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• J. Fang • A. Kempf • M. Trapp

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Jieyan Fang[1] Alexander Kempf[2] Monika Trapp[3]

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Abstract

We show that fund families allocate their fund managers to different market segments such that their skill is rewarded best. Whether a fund manager's skill is rewarded by higher alpha depends on the efficiency of the market segment in which she works. Even skilled managers can generate alpha only if the market segment is inefficient. Fund families take this relation between skill and inefficiency into account and allocate their best managers to the least efficient market segment. They use this rationale when assigning newly hired fund managers as well as when reassigning managers they already employ. Depending on the manager's tenure, fund families use different signals for skill. For young managers, fund families rely mainly on the manager's general ability and education as measured by GMAT. For more experienced managers, they rely mainly on the manager's track record which reflects overall investment skill.

JEL classification: G 20, G23, G14, J24

Keywords: manager allocation, performance, skill, market efficiency

[1] DWS Investment GmbH, D-60327 Frankfurt, jieyan.fang@db.com. Note that this paper is not connected with DWS Investment GmbH and expresses the authors' views that do not have to coincide with those of DWS Investment GmbH.

[2] University of Cologne, D-50931 Cologne, and Centre for Financial Research, kempf@wiso.uni-koeln.de

[3] University of Cologne, D-50931 Cologne, and Centre for Financial Research, trapp@wiso.uni-koeln.de

Introduction

This paper is the first to study whether fund families allocate fund managers to market segments in an efficient way, i.e., such that fund managers work in market segments where their skill is rewarded best. This question is vital since fund performance crucially depends on the fund manager (e.g., Baks 2003) and determines the money inflow into the fund (e.g., Sirri and Tufano 1998). As a fund family typically charges a fixed percentage fee on its assets under management, the manager allocation ultimately determines the profitability of the fund family.

We hypothesize that manager skill pays off more in less efficient markets. In fully efficient markets, prices reflect all information, and even highly skilled managers should be unable to generate systematic excess returns. If the market is less efficient, skilled managers can generate excess returns, which unskilled managers cannot. Thus, a fund family should allocate its best managers to inefficient market segments.

We test this basic hypothesis by analyzing how fund families allocate fund managers to two market segments which differ only with respect to their efficiency. In particular, we focus on corporate bond funds investing in the investment grade (IG) and high yield (HY) market segment. The bonds traded in these market segments have very similar features (fixed-income securities, similar taxation, subject to the same types of risk, traded on decentralized OTC markets), but the two segments differ with respect to their efficiency.

The HY segment is far less efficient due to regulatory constraints preventing many institutional investors from holding HY debt leading to a lower liquidity.[1]

In our first set of tests, we analyze whether skill pays off more in the less efficient HY segment than in the more efficient IG segment using two proxies for manager skill. First, we measure skill as the average matriculates' GMAT score of the institution where the manager obtained her MBA degree. Thus, GMAT reflects the manager's general ability and the quality of her education. Our second measure of skill, manager track record, is broader and reflects overall investment skill. We hypothesize that a higher GMAT score and a better track record result in a higher fund alpha in the inefficient HY market. Our regression analysis clearly confirms this hypothesis, even after controlling for various manager and fund characteristics. Skill pays off more in the inefficient HY segment than in the IG segment. For young managers, general ability and education (as measured by GMAT) matters, but for more experienced managers, track record is the best signal of skill.

In our second set of tests, we analyze whether fund families allocate their managers such that their skill pays off best. We find strong evidence for such a behavior: First, we show that managers with higher skill are more likely to run a HY fund. For young managers, the probability of running a HY fund mainly depends on their GMAT, while track record gains importance for more experienced managers. Second, we show that fund families assign newly hired managers to HY funds based on skill. We find that

[1] Kwan (1996) and Hotchkiss and Ronen (2002) provide empirical evidence that the HY segment is less efficient than the IG segment. We test this ranking with respect to efficiency in a time-series analysis of the corporate bond market and the CDS market. A vector autoregressive (VAR) analysis shows that lagged bond index returns and CDS premium changes predict HY bond index return changes. In contrast, IG bond index return changes cannot be predicted by CDS premia and bond index return changes. This finding clearly confirms the conclusions drawn from earlier papers: The HY bond market is less efficient than the IG bond market.

beginner fund managers are assigned to HY funds according to their GMAT. However, when a fund family hires a manager from another company, the fund family considers the manager's GMAT and her track record achieved at the former employer for the allocation decision. Again, the fund family relies more on GMAT for young managers, and more on track record for experienced managers. Finally, we show that fund families re-assign already employed managers to HY funds depending on how much performance they are expected to generate in HY compared to IG funds. All these findings lead to our bottom line conclusion: Fund families allocate fund managers in an efficient way and exploit the managers' comparative advantages.

Our paper is related to several strands of the literature: First, it contributes to the growing literature on decisions taken by fund families. For example, a fund family decides on its product policy (e.g., Mamaysky and Spiegel 2002, Massa 2003, Khorana and Servaes 2004), the fees charged by their funds (e.g., Chordia 1996, Nanda, Narayanan, and Warther 2000), the advertising strategy (e.g., Gallaher, Kaniel, and Starks 2006, Jain and Wu 2000), the management approach (e.g., Massa, Reuter, and Zitzewitz 2010, Baer, Kempf, and Ruenzi 2011), and cross-subsidization between funds (e.g., Gaspar, Massa, and Matos 2006). We extend this literature by showing how fund families allocate fund managers to different market segments. While other papers analyze hiring and firing of managers by fund families (e.g., Khorana 1996, Chevalier and Ellison 1999a), to our knowledge ours is the first paper to address this manager allocation issue.

Second, our paper is related to studies which explore how managers are assigned. Only few papers analyze initial assignment: Drazin and Rao (2002) analyze how fund families assign their already employed managers to newly founded funds. They find that related experience is a key characteristic. Fee and Hadlock (2003) show that the manager of a successful company is more likely to be hired as CEO by a competing company.[2] We add to this literature by demonstrating that a manager's allocation to a market segment is simultaneously driven by manager skill and by the market segment's efficiency.

Third, this paper complements the literature by analyzing the impact of manager skill on fund performance. Golec (1996) and Chevalier and Ellison (1999b) show that the impact of an MBA degree on performance is mixed. Golec (1996) reports a positive impact, Gottesman and Morey (2006) also find a positive impact but depending on the quality of the MBA program, and Chevalier and Ellison (1999b) find no significant impact. In contrast, Li, Zhang, and Zhao (2011) show that hedge fund managers (which may be argued to invest in relatively inefficient segments) from high-SAT undergraduate institutions generate higher performance. We complement this literature by showing (i) that the impact of skill on performance depends on how efficient the market segment is, and (ii) that skill can be captured by GMAT for young managers and by track record for more experienced managers.

The remainder of the paper is structured as follows. Section I describes the data which we use in this study. In Section II, we relate fund performance to manager skill. Section III analyzes how fund families assign their managers to the different market segments. In Section IV, we provide several robustness checks. Section V summarizes and concludes.

[2] Several papers analyze the impact of the CEO on firm performance. See, e.g., Pérez-González (2006), Hayes and Schaefer (1999), Denis and Denis (1995), Bertrand and Schoar (2003), and Malmendier and Tate (2009).

I. Data

Our main data source is the CRSP Survivor Bias Free US Mutual Fund Database from which we obtain our data on funds and fund managers.[3] We focus on the fact sheets from the CRSP Mutual Fund Database via WRDS from 1962 to 2010. The fact sheets contain the fund name and unique identifier number, the name of the managers responsible for the fund at the report date, the name of the managing company, and the date that the current managers assumed responsibility for the fund. The fund objective codes, monthly total net assets, monthly returns, expense ratios, and turnover ratios are also obtained from CRSP. All this data is at fund share class level. We aggregate the data to the fund level based on the total net assets of the share classes, and perform our analysis at the fund level. We focus on funds with a single manager since it is unclear how the skill of the team members translates into the skill of a team. We verify whether a fund is single-managed via the fund's SEC filings starting from 1994 via the EDGAR system. We also restrict ourselves to funds where we are able to determine the manager's GMAT score as described below.

We use three CRSP codes to identify the fund's objective: the Lipper objective code, the Wiesenberger fund type code, and the Strategic Insights objective code. We focus on funds classified either as Investment Grade (IG) corporate bond funds or as High Yield (HY) corporate bond funds. Compared to the Morningstar classification, our IG category corresponds to the "Corporate Bond – General" and "Corporate Bond – High Quality" categories, and HY to "Corporate Bond – High Yield". Even though these funds are at

[3] Source: CRSP™, Center for Research in Security Prices, Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. crsp.uchicago.edu. For a more detailed description of the CRSP database, see Carhart (1997) and Elton, Gruber, and Blake (2001).

the core of our analysis, we collect data on all funds the managers have been responsible for. This allows us to determine the managers' track record.

For each fund, we take the time series of end-of-month fund net asset values, expense ratios, turnover ratios, and fund age for the sample period January 1962 to December 2010 from CRSP. We determine the fund age from the date that the fund first was offered. From the time series of fund net asset values, we determine for each fund the monthly net return and, by adding the total expense ratio, the gross return. Since gross returns better reflect manager ability, we henceforth focus on gross returns.[4]

To obtain information on the manager characteristics, we first verify the managers' names via SEC filings, the fund management companies' websites, fund prospectuses, and other online resources. Using these sources in addition to the Morningstar Principia database, we collect data on the managers' education: whether, when, and from which school the manager obtained a BA, an MBA, a non-business master's degree, CFA, or another graduate degree. For all managers with an MBA degree, we identify the average matriculates' GMAT score of the institution where the manager obtained her MBA from the websites mba.com, businessweek.com, entrepreneur.com, and the schools' websites for the Master class entering in 2010. Thus, GMAT is a proxy for the manager's general ability and the quality of her education. We compute manager tenure as the difference between the current date and the beginning of the manager's investment experience. To determine the latter, we use information from the SEC filings or other sources named above, or, where this information is unavailable, the year the manager

4 Clearly, from an investor's perspective, net returns are more interesting. However, our research objective is not whether HY managers deserve the fees they charge, but whether they are able to exploit bond market inefficiencies. To address this question, gross returns are more appropriate.

completed her BA. When both dates are unavailable, we use the year the manager completed her MBA minus the average time between BA and MBA for those managers where both dates are available.[5]

Table I shows the average characteristics of the 92 HY funds, the 248 IG funds, and the respective fund managers in our sample.

Insert Table I about here

Panel A of Table I shows that HY funds yield higher gross annualized returns of 10.0% p.a. compared to IG funds with 7.9% p.a. These values are in line with the gross returns documented by Gutierrez, Maxwell, and Xu (2009), Chen, Ferson, and Peters (2010), and Comer and Rodriguez (2011) for high and low quality bond funds. Expense ratios are also higher in the HY segment, which is consistent with a higher cost of information gathering in the less efficient market segment.[6] Interestingly, the higher expense ratios of HY funds do not correspond to higher turnover ratios. In fact, the turnover of HY funds is significantly smaller than the turnover of IG funds. This might reflect the higher costs of trading in the HY bond market segment due to lower liquidity as documented by Longstaff, Mithal, and Neis (2005). Also, IG funds are smaller than HY funds and have a lower average age, which has also been documented by Gutierrez, Maxwell, and Xu (2009).

5 It seems an obvious solution to use the date the manager first appears in the CRSP database. However, for those managers where the beginning of their investment experience is available from public documents, the first date the manager appears can be identified by name in the CRSP database is up to 20 years later than the former. Naturally, the manager could be member of an anonymous team (CRSP uses the tag "Team Managed") and, therefore, does not show up by name.

6 Consequently, the difference in net returns is smaller than in gross returns, but remains significant at the 1% level. HY funds yield net annualized returns of 8.7% p.a. compared to IG funds with 7.0% p.a.

Panel B of Table I reports characteristics of managers running HY funds and IG funds. We find that HY managers have attended business schools with higher matriculates' GMAT scores. This ranking implies that highly skilled managers more frequently manage funds in the less efficient HY bond market segment. Only a few managers hold non-MBA degrees, and managers of HY funds do not hold non-MBA degrees more frequently than managers of IG funds do. Looking at tenure shows that HY fund managers are slightly less experienced than IG fund managers.

II Market Efficiency, Manager Skill, and Fund Performance

II.1 Does Skill Pay Off in General?

We first explore whether manager skill has a positive impact on fund performance in general. To do so, we calculate a time series of performance metrics for each fund. We use four different ways to measure performance. Our first measure is the peer-group adjusted return, i.e., the return of the fund minus the average return of all funds in our sample belonging to the same market segment. In addition, we measure performance as the alpha from three different factor models. Our factor models are the Fama and French (1993) five-factor model, the Gebhardt, Hvidkjaer, and Swaminathan (2005) model, and the Blake, Elton, and Gruber (1993) three-index model.[7] For each factor model, we

[7] The Fama-French (1993) five-factor model uses the default spread (spread between a high-yield index return and an intermediate treasury index return) and the term spread (spread between a long-term treasury index return and the one-month T-bill rate) in addition to the market return, the size factor, and the book-to-market factor to determine fund performance in excess of the risk-free rate (one-month T-bill rate). The Gebhardt el al. (2005) model only uses the default and term spread to determine alpha. The Blake et al. (1993) three-index model uses the spread of a high-yield index, a government bond index, and a mortgage-backed security index in excess of the one-month T-bill rate to determine alpha.

determine factor loadings using a rolling window of 36 months and compute the one-month ahead alpha from these factor loadings and the realized returns.

This estimation procedure gives us a time series of four annualized alphas (peer-group alpha, Fama-French alpha, Gebhardt et al. alpha, Blake et al. alpha) for each fund. We then run the following cross-sectional regression using all funds in our sample:

$$\begin{aligned}\alpha_{i,t} = \beta_0 + \beta_1 \mathrm{GMAT}_{i,t} \\ + \beta_2 \mathrm{Ten}_{i,t} + \beta_3 D_{i,t}^{\text{Non-MBA}} + \beta_4 D_{i,t}^{\text{CFA}} + \beta_5 D_{i,t}^{\text{OtherDesignation}} \\ + \beta_6 \mathrm{Size}_{i,t-1} + \beta_7 \mathrm{Age}_{i,t-1} + \beta_8 \mathrm{Expense}_{i,t-1} + \beta_9 \mathrm{Turnover}_{i,t-1} + \varepsilon_{i,t}\end{aligned} \quad \text{(I)}$$

where $\alpha_{i,t}$ is the alpha of fund i at date t and $\mathrm{GMAT}_{i,t}$ is the GMAT score for the manager of fund i at date t. We divide the GMAT score by 100 to obtain a more intuitive coefficient size. We also include manager- and lagged fund control variables. The manager control variables are the tenure ($\mathrm{Ten}_{i,t}$) of the manager of fund i at date t, measured in years, and various dummy variables which take on a value one if the manager has a non-MBA master's degree ($D_{i,t}^{\text{Non-MBA}}$), CFA ($D_{i,t}^{\text{CFA}}$), or another post-graduate degree ($D_{i,t}^{\text{OtherDesignation}}$) at date t. The lagged fund control variables are the log of the assets under management ($\mathrm{Size}_{i,t-1}$), the log of the fund age ($\mathrm{Age}_{i,t-1}$), the expense ratio ($\mathrm{Expense}_{i,t-1}$), and the turnover ratio ($\mathrm{Turnover}_{i,t-1}$). The regression results are given in Table II.

Insert Table II about here.

Table II shows that GMAT does not have a positive impact on alpha in general. Only one model delivers a significant positive coefficient β_1, but two models significantly negative ones. In one model, GMAT has no significant impact on alpha. No manager control variable has a consistent impact on performance across the various models, but the lagged fund control variables do. Fund size, expense ratio, and turnover ratio have a positive impact on performance and age a negative impact across all models showing controlling for fund characteristics matters when explaining the impact of manager skill on fund performance. Overall, we conclude from Table II that skill does not pay off in general: Fund managers cannot translate skill into higher performance.

II.2 Does Skill Pay Off in General in Inefficient Markets?

We now explore whether fund managers can translate skill into higher performance in inefficient market segments. HY and IG funds operate in bond market segments which differ with respect to their efficiency. Kwan (1996) and Hotchkiss and Ronen (2002) show that the IG bond market segment is more efficient than the HY bond market segment.[8] Therefore, we hypothesize that GMAT has a stronger impact on performance in HY funds than in IG funds.

To test this hypothesis, we extend equation (I) and interact the GMAT variable with a dummy variable $D_{i,t}^{HY}$ which takes on a value of one for a HY fund, and a value of zero for an IG fund. The model now reads:

$$\begin{aligned}\alpha_{i,t} = \beta_0 + \beta_1 D_{i,t}^{HY} &+ \beta_2 \mathrm{GMAT}_{i,t} + \beta_3 \mathrm{GMAT}_{i,t} \cdot D_{i,t}^{HY} \\ &+ \beta_4 \mathrm{Ten}_{i,t} + \beta_5 D_{i,t}^{\text{Non-MBA}} + \beta_6 D_{i,t}^{\text{CFA}} + \beta_7 D_{i,t}^{\text{OtherDesignation}} \\ &+ \beta_8 \mathrm{Size}_{i,t-1} + \beta_9 \mathrm{Age}_{i,t-1} + \beta_{10} \mathrm{Expense}_{i,t-1} + \beta_{11} \mathrm{Turnover}_{i,t-1} + \varepsilon_{i,t} \qquad \text{(II)}\end{aligned}$$

8 We test the efficiency ranking by analyzing the extent to which returns are predictable within the two different market segments. Similar to Blanco, Brennan, and Marsh (2005), we explore the relation between the bond and the credit default swap (CDS) market in a vector autoregression (VAR) analysis. The tests clearly support the hypothesis that the HY segment is less efficient than the IG segment: The HY market segment can be well predicted using its own history and lagged CDS premia, but there is no predictability for the IG market.

The regression results are given in Table III.

Insert Table III about here.

Table III shows that GMAT pays off more in the inefficient HY market segment than in the efficient IG market segment. The coefficient β_3 is significantly positive at least at the 5% level in all models. From an economic perspective, the performance increase due to a higher GMAT is also sizeable: a GMAT increase of 100 (corresponding to the difference between, e.g., Harvard and Northeastern University) increases performance in the HY segment more than in the IG segment by 14 bp (peer group alpha) to 49 bp (Fama-French alpha). This finding supports our hypothesis: Fund managers can better translate skill into performance in the inefficient market segment. Hence, fund families should assign their smartest managers to the least efficient segments.

II.3 Which Type of Skill Pays Off?

So far, we have used GMAT as our proxy for skill since it provides information about the fund manager's general ability and the quality of her education. However, the impact of education should decrease as the manager becomes older and more experienced. Instead, job specific skill should gain importance. To test this hypothesis, we use an extended version of the previous model where we interact GMAT with manager tenure (Ten):

$$\alpha_{i,t} = \beta_0 + \beta_1 D_{i,t}^{HY} + \beta_2 \text{GMAT}_{i,t} + \beta_3 \text{GMAT}_{i,t} \cdot D_{i,t}^{HY} \\ + \beta_4 \text{GMAT}_{i,t} \cdot \text{Ten}_{i,t} + \beta_5 \text{GMAT}_{i,t} \cdot \text{Ten}_{i,t} \cdot D_{i,t}^{HY} + \beta_6 \text{Ten}_{i,t} \cdot D_{i,t}^{HY} \\ + \beta_7 \text{Ten}_{i,t} + \beta_8 D_{i,t}^{\text{Non-MBA}} + \beta_9 D_{i,t}^{\text{CFA}} + \beta_{10} D_{i,t}^{\text{OtherDegree}} \\ + \beta_{11} \text{Size}_{i,t-1} + \beta_{12} \text{Age}_{i,t-1} + \beta_{13} \text{Expense}_{i,t-1} + \beta_{14} \text{Turnover}_{i,t-1} + \varepsilon_{i,t} \qquad \text{(III)}$$

Table IV presents the results of this extended regression model.

Insert Table IV about here.

As Table IV shows, GMAT still has a significant positive impact on alpha in the HY segment. β_3 is significantly positive at least at the 5% level in all cases. However, the impact of GMAT decreases as the manager gains more experience. β_5 is smaller than zero in all cases and significant at the 1% level in all cases but one. Jointly, β_3 and β_5 imply that a manager with a 100 points higher GMAT and an average tenure delivers a performance which is up to 95 bp (Gebhardt et al. alpha) higher in the HY segment than in the IG segment. However, this difference decreases by 11.23 bp (Gebhardt et al. alpha) for each additional year of tenure such that the performance effect of the higher GMAT is entirely compensated if the manager is nine years older. Hence, fund families should consider the GMAT of their managers primarily when the managers are young.

We next test whether the impact of job specific skill becomes more important when the manager gains experience. We use track record as a broad measure of all investment skills of the manager. We measure the track record over the manager's entire investment career (i.e., since the manager first appeared in the CRSP database by name) and all funds managed by her. To eliminate possible time trends in alpha, we define the track record as the difference between the manager's alpha and the average alpha of all managers in the respective market segment.[9] The average of these differences in alpha is our measure of manager track record. We again run regression (III) but replace GMAT by track record.[10] Table V shows the results.

Insert Table V about here.

Table V provides support for our hypothesis: Track record matters more for fund managers with longer tenure. The coefficient β_5 is significantly larger than zero in three out of four cases. With respect to the economic significance, one additional percentage point of track record increases the performance of a manager with average tenure by 14 bp (peer-group adjusted alpha) more in the HY segment than in the IG segment. For each additional year of tenure, the difference increases by 1.25 bp (peer group alpha). The impact of the manager- and fund control variables is small in statistic and economic terms.

Overall, we draw two main conclusions from Section II: First, fund families should assign their best managers to the least efficient market segment since skill pays off more than in less efficient segments. Second, fund families should judge the quality of less experienced managers based on their general ability and education (measured by GMAT) and the quality of their more experienced managers based on their demonstrated investment skill (measured by track record). We analyze whether fund families behave in this way in the next section.

9 We indeed find that the average factor model alphas of the fund managers tend to be higher in the beginning of our research period and smaller in later years. The average peer-group alpha is zero by construction.

10 We also run our basis regressions using track record as the main explanatory variable and come to the same conclusions as in Sections II.1 and II.2: Skill pays off more in the inefficient market segment. Track record has no positive impact on alpha in general, but typically has a positive impact when interacted with a HY dummy.

III Manager Allocation

III.1 Do Fund Families Assign Managers Based on Skill?

To test whether fund families assign their most skilled managers to HY funds, we run the following probit regression:

$$\Pr\left(D_{i,t}^{HY} = 1\right) = \Phi\left(\beta_0 + \beta_1 \text{Skill}_{i,t} + \gamma \text{Controls Manager}_{i,t} + \varepsilon_{i,t}\right). \qquad \text{(IV)}$$

$D_{i,t}^{HY}$ is a dummy variable which takes on a value of one if the fund manager is assigned to a HY fund, and skill is measured based on GMAT and track record, respectively. Controls Manager consists of the same manager control variables as before, and Φ is the cumulative normal distribution.

In Table VI, we report the results obtained when measuring skill via GMAT. We use three GMAT-based measures. $\text{GMATFam}_{i,t}$ is the manager's GMAT minus the average GMAT across all managers employed by the same fund family. $\text{GMATSeg}_{i,t}$ is the manager's GMAT minus the average GMAT across all managers in the market segment, and GMAT is the manager's GMAT. Thus, the former two measures capture how skilled a manager is compared to her peer group. The rationale for taking a relative GMAT measure is that the fund family has to choose the manager out of a given group of fund managers. $\text{GMATFam}_{i,t}$ is based on the idea that the fund family chooses among the managers already employed in the company, and $\text{GMATSeg}_{i,t}$ uses all managers of the market segment as the peer group.

Besides the basis model (IV), we run an extended version where we also interact the GMAT-based skill variables with manager tenure. This allows us to test whether fund families use GMAT primarily for the allocation of non-experienced managers. All results are provided in Table VI.

Insert Table VI about here.

Table VI provides strong support for our basis hypothesis: Fund families assign managers with high GMAT to HY funds. $GMATFam_{i,t}$ has a stronger influence on the segment assignment than $GMATSeg_{i,t}$ and $GMAT_{i,t}$.[11] This suggests that fund families choose the manager to be assigned from the pool of managers already employed by the company.

Table VI also shows that GMAT drives the fund family's decision more for less experienced managers (Model 4 – 6). GMAT interacted with Tenure has a significant negative impact on the probability of managing a HY fund. Thus, fund families allocate young managers with high GMAT to HY funds – a sensible strategy given our results in Section II.

The control variables show that fund families hesitate to assign managers with non-MBA or other graduate degrees to HY funds. The coefficients β_7 and β_9 are significantly negative at the 1% level in all cases but one. Furthermore, fund families do not prefer CFA holders for running a HY fund, and higher tenure itself also does not increase the chance of managing a HY fund.

We next use manager track record as proxy for skill. The results are provided in Table VII.

[11] When we use both $GMATFam_{i,t}$ and $GMATSeg_{i,t}$ or $GMAT_{i,t}$ in the probit regression, only the loading on $GMATFam_{i,t}$ remains positive and significant.

Insert Table VII about here.

Table VII shows that a better track record makes it more likely that a fund family assigns a manager to a HY fund, and that fund families rely more on track record for managers with higher tenure. This behavior is highly sensible since the information contained in the track record is more precise for managers with a longer track record.

Overall, Table VII leads to the same conclusion as Table VI. Fund families assign the best managers to HY funds. This result holds whether we measure skill based on GMAT (as in Table VI) or based on track record (as in Table VII).[12]

III.2 Do Fund Families Adjust their Manager Portfolio Based on Skill?

In Section III.1, we analyze the composition of the fund family's manager portfolio. We now investigate how fund families adjust their manager portfolios over time. We distinguish three cases: (i) The fund family hires a beginner fund manager. (ii) The fund family hires a fund manager from another fund family. (iii) The fund family switches an already employed manager from one fund to another.

We start by analyzing managers when they do not yet have a track record, i.e., when they appear by name in the CRSP database for the first time. For these new managers, fund families have to rely solely on the manager's GMAT since there is no track record available. Therefore, we hypothesize that a new manager is more like to run a HY fund if

[12] We get the same result when using excess track record within the firm (difference between the track record of the manager and the average track record of all managers in the fund family) instead of track record.

she has a high GMAT relative to colleagues in the new company. We test this hypothesis by running the following regression:

$$\Pr\left(D_{i,t}^{HY}=1 \text{ and Manager = New}\right)=\Phi\left(\beta_0+\beta_1\text{GMATFam}_{i,t}+\gamma\text{Controls Manager}_{i,t}+\varepsilon_{i,t}\right). \tag{V}$$

We find a positive impact of $\text{GMATFam}_{i,t}$ ($\beta_1=0.0999$) on the probability of running a HY fund. The coefficient is significant at the 10% level. This result supports our basis hypothesis: When fund families hire a beginner fund manager, they use GMAT to decide which fund they assign the manager to. The higher her GMAT, the more probable the fund family will assign her to a HY fund.[13]

We next analyze how fund families allocate a newly hired manager who has been employed by another fund family before. This allows us to study whether fund families consider the experience the manager has gained at other fund families. We hypothesize that fund families allocate non-experienced managers based on GMAT, and managers with a long investment experience based on track record. We test this hypothesis by running the following regression:

$$\begin{aligned}&\Pr\left(D_{i,t}^{\text{HY in New Family}}=1\right)\\&=\Phi\left(\beta_0+\beta_1\text{Skill}_{i,t}+\beta_2\text{Skill}_{i,t}\cdot\text{Tenure}_{i,t}+\gamma\text{Controls Manager}_{i,t}+\varepsilon_{i,t}\right).\end{aligned} \tag{VI}$$

$D_{i,t}^{\text{HY in New Family}}$ is a dummy variable that takes on a value of one if the manager immediately manages a HY fund in the fund family she joins. Table VIII shows the results when skill is based on GMAT, Table IX shows the respective results based on track record.

13 We also get a positive coefficient β_1 when we use $\text{GMATSeg}_{i,t}$ or $\text{GMAT}_{i,t}$ instead of $\text{GMATFam}_{i,t}$, but the coefficient is not statistically significant at the usual levels.

Insert Table VIII about here.

Table VIII supports our hypothesis: GMAT matters when assigning newly hired managers, and the impact of GMAT is stronger for less experienced managers. The respective coefficients are significant at the 5% level for $GMATFam_{i,t}$. When using $GMATSeg_{i,t}$ and $GMAT_{i,t}$, the significance decreases, again suggesting that fund families evaluate managers with respect to the peer group of currently employed managers.

When running a similar analysis using track record as our measure of skill, we find again a positive impact of skill (Panel A of Table IX). For three out four models, we find the expected tenure effect (Panel B of Table IX): When hiring a HY manager, track record matters more for more experienced managers. This is highly sensible since a long track record provides the fund family with a reliable signal about the overall investment skill of the fund manager.

Insert Table IX about here.

Our final analysis explores how fund families reassign fund managers they already employ. Our hypothesis is that fund families allocate IG managers to HY funds depending on the additional performance they are expected to earn in the HY segment.

We perform a two-step analysis to explore whether fund families pursue this policy. In the first step, we calculate the alpha the manager is expected to earn in the HY segment and the IG segment, respectively. To do so, we use the coefficient estimates we obtain when calibrating our most sophisticated performance regression model, and compute the expected alpha for a given fund and manager one month ahead. To calculate the alpha the manager is expected to earn in the HY segment we treat the fund as if it were a HY fund, i.e., we set the HY dummy variable to one. We measure skill by GMAT and by track record, respectively. Based on GMAT, the alpha manager i is expected to earn in a particular fund (j) in the HY segment is given as:[14]

$$\begin{aligned}\hat{\alpha}_{i,j,t}^{HY} = \hat{\beta}_0 + \hat{\beta}_1 + \left(\hat{\beta}_2 + \hat{\beta}_3\right)\text{GMAT}_{i,t-1} + \left(\hat{\beta}_4 + \hat{\beta}_5\right)\text{GMAT}_{i,t-1} \cdot \text{Ten}_{i,t} \\ + \left(\hat{\beta}_6 + \hat{\beta}_7\right)\text{Ten}_{i,t} + \hat{\beta}_8 D_{i,t-1}^{\text{Non-MBA}} + \hat{\beta}_9 D_{i,t-1}^{\text{CFA}} + \hat{\beta}_{10} D_{i,t-1}^{\text{OtherDegree}} \\ + \hat{\beta}_{11}\text{Size}_{j,t-1} + \hat{\beta}_{12}\text{Age}_{j,t-1} + \hat{\beta}_{13}\text{Expense}_{j,t-1} + \hat{\beta}_{14}\text{Turnover}_{j,t-1} \qquad \text{(VII)}\end{aligned}$$

To calculate the alpha the manager is expected to earn in a particular fund in the IG segment, we also use equation (VII), but set $\hat{\beta}_1 = \hat{\beta}_3 = \hat{\beta}_5 = \hat{\beta}_7 = 0$. We then calculate the average expected alpha across all funds for manager i and obtain the manager's expected HY alpha $\bar{\alpha}_{i,t}^{HY}$ and IG alpha $\bar{\alpha}_{i,t}^{IG}$. Finally, we calculate the manager's expected alpha add-on $\Delta\bar{\alpha}_{i,t}$ as the difference between the manager's expected HY alpha and IG alpha. We hypothesize that a manager is re-allocated from the IG to the HY segment depending on the excess alpha she is expected to earn in the HY segment.

In the second step we test this hypothesis. We focus on cases where an IG fund manager in t-1 is moved to a HY fund in t. Thus, the IG fund manager newly takes on at least one HY fund and at the same time gives up responsibility for all IG funds. The probability for this to occur is denoted by $\Pr\left(D_{i,t}^{HY} = 1, D_{i,t-1}^{IG} = 0 \middle| D_{i,t-1}^{HY} = 0, D_{i,t-1}^{IG} = 1\right)$ in the following probit regression:

$$\Pr\left(D_{i,t}^{HY} = 1, D_{i,t-1}^{IG} = 0 \middle| D_{i,t-1}^{HY} = 0, D_{i,t-1}^{IG} = 1\right) = \Phi\left(\beta_0 + \beta_1\Delta\bar{\alpha}_{i,t} + \varepsilon_{i,t}\right), \qquad \text{(VIII)}$$

14 When measuring skill by track record, we use track record instead of GMAT in equation (VII).

The results are reported in Panel A of Table X. They clearly show that fund families allocate their IG fund managers to HY funds depending on the additional performance the manager can generate in this segment. The coefficient is positive and significant at the 1% level in seven out of eight cases.

Insert Table X about here.

In Panel B, we report the results of additional tests where we consider all cases in which an IG manager newly takes on at least one HY fund in t, irrespective of whether she remains responsible for her IG funds. We test whether the probability that an IG fund manager in t-1 will take on a HY fund in t, $\Pr\left(D_{i,t}^{HY}=1 \middle| D_{i,t-1}^{HY}=0, D_{i,t-1}^{IG}=1\right)$, depends positively on the manager's expected HY alpha by running the following probit regression:

$$\Pr\left(D_{i,t}^{HY}=1 \middle| D_{i,t-1}^{HY}=0, D_{i,t-1}^{IG}=1\right)=\Phi\left(\beta_0+\beta_1\bar{\alpha}_{i,t}^{HY}+\varepsilon_{i,t}\right), \qquad \text{(IX)}$$

The results presented in Panel B of Table X support our hypothesis for six out of eight models. The higher the alpha the IG manager is expected to earn in the HY segment, the higher is the probability that she takes on responsibility for a HY fund.

Jointly, the results of Section III highlight that fund families allocate fund managers in a fully rational way. They assign the best managers to HY funds where their skill pays off most. They do so by re-allocating fund managers already employed managers according to the additional performance they are expected to earn in HY funds. When hiring new managers, fund families rely on GMAT as a proxy for skill of young managers, but judge more experienced managers based on track record. This is highly sensible since GMAT is a good proxy for future performance for non-experienced managers and track record for experienced managers, as shown in Section II.

IV Robustness Section

In this section we perform several robustness tests. First, we use alternative skill measures (Section IV.1). Second, we calculate alphas based on conditional factor models (Section IV.2). Finally, we test whether our results are driven by differences in liquidity between the bonds held by IG and HY funds (Section IV.3).

IV.1 Alternative Skill Measures

So far, we have used two measures of manager skill, (i) the average matriculates' GMAT score of the institution where she obtained her MBA degree, and (ii) the track record over the entire investment career of the manager. To test the robustness of our results, we now repeat our analyses using different skill measures.

As a first alternative to our GMAT measure, we classify business schools according to their GMAT into quintiles and assign scores from 1 (worst quintile) to 5 (top quintile) to the managers who have attended them. As a second alternative, we define the dummy variable TopSchool that takes on a value of one if the manager has attended a top 10% GMAT school (Stanford, Columbia, Wharton, Harvard, Berkeley, New York, Chicago, Dartmouth College, UCLA, MIT).

We also employ two additional track record measures. Instead of calculating the manager's track record over her entire investment career, we also calculate the track record over shorter periods. Specifically, we calculate the track record over the last three years and the track record over the previous year.

We run the entire analysis based on these alternative skill measures, but do not report all results for sake of brevity in Table XI. Instead, we report only results for alphas obtained from the Fama-French factor model and restrict the presentation to the most important variables.

Insert Table XI about here.

Table XI leads to the same conclusion as above. GMAT pays off more in the inefficient HY segment (Panel A) and matters more for less experienced managers (Panel B). The fund family takes this effect into account and assigns managers from better schools to HY funds, especially when managers have little experience (Panel D and F).

The results for track record are qualitatively the same as in the standard model as well, but the impact on performance is statistically weaker. This is especially prevalent when we use track record over the previous year (Variation 2, Panel C). We find these differences to the standard model sensible since they suggest that long-term track record is a more precise signal of manager skill. Consequently, fund families base their decisions not on short term track record, but on long-term performance (Panel E, G, and H, Variation 1 and 2).

IV.2 Conditional Models to Estimate Alpha

To calculate alphas in the Fama-French model, the Gebhardt et al. model, and the Blake et al. model, we assumed the factor loadings to be constant over time. However, fund managers may follow dynamic trading strategies and vary factor loadings over time. To capture this effect, we now estimate alphas using conditional betas. Since conditional and constant beta models may deliver statistically and economically significant differences in fund performance as shown by Ferson and Schadt (1996) and Silva, Cortez, and Armada (2005), this allows us to test the stability of our results with respect to different ways of estimating alpha. We re-run the entire analysis and present the main results in Table XII.[15]

Insert Table XII about here.

Table XII clearly shows that our main results remain unchanged when we use conditional factor models to determine performance. GMAT leads to better performance only in the inefficient HY segment (Panel A) and matters more for less experienced managers (Panel B). For more experienced managers, track record gains importance (Panel C). Fund companies take this into account and assign their managers to the HY and IG segment accordingly (Panel D-F).

IV.3 The Impact of Liquidity

In the previous sections, we have used three factor models which are well-established in the literature on bond funds to determine alphas. None of these models, however, explicitly accounts for illiquidity as a potentially priced risk factor. Hence, the alphas we

[15] Note that Table VI and VIII are independent from the way alpha is computed.

determine may not signal manager skill, but simply arise because fund managers actively take on liquidity risk.[16] We therefore re-estimate alphas by adding the TED spread (the difference between the three-months USD-LIBOR and the three-months US T-bill rate) as a proxy for liquidity risk to all three models as an explanatory variable.[17] We then repeat the entire analysis. The results are presented in Table XIII.

Insert Table XIII about here.

Panel A of Table XIII shows that the relation between skill and performance in the HY segment is not caused by higher liquidity risk in this segment. As before, GMAT (track record) matters less (more) for more experienced managers (Panel B and C). Since the relation between skill and performance is not a spurious finding caused by liquidity risk, it remains sensible for fund families to assign more skilled managers to the HY segment (Panel D-F).

V Conclusion

In this paper, we show that fund families allocate fund managers in an efficient way. They assign their best managers to the least efficient market segment where their skill pays off most.

We come to this bottom line conclusion by studying US fund managers in the investment grade (IG) and the high yield (HY) corporate bond market. Our empirical study leads to

[16] Sadka (2010) shows that hedge funds that significantly load on liquidity risk subsequently outperform low-loading funds by about 6% annually.

[17] The TED spread has recently been interpreted as a measure of funding liquidity, see ,e.g., Brunnermeier (2009), or Fontaine and Garcia (2011). Cornett et al (2011) provide evidence that the TED spread measures market-wide liquidity conditions.

four main results: (i) Fund performance increases with the fund manager's skill (measured as GMAT or track record) only in the inefficient HY segment. In the more efficient IG market, skill does not pay off. (ii) The impact of track record (GMAT) on performance is stronger for more (less) experienced managers. (iii) Fund families seem to be aware of this fact and assign their most skilled managers to HY funds. The more (less) experienced the fund manager is, the more the fund family relies on track record (GMAT) as a signal of skill. (iv) Fund families reassign IG managers to HY funds according to the alpha add-on managers can generate in the HY segment.

These manager allocation strategies are highly sensible since they increase HY fund alphas. Hence, average alpha in the fund family increases and, as a consequence, the family attracts new money inflow and fee income. Manager allocation is thus a decision of similar importance as advertising and cross-subsidization. In these latter decisions, the fund family generates advantages for one manager at another manager's expense. Allocating the most highly skilled managers to the least efficient segment, however, does not put less highly skilled managers at a disadvantage.

Table I: Summary Statistics

We present summary statistics for all variables used in the analysis. The fund characteristics include the mean annualized gross return in percentage points, the mean expense and turnover ratios in percentage points per year, the assets under management in million USD (size), and the mean fund age in years. GMAT denotes the 2010 GMAT average across matriculates at the manager's MBA institution, averaged across all managers. Tenure is measured as the difference between the current date and the beginning date of the manager's investment experience in years. Managers w/ other master, w/ CFA and w/ other designation is measured as the percentage of managers in the sample holding the stated degree. Averages are taken first over time for each fund, and then across funds. ***, **, and * denote that the differences between the HY and IG are significant at the 1%, 5%, and 10% level, respectively.

	High Yield (HY)	Investment Grade (IG)	Difference (HY-IG)
	Panel A: Fund Characteristics		
Gross Return [%/year]	10.0008	7.8723	2.1285***
Expense Ratio [%/year]	1.3359	0.9071	0.4288***
Turnover Ratio [%/year]	112.0816	198.8104	-86.7288***
Size [mn USD]	792.6285	674.7659	117.8626***
Age [years]	13.0511	11.8558	1.1953***
# Obs. (Fund-Months)	10,439	30,404	
	Panel B: Manager Characteristics		
GMAT	652.9664	641.8334	11.1330***
Tenure [years]	18.0566	19.7442	-1.6876***
Managers w/ other master [%]	1.1782	2.1609	-0.9827***
Managers w/ CFA [%]	9.7423	10.2026	-0.4603
Managers w/ other designation [%]	0.1437	0.4539	-0.3102***

Table II: Overall Impact of GMAT on Alpha

We present the results of the regression in equation (I) of alpha on GMAT and on manager and lagged fund control variables. Alphas are determined as described in the main text, and used as annualized values in percentage points. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. R^2 are in percentage points.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
Constant	-5.4336***	-2.5554***	-1.7585**	6.0021***
GMAT	-0.1693***	-0.3813***	-0.0714	0.1588**
	Manager Control Variables			
Tenure	0.0786***	0.0780***	0.0162	-0.2078***
Non-MBA Master	0.0232***	0.0165*	0.0073	-0.0272
CFA	0.0023	0.0000	-0.0015	-0.0101
Other Designation	0.0072	0.0134	0.0060	0.0139
	Fund Control Variables			
Size	0.1909***	0.1876***	0.3046***	0.3093***
Age	-0.0289***	-0.0213**	-0.0343*	-0.0085
Expense Ratio	2.2928***	1.2064***	3.2272***	3.6570***
Turnover Ratio	0.0028***	0.0013**	0.0026***	0.0015**
# Obs.	24,436	24,116	24,171	24,152
R^2	1.2760	0.3723	0.9253	1.8343

Table III: Impact of GMAT on Alpha: Segment Specific Analysis

We present the results of the regression in equation (II) of alpha on GMAT, GMAT interacted with a dummy variable for the high-yield segment, and manager and lagged fund control variables. Alphas are determined as described in the main text, and used as annualized values in percentage points. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors. R^2 are in percentage points.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
Constant	-5.3006***	-2.5659***	-1.6953**	6.2125***
HY	-0.8954***	-1.0765***	-0.1124	1.1312***
GMAT	-0.2198***	-0.5075***	-0.1501**	0.0955
GMAT * HY	0.1397**	0.4891***	0.3152**	0.2806**
	Manager Control Variables			
Tenure	0.0789***	0.0878***	0.0200	-0.2101**
Non-MBA Master	0.0231***	0.0191**	0.0095	-0.0239*
CFA	0.0020	-0.0007	-0.0013	-0.0096
Other Designation	0.0057	0.0141	0.0073	0.0168
	Fund Control Variables			
Size	0.1918***	0.1733**	0.2871***	0.2760***
Age	-0.0308***	-0.0231**	-0.0344***	-0.0062
Expense Ratio	2.5274***	1.3778***	3.1742***	3.2636***
Turnover Ratio	0.0024***	0.0010	0.0027***	0.0022***
# Obs.	24,436	24,116	24,171	24,152
R^2	1.3600	0.4636	0.9590	1.9180

Table IV: Tenure and the Impact of GMAT on Alpha: Segment Specific Analysis

We present the results of the regression in equation (III) of alpha on GMAT, GMAT interacted with a dummy variable for the high-yield segment, GMAT interacted with manager tenure, GMAT interacted with tenure interacted with the dummy for the high-yield segment, tenure interacted with the dummy for the high-yield segment, and manager and lagged fund control variables. Alphas are determined as described in the main text, and used as annualized values in percentage points. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. R^2 are in percentage points.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
Constant	-5.0825***	-3.6359***	-0.8887	8.2945***
HY	-1.9575***	-0.3297	-3.3031**	2.3359*
GMAT	-0.3239**	-0.2598	-0.8415***	-1.7229***
GMAT * HY	0.9927***	1.9361***	2.9772***	1.0477**
GMAT * Ten	0.0038	-0.0110	0.0265***	0.0720***
GMAT * HY * Ten	-0.0367***	-0.0644***	-0.1123***	-0.0271
HY * Ten	0.0441*	-0.0293	0.1288**	-0.0437
	Manager Control Variables			
Tenure	0.0715***	0.1338***	-0.0143	-0.2958***
Non-MBA Master	0.0210***	0.0187**	0.0125	-0.0122
CFA	0.0041	0.0048	0.0017	-0.0143**
Other Designation	0.0051	0.0107	0.0065	0.0224
	Fund Control Variables			
Size	0.1909***	0.1618**	0.2963***	0.2939***
Age	-0.0293***	-0.0215**	-0.0289***	-0.0048
Expense Ratio	2.4699***	1.3193***	3.0507***	3.1522***
Turnover Ratio	0.0024***	0.0009	0.0028***	0.0024***
# Obs.	24,436	24,116	24,171	24,152
R^2	1.4280	0.6149	1.1060	2.2400

Table V: Tenure and the Impact of Track Record on Alpha: Segment Specific Analysis

We present the results of the regression of alpha on track record, track record interacted with a dummy variable for the high-yield segment, track record interacted with manager tenure, track record interacted with tenure interacted with the dummy for the high-yield segment, tenure interacted with the dummy for the high-yield segment, and manager and lagged fund control variables. Track record is measured as the difference between the alpha of the manager and the average alpha of all managers in the respective market segment. We calculate the relative performance of the manager for all past months and all funds managed by her. The average of these differences in alpha is our measure of the manager's track record. Alphas are determined as described in the main text, and used as annualized values in percentage points. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. R^2 are in percentage points.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
Constant	-3.5233***	-4.3554	-4.3974	0.4669
HY	-1.5360**	21.1800**	20.5208**	10.8871
Track Record	0.8711***	0.2743	-0.2049	1.2934***
Track Record * HY	-0.0922	-0.2744	0.8975	-0.0944
Track Record * Ten	-0.0152***	-0.0119	0.0127	-0.0421*
Track Record * HY * Ten	0.0126**	0.0157*	0.0408**	-0.0089
HY * Ten	0.0144	-0.8404**	-0.9127**	-0.3531
	Manager Control Variables			
Tenure	0.0350**	0.0814	0.2402	0.0346
Non-MBA Master	0.0000	0.0324	0.0481	0.0875
CFA	-0.0058**	-0.0018	0.0077	0.0032
Other Designation	-0.0103	0.0000	0.0000	0.0000
	Fund Control Variables			
Size	0.0489	0.7175	0.0242	1.1060
Age	-0.0092	0.0241	-0.0275	-0.0413
Expense Ratio	2.4270***	-1.0754	1.5210	2.3717
Turnover Ratio	0.0017***	-0.0076	0.0065	-0.0091
# Obs.	24,436	24,116	24,171	24,152
R^2	5.8370	1.7070	2.0520	3.0780

Table VI: Impact of GMAT on Segment Assignment

We present the results of the probit regressions in equation (IV) of a manager's assignment to the high yield segment on GMAT measures and manager control variables. The dependent variable is the probability of a manager being assigned to a HY fund. The explanatory variables are three different GMAT measures, each of these GMAT measures interacted with the manager's tenure, and the manager control variables. The GMAT measures are the deviation of the manager's GMAT from the average GMAT within the fund family (GMATFam), the deviation of the manager's GMAT from all managers in the market segment (GMATSeg), and the manager's GMAT score (GMAT), all divided by 100. The manager control variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.6275***	-0.6278***	-0.6471***	-0.6715***	-0.6654	-0.7089***
GMATFam	0.0214***			0.0550***		
GMATSeg		0.0186**			0.0986***	
GMAT			0.0074**			0.0756***
GMATFam * Ten				-0.1532***		
GMATSeg * Ten					-0.0035***	
GMAT * Ten						-0.0030***
	Manager Control Variables					
Tenure	-0.0016*	-0.0015*	-0.0009	0.0004	0.0003	0.0019*
Non-MBA Master	-0.0037***	-0.0038***	-0.0035***	0.0000	-0.0040***	-0.0038***
CFA	-0.0005*	-0.0007**	-0.0003	-0.0004	-0.0005*	-0.0002
Other Designation	-0.0063***	-0.0064***	-0.0061***	-0.0069***	-0.0063***	-0.0060***
# Obs.	12,348					

Table VII: Impact of Track Record on Segment Assignment

We present the results of the probit regressions in equation (IV) of a manager's assignment on track record and manager control variables. The dependent variable is the probability of a manager being assigned to a high yield fund. The explanatory variables are the manager's track record as defined in Table V, the manager's track record interacted with the manager's tenure, and the manager control variables. Panel B presents the results of the regressions where the track record is interacted with the manager's tenure. Alphas are determined as described in the main text, and used as annualized values in percentage points. The manager control variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
	Panel A: Impact of Track Record			
Constant	-0.4664***	-0.5757***	-0.5784***	-0.5498***
Track Record	0.0060***	0.0053	0.0180**	0.0128
Manager Controls	Yes			
	Panel B: Impact of Track Record Interacted with Tenure			
Constant	-0.4610***	-1.0874***	-1.0177***	-0.8950***
Track Record	-0.0079***	-0.7796***	-0.3938***	-0.3251***
Track Record * Ten	0.0008***	0.4673***	0.2317***	0.1812***
Manager Controls	Yes			
# Obs.	12,348			

Table VIII: Impact of GMAT on Segment Assignment for Newly Hired Managers

We present the results of the probit regression in equation (VI) of a manager's assignment on GMAT and manager control variables for managers newly hired by the fund family. The dependent variable is the probability of a manager being assigned to a HY fund in the new fund family. The explanatory variables are the three different GMAT measures as defined in Table VI, the GMAT measures interacted with the manager's tenure, and the manager control variables. The manager control variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.7517***	-0.7843***	-0.8512	-0.8115***	-0.7954***	-0.8842***
GMATFam	0.0299**			0.0741**		
GMATSeg		0.0008**			0.0009*	
GMAT			0.0766*			0.0864*
GMATFam * Ten				-0.0025**		
GMATSeg * Ten					0.0000	
GMAT * Ten						-0.0008
	Manager Control Variables					
Tenure	-0.0191*	-0.0317**	-0.0300**	-0.0147	-0.0304	-0.0265
Non-MBA Master	-0.0020	-0.0017	-0.0017	-0.0019	-0.0016	-0.0016
CFA	-0.0018	-0.0020	-0.0020	-0.0018	-0.0020	-0.0020
Other Designation	-0.0032	-0.0031	-0.0031	-0.0029	-0.0030	-0.0030
# Obs.	291					

Table IX: Impact of Track Record on Segment Assignment for Newly Hired Managers

We present the results of the probit regression in equation (VI) of a manager's assignment on track record and manager control variables for managers newly hired by the fund family. The dependent variable is the probability of a manager being assigned to a HY fund in the new fund family. The explanatory variables are the manager's track record as defined in Table V, the manager's track record interacted with the manager's tenure, and the manager control variables. Panel B presents the results of the regressions where the track record is interacted with the manager's tenure. Alphas are determined as described in the main text, and used as annualized values in percentage points. The manager control variables are as in Table I. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
	Panel A: Impact of Track Record			
Constant	-0.3188	-0.7766***	-0.7751***	-0.9146***
Track Record	0.0799*	0.1305**	0.0498*	0.2194*
Manager Controls	Yes			
	Panel B: Impact of Track Record Interacted with Tenure			
Constant	-0.3633	-0.7353**	-0.9218**	-1.2115***
Track Record	-0.3397*	-0.2361**	-0.3976**	0.6859**
Track Record * Ten	0.0235**	0.0186**	0.0175**	-0.0239**
Manager Controls	Yes			
# Obs.	291			

Table X: Manager Reassignment

We present the results of the probit regressions in equation (VIII) and (IX) of a manager's re-allocation from the IG to the HY segment on the manager's expected alpha in the HY segment (Panel A), and the manager's expected alpha add-on (Panel B). The dependent variables are the probability of a manager being newly assigned to a HY fund after having managed an IG fund in Panel A, and the probability of being newly assigned to a HY fund and giving up all previously managed IG funds in Panel B. The explanatory variables are the average expected alpha the fund manager can generate in the HY segment in Panel A, and the expected alpha add-on, defined as the difference between the average expected alpha the fund manager can generate in the HY segment and the IG segment, in Panel B. The expected alpha for each manager/fund combination is computed using equation (VIII). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Peer Group Adj.	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
	Panel A: IG fund manager takes over HY funds			
Constant	-1.0421***	-1.5993***	-1.6212***	-1.6310***
$\overline{\alpha}^{HY}$ (GMAT)	0.1694***	0.1278***	0.1225***	-0.0537***
Constant	-0.9432***	-1.6142***	-1.5992***	-1.4856***
$\overline{\alpha}^{HY}$ (Track Record)	0.0127**	0.0017***	0.0008**	-0.01862***
	Panel B: IG fund manager takes over HY funds and gives up all IG fund			
Constant	-1.5656***	-1.7861***	-1.7934***	-1.9594***
$\Delta\overline{\alpha}$ (GMAT)	0.2776***	0.0707***	0.0922***	0.0739***
Constant	-0.7352***	-1.6214***	-1.5997***	-1.5129***
$\Delta\overline{\alpha}$ (Track Record)	0.2082***	0.0018****	0.0001***	-0.0196***
# Obs.	12,348			

Table XI: Alternative Skill Measures

We present results of various regressions where we use different skill measures. Alphas are estimated using the Fama-French five factor model. In the first column (Standard Skill Measure), we again report results based on our standard measures (GMAT, Track Record). In the second column (Variation 1), we use GMATQuintiles instead of GMAT (Panel A, B, D, F, and H) and 3-year track record instead of the track record over the entire investment career (Panel C, E, G, and H). In the third column (Variation 2), we use the dummy TopSchool instead of GMAT (Panel A, B, D, F, and H) and 1-year track record instead of the track record over the entire investment career (Panel C, E, G, and H). Using these alternative skill measures, we replicate Table III (Panel A), Table IV (Panel B), Table V (Panel C), Model 4 of Table VI (Panel D), Panel B of Table VII (Panel E), Model 4 of Table VIII (Panel F), Panel B of Table IX (Panel G), and Panel B of Table X (Panel H). For sake of brevity, we report only the results for the main variables. The variables are defined as in the respective tables. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Standard Skill Measure	Variation 1	Variation 2
	Panel A: Replication of Table III Impact of GMAT on Alpha: Segment Specific Analysis		
GMAT	-0.5075***	-1.8413***	-0.7991***
GMAT * HY	0.4891***	0.8892***	3.4823**
	Panel B: Replication of Table IV Tenure and the Impact of GMAT on Alpha: Segment Specific Analysis		
GMAT * HY	1.9361***	3.2007***	2.0832***
GMAT * HY * Ten	-0.0644***	-0.1058***	-0.8795**
	Panel C: Replication of Table V Tenure and the Impact of Track Record on Alpha: Segment Specific Analysis		
Track Record * HY	-0.2744	-0.3573	-0.2720
Track Record * HY * Ten	0.0157*	0.0144*	0.0051
	Panel D: Replication of Table VI, Model 4 Impact of GMAT on Segment Assignment		
GMATFam	0.0550***	0.1342***	0.9702***
GMATFam*Ten	-0.1532***	-0.0046***	-0.0471***
	Panel E: Replication of Table VII, Panel B Impact of Track Record on Segment Assignment		
Track Record	-0.7796***	-2.0603***	-0.0356***
Track Record * Ten	0.4673***	0.1042***	0.0004
	Panel F: Replication of Table VIII, Model 4 Impact of GMAT on Segment Assignment for Newly Hired Managers		
GMATFam	0.0741**	0.5980***	0.2851
GMATFam*Ten	-0.0025**	-0.0380***	0.0033
	Panel G: Replication of Table IX, Panel B Impact of Track Record on Segment Assignment for Newly Hired Managers		
Track Record	-0.2361**	0.6870	0.7987
Track Record * Ten	0.0186**	-0.9838	-0.0375
	Panel H: Replication of Table X, Panel B Reassignment of Managers		
$\Delta\overline{\alpha}$ (GMAT)	0.2776***	0.0377***	0.0122***
$\Delta\overline{\alpha}$ (Track Record)	0.2082***	0.0023	0.0203***

Table XII: Conditional Models to Estimate Alpha

We present results of various regressions where we use alphas obtained from conditional factor models instead of alphas from unconditional models. Using these alphas we replicate Table III (Panel A), Table IV (Panel B), Table V (Panel C), Panel B of Table VII (Panel D), Panel B of Table IX (Panel E), and Panel B of Table X (Panel F). For sake of brevity, we report only the results for the main variables. The variables are defined as in the respective tables. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
	Panel A: Replication of Table III Impact of GMAT on Alpha: Segment Specific Analysis		
GMAT	-0.5075***	-0.1501**	0.0955
GMAT * HY	0.4891***	0.3152**	0.2806**
	Panel B: Replication of Table IV Tenure and the Impact of GMAT on Alpha: Segment Specific Analysis		
GMAT * HY	2.5159***	3.3553***	1.9747***
GMAT * HY * Ten	-0.1144***	-0.1175***	-0.0592**
	Panel C: Replication of Table V Tenure and the Impact of Track Record on Alpha: Segment Specific Analysis		
Track Record * HY	-3.9440*	-1.6623	-2.3630*
Track Record * HY * Ten	0.2111**	0.1148**	0.1075*
	Panel D: Replication of Table VII, Panel B Impact of Track Record on Segment Assignment		
Track Record	-0.4876***	-0.5455***	-0.4776***
Track Record * Ten	0.2440***	0.3210***	0.2746***
	Panel E: Replication of Table IX, Panel B Impact of Track Record on Segment Assignment for Newly Hired Managers		
Track Record	-0.5184**	-1.1842***	-0.1294*
Track Record * Ten	0.0178**	0.0666***	0.0104**
	Panel F: Replication of Table X, Panel B Reassignment of Managers		
$\Delta\bar{\alpha}$ GMAT)	0.0714***	0.0372***	0.0904***
$\Delta\bar{\alpha}$ (Track Record)	0.0042****	0.0126***	-0.0393***

Table XIII: Factor Models with Liquidity Risk to Estimate Alpha

We present results of various regressions where we use alphas obtained from the factor models extended by TED spread as a proxy for liquidity risk. Using these alphas, we replicate Table III (Panel A), Table IV (Panel B), V (Panel C), Panel B of Table VII (Panel D), Panel B of Table IX (Panel E), and Panel B of Table X (Panel F), For sake of brevity, we report only the results for the main variables. The variables are defined as in the respective tables. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Fama-French Model	Gebhardt et al. Model	Blake et al. Model
	Panel A: Replication of Table III Impact of GMAT on Alpha: Segment Specific Analysis		
GMAT	-1.0341***	-1.3491***	-1.1903***
GMAT * HY	1.6610***	1.8278***	2.0356***
	Panel B: Replication of Table IV Tenure and the Impact of GMAT on Alpha: Segment Specific Analysis		
GMAT * HY	3.4360***	6.2176***	5.7225***
GMAT * HY * Ten	-0.0839***	-0.1969***	-0.1654***
	Panel C: Replication of Table V Tenure and the Impact of Track Record on Alpha: Segment Specific Analysis		
Track Record * HY	0.4727	-0.5413	-0.0907
Track Record * HY * Ten	0.0264**	0.0238**	-0.0025
	Panel D: Replication of Table VII, Panel B Impact of Track Record on Segment Assignment		
Track Record	0.0593	0.1860***	0.2070***
Track Record * Ten	0.0147***	0.0073***	0.0109***
	Panel E: Replication of Table IX, Panel B Impact of Track Record on Segment Assignment for Newly Hired Managers		
Track Record	0.2526**	0.7649*	0.2277**
Track Record * Ten	0.0351*	-0.0281	0.0272**
	Panel F: Replication of Table X, Panel B Reassignment of Managers		
$\Delta\bar{\alpha}$ (GMAT)	0.0003	0.0367***	0.0282***
$\Delta\bar{\alpha}$ (Track Record)	0.0001	0.0010***	0.0035***

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centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de