossBorder$				-0.003***	-0.006***
				(-2.63)	(-2.90)
$PostM\&A \times HighPortfolioDistance$	-0.002				-0.004
	(-1.22)				(-1.45)
$PostM\&A \times HighManagerDistance$		-0.001			0.001
		(-0.71)			(0.58)
$PostM\&A \times \Delta Managers$			-0.002		-0.001
			(-1.08)		(-0.91)
$PostM\&A \times CrossBorder$				-0.000	0.002
				(-0.07)	(1.03)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y
R^2	0.093	0.093	0.090	0.093	0.089
N	29,851	31,216	26,880	31,878	25,401

Table IA.8: Fund net purchase in "core" and "peripheral" areas and deal-level characteristics – continued

Panel B: Net purchase in "peripheral" areas and deal-level characteristics

	Fund net purchase NP in the $Peripheral$ sub-portfolio				
	(1)	(2)	(3)	(4)	(5)
$PostM\&A$	0.002**	0.002**	0.002***	0.001	0.002*
	(2.13)	(2.47)	(2.68)	(1.44)	(1.68)
$HighPortfolioDistance$	0.005***				0.004
	(3.21)				(1.05)
$HighManagerDistance$		0.002			-0.003
		(1.64)			(-0.81)
$\Delta Managers$			-0.002		-0.003**
			(-1.05)		(-1.96)
$CrossBorder$				0.004***	0.005***
				(2.77)	(2.94)
$PostM\&A \times HighPortfolioDistance$	-0.002				0.000
	(-1.37)				(0.01)
$PostM\&A \times HighManagerDistance$		-0.001			-0.002
		(-0.65)			(-0.84)
$PostM\&A \times \Delta Managers$			-0.001		-0.001
			(-0.66)		(-0.80)
$PostM\&A \times CrossBorder$				0.000	-0.000
				(0.26)	(-0.19)
Fund controls, fund and time f.e.	Y	Y	Y	Y	Y
R^2	0.080	0.081	0.079	0.080	0.079
N	29,851	31,216	26,880	31,878	25,401