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Contents

List of Tables

List of Figures

Chapter 1

Introduction

This thesis consists of three essays analyzing the returns to human capital in the asset management industry. In particular, I study how different dimensions of human capital that managers can acquire before and during their careers in asset management impact the performance of the equity mutual fund portfolios they manage.

Worldwide, the United States of America has the largest market for mutual funds. By the end of 2015, there have been nearly $16 trillion in mutual fund assets. Equity funds alone comprise around 52 percent of these assets and retail investors hold the vast majority (89 percent) of mutual fund assets. In recent years however, retail investors have increasingly shifted money from equity mutual funds to passively managed Exchange Traded Funds (ETFs).[1] A possible reason behind this is the ongoing active vs. passive debate. In the past decades, the academic literature has provided extensive evidence that the average active mutual fund manager is not able to perform better than a passive benchmark index after costs.[2] There are several theories why retail investors accept this phenomenon in equilibrium.[3] Albeit, as it seems, more and more investors are inclined to invest their money in passively managed funds that have lower costs. Nevertheless, it is still very likely that at least some managers have an edge over other managers in an informationally efficient

[1] See Investment Company Institute (2016).
[2] See, e.g., Gruber (1996); French (2008); and Fama and French (2010).
[3] Gruber (1996) pointed out that retail investors might be ignorant or irrational. Adhering to that, Del Guercio and Reuter (2014) show that funds sold indirectly to investors have weaker incentives to generate alpha. Glode (2011) argues that it is rational to accept negative alphas as long as actively managed funds outperform in recessionary periods.

market.[4] There are many studies on whether active mutual fund managers possess skill.[5] Fewer studies, however, ask where this skill originates from. Differences in managerial skill must be due to differences in human capital among managers. The economics literature has prominently studied the effect of human capital on productivity.[6] A relatively small strand of the literature on mutual fund skill analyzes the relation between productivity measured by fund returns and human capital differences measured by manager characteristics. Mutual funds provide an excellent setting to study the returns to human capital because a person's actions and the consequences thereof are observable to a certain degree. Studies usually focus on observable sources of human capital differences like schooling, schooling quality, and training.[7] This thesis contributes to this literature by analyzing new manager characteristics that capture different dimensions of human capital.

The first essay of this thesis (Cici, Gehde-Trapp, Göricke, and Kempf (2016)) adds to the literature by addressing the potential advantage of industry-specific human capital. Using hand-collected data, we are the first to identify mutual fund managers who were able to gain practical experience in industries outside the financial sector prior to becoming portfolio managers.[8] We hypothesize that managers with industry experience have an advantage because they can interpret soft information in their familiar industries faster.[9] The literature has documented that apart from hard information, soft information is very important in asset pricing. For instance, investors generally take longer to fully interpret the soft information in earnings announcements.[10]

In our study, we deliberately focus on single-managed diversified funds. We can therefore distinguish between investments in stocks that are familiar and stocks that are unfamiliar to the responsible manager. Our approach of splitting the portfolio holdings into experience and non-experience industry stocks also allows us to effectively control for unobservable fund and manager characteristics. Since, there could be other dimensions of

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[4] See, e.g., Grossman and Stiglitz (1976) for a theoretical foundation.
[5] See Jones and Wermers (2011) for a survey on the vast empirical literature on mutual fund manager skills.
[6] See, e.g., Becker (1964) and Mincer (1974).
[7] Regarding schooling and schooling quality see, e.g., Golec (1996). Chevalier and Ellison (1999); Gottesman and Morey (2006); or Fang, Kempf, Trapp (2014). Ding and Wermers (2009) and Greenwood and Nagel (2009) study the effect of training measured by industry tenure.
[8] Bradley, Gokkaya, and Liu (2017) document that industry experience is valuable for equity analysts. Doskeland and Hvide (2011) analyze the investment value of industry specific human capital for retail investors. Building on our research, Kostovetsky and Ratushny (2016) analyze the performance of health sector mutual funds.
[9] Additionally, managers could have valuable personal contacts that provide useful insights.
[10] See Demers and Vega (2008).

manager human capital like talent, schooling, or asset management specific training. At the same time, we control for differences in the quality of the fund organization. All of these factors should affect both parts of the portfolio. We show that the managers in our sample achieve significant positive risk-adjusted returns in their experience industries whereas their performance in the remaining industries is not better than active and passive benchmarks. We validate our finding by showing that the outperformance is stronger for managers that gained comparatively long practical experience. Further, managers time their investments in experience industries better than in other industries.

The results from the first essay suggest that industry-specific human capital indeed has investment value. We provide evidence that some managers have an edge over other managers due to practical training. We also show that peer managers within a fund family make use of the ideas of experienced managers in their experience industries. As industry-specific human capital is rare, it is sensible that affiliated managers who lack this kind of knowledge try to profit from it.

The second essay of my thesis (Göricke (2016)) takes up this idea. Exchanging ideas with specialists is a possible supplement to developing a deeper understanding for different market segments in a learning fashion while being a portfolio manager.[11] If managers that have to oversee many industries can access the knowledge of many industry specialists, they should have an advantage.

For identification, I distinguish between families that offer sector funds and fund families that do not offer this type of mutual fund.[12] By definition, sector funds are specialists for certain segments in the stock market. Their focus of investment is narrowed down to only a few industries. This increased focus can give them an advantage in selecting stocks.[13] Additionally, there is some evidence that fund families put managers with specialized knowledge in sector funds.[14] To date, only very few academic papers test the

[11] For a survey on the economic literature on learning by doing see, e.g., Thompson (2010). See Kempf, Manconi, and Spalt (2014) for a study on portfolio managers learning about different industries during their career in asset management.

[12] In recent years, academic research has highlighted the qualities of the fund family as an important factor for fund performance. See, e.g., Gaspar, Massa, and Matos (2006); Kacperczyk and Seru (2012); and Chen, Hong, Jiang, and Kubik (2013).

[13] Kacperczyk, Sialm, and Zheng (2005) show that diversified mutual funds that concentrate their investments in fewer industries have higher alphas.

[14] Kostovetski and Ratushny (2016) show that sector fund managers with specialized knowledge perform better than their peers. Dellva, DeMaskey, and Smith (2001) show that many sector funds have stock selection abilities.

hypothesis that sector fund managers possess skills. In line with prior evidence, I first show that sector funds are in fact specialists for their segments.[15] Other than diversified funds, they have positive net alphas. To address the question whether other managers profit from sector manager skill, I analyze the behavior and performance of affiliated diversified equity funds. By definition, diversified funds have to analyze stocks from far more industries than sector funds. The idea is that due to spillover effects, diversified fund managers from fund families that offer sector funds have an advantage over comparable managers from fund families that do not offer sector funds. I show that the number of distinct sectors covered by specialists within a fund family is positively related to the overall performance of affiliated diversified funds. This is due to two reasons:

First, managers from diversified funds take over ideas from specialists. To identify the source of information creation, I look at individual fund portfolio overlap between diversified and sector funds in a family as a measure of information sharing. I can show that information sharing is increased if the expert signals his ability by either having longer tenure or a positive track-record in the past year. This is an indication for information flowing from specialists to generalists.

The second reason is that the possibility of taking ideas from specialists for their own portfolios saves managers time, which is very limited given that managers have to oversee hundreds of (possible) investments. For identification, I compare the fraction of hard-to-value stocks and overall portfolio turnover between diversified funds of families offering sector funds and comparable funds without access to these types of specialists. I find evidence that diversified funds give a higher portfolio weight to hard-to-value stocks and trading increases with access to more specialist knowledge.

Taken together, my results imply that it pays off for fund families to invest in their managers. The sector-specific human capital managers gain by training is beneficial not only for their own performance but it also positively impacts the performance of affiliated funds. All in all, accumulation of human capital is not only beneficial to one manager alone, it can have a multiplier effect.

The first two essays document positive performance results from different forms of specialized training outside and inside the asset management industry. The third essay

[15] Dellva, DeMaskey, and Smith (2001) show that many sector funds have stock selection abilities.

(Göricke (2017)) supplements them by analyzing the effect of managers' schooling and schooling quality on mutual fund performance.

Undergraduate university education is generally the first major investment in their own human capital for future mutual fund managers. Aside from choosing the right field, which supplies the theoretical background for a future job, the decision for a particular institution is highly important since it also provides its students with a network.[16] Apart from this, managers might also chose a top-tier university to signal their abilities.[17] The existing literature on mutual fund manager education has focused on the quality of the institution and postgraduate degrees like Master of Business Administration (MBA) or Chartered Financial Analysts (CFA).[18] Using hand-collected data, I identify the field of study for managers' undergraduate degrees and the corresponding institution for a large sample of diversified equity fund managers.

I add to the literature by analyzing the effect of the field of undergraduate study chosen by the manager. In contrast to other careers like medicine or engineering, there is no (official) educational prerequisite for a career in asset management. Nevertheless, it is intuitive that the thematically best fitting degree is one in an economic field. I find evidence that economists have a significantly higher performance than managers that lack economic undergraduate university education (non-economists).

I further connect this finding with the literature on the performance of managers with MBA degrees. I can show that an MBA degree has a significantly lower performance impact for economists compared to non-economists. Non-economists with MBA degrees have a performance comparable to economists. This implies that having either undergraduate or postgraduate economic education is sufficient.

As mentioned before, the quality of the mutual fund family can be an important factor for individual fund performance. Given that the job market is highly competitive for mutual fund managers, it is not very likely that the allocation of managers with different educational backgrounds to different families is arbitrary. Therefore, I explicitly address the effect of education on the allocation of managers to different families.

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[16] See Cohen, Frazzini, and Malloy (2008).
[17] See, e.g., Spence (1973); Weiss (1983); and Hvide (2003).
[18] See, e.g., Golec (1996); Chevalier and Ellison (1999); Gottesman and Morey (2006); or Andreu and Pütz (2016).

My results show that manager education variables are strongly correlated with the size of the fund family. Despite this finding, my additional analyses show that family heterogeneity does not seem to be the reason behind performance differences between economists and non-economists.

Taken that economists have, e.g., better business networks via their alma mater, this advantage should become smaller when non-economists have been in the asset management industry for a long time. In line with this argument, I only find a difference between economists and non-economists in a sub-sample of relatively unexperienced fund managers. Non-economists seem to be able to make up for their disadvantages over time.

Further, if economists have an information advantage, they should perform especially well in market phases where insecurity is high and stock prices deviate from their fundamental values.[19] I show that economists generate strong outperformance after periods of high negative sentiment, measured by peaks in the Chicago Board Options Exchange Volatility Index (VIX), while there is no outperformance when the index has been relatively stable at a low level. Taken together, my results imply that economic university education is an important factor to consider for the selection of diversified equity fund managers.

Overall, all three essays provide evidence that there are returns to human capital in asset management. Several dimensions of human capital provide managers with an advantage. They are associated with active managers that are better than the average active manager who is not able to perform better than a benchmark after fees. Acknowledging the importance of family qualities behind each fund, this thesis provide evidence that the individual portfolio manager also matters in the process of generating performance. It is therefore useful to practitioners and academics who try to identify successful asset managers for future investments. Bringing to mind the increasing fraction of assets managed passively, there could be even higher returns for managers with superior human capital in the future.[20]

[19] See, e.g., Shleifer and Vishny (1997); Simon and Wiggins (2001); or Baker and Wurgler (2006).
[20] This assumption is based on the intuitive model in Pastor and Stambaugh (2012).

Chapter 2

What They Did in their Previous Lives: The Investment Value of Mutual Fund Managers' Experience outside the Financial Sector*

2.1 Introduction

Work experience and its impact on productivity has featured prominently in economic theories of human capital (e.g., Becker (1964) and Mincer (1974)). Building on these earlier studies, a growing body of work examines how experience of investment managers relates to investment performance.[21] The focus of these studies has been on-the-job experience, experience acquired by fund managers in a learning-by-doing fashion during their careers in the mutual fund industry. While this type of experience is an important component of investment managers' human capital, some investment managers have had the opportunity to work in other industries in their prior careers, which provides them with industry-specific experience and human capital. This raises the question whether such industry-specific human capital shaped by fund managers' work experience outside the

* This chapter is based on Cici, Gehde-Trapp, Göricke, and Kempf (2016).

[21] See, e.g., Golec (1996); Chevalier and Ellison (1999); Greenwood and Nagel (2009); and Kempf, Manconi, and Spalt (2014).

investment industry helps them make better investment decisions. Being the first to study this question, we hypothesize that industry-specific human capital previously acquired by fund managers outside the investment industry benefits them when they switch to fund management.[22] The basic idea is that such industry-specific human capital puts a fund manager at an advantage when generating and processing information in that specific industry (hereafter, experience industry),[23] enabling her to earn higher performance in her experience industry than in industries in which she has no prior work experience (hereafter, non-experience industries).

We test this hypothesis using information on portfolio holdings of fund managers with prior industry experience who run diversified U.S. mutual funds. Diversified funds provide an identification advantage in that they allow us to isolate the impact of industry-specific human capital on performance. The performance that a fund manager generates in the part of the portfolio invested in her non-experience industries (hereafter, non-experience portfolio) reflects general human capital shaped by education, talent, wisdom, as well as more investment-specific human capital acquired while working in fund management. However, the performance that this same manager generates in the part of the portfolio invested in her experience industry (hereafter, experience portfolio) additionally reflects her human capital specific to that particular industry. Thus, the difference between the performance of a manager's experience and non-experience portfolios gives us an estimate of the investment value of the manager's industry experience.

Our results show that prior industry experience outside the investment industry has considerable investment value, suggesting that industry-specific human capital acquired outside the investment industry is useful when working in the fund industry. The average performance of a fund manager in her experience portfolio is up to 5 percent per year higher than that in her non-experience portfolio. This difference comes from outperformance of their experience portfolios, not from underperformance of their non-experience portfolios,

[22] Our thinking is in line with evidence from the economics literature that workers benefit from their industry-specific human capital after they switch industries because part of their industry-specific human capital might be transferrable. For example, Neal (1995) shows that workers receive compensation for industry-specific human capital even when switching the industry. The general importance of industry-specific human capital is documented in Parent (2000), and Weinberg (2001), among others.

[23] For example, prior industry experience might help the fund manager to better understand the economic forces affecting companies in that industry. In addition, it might provide fund managers with personal contacts in that industry that can be used to get valuable insights and perspective on industry- or company-specific developments.

which perform not differently from passive benchmarks or peer funds. This suggests that the remaining human capital (excluding industry-specific human capital) of fund managers with industry experience is average and comparable to that of managers without industry experience.

The informational advantage of fund managers in their experience industries manifests itself over long horizons. Extending the holding periods of the experience and non-experience portfolios shows that the outperformance of the experience portfolio relative to the non-experience portfolio reaches its peak in about two years. This suggests that managers with industry experience have an informational advantage relative to other market participants, which is hard to emulate without such experience.

Industry experience puts fund managers at an advantage in understanding not only the fundamentals of individual companies in their experience industries but also general industry trends and developments at a macro level. Specifically, they are able to time the returns of their experience industries but not the returns of industries in which they have no experience. Importantly, this ability to time their experience industries is also economically significant, as it contributes a considerable part to the active return component of the experience portfolio (roughly 40 percent).

Besides looking at the value of experience from the point of view of fund managers, we also look at its value from the perspective of investors and fund families, i.e. the managers' possible clients and employers. The first question we ask is: How can investors benefit from the industry experience of fund managers? Simply buying funds run by managers with industry experience might not be the best option because our sample managers run diversified funds, with the overall fund performance mainly determined by their non-experience portfolios. Instead, investors might be better off mimicking the stock holdings of fund managers in their respective experience portfolios. We show that even though investors receive holdings information with a delay of up to 60 days (as required by the filing rules enforced by the SEC), they can benefit by replicating the experience portfolios of managers with industry experience. This is consistent with our earlier finding that the information advantage of managers with experience materializes gradually over a relatively long period of time. Moreover, it suggests that mimicking the portfolio holdings of managers with industry experience might be a valuable strategy for investors, which would constitute a violation of semi-strong market efficiency.[24]

The second question is whether the reach of individual managers' industry experience extends to other funds in the family. A sensible strategy from the perspective of a fund family would be for the other fund managers in the family (hereafter, affiliated managers) who do not have industry experience to exploit the expertise of managers with industry experience. Consistent with this prediction, we find that affiliated managers assign much bigger weights to stocks that overlap with their colleague's experience portfolio than to stocks that overlap with their colleague's non-experience portfolio. They also tend to follow the new ideas that their colleagues generate in their experience industries more than the new ideas these same colleagues generate in their non-experience industries. This suggests that fund families and affiliated fund managers are aware of the investment value of industry experience and employ the industry-specific human capital of their managers with industry experience in a sensible way by applying this knowledge to a larger asset base.[25] More broadly, this is consistent with fund families striving to optimally deploy their managers' human capital within their organizations.[26]

Our paper is related to the literature that examines whether experience that professional investors develop on the job translates into superior performance (see, e.g., Golec (1996); Chevalier and Ellison (1999); Greenwood and Nagel (2009); and Kempf, Manconi, and Spalt (2014)).[27] These studies generally focus on experience gained through actively managing investments, i.e., on the part of managers' human capital shaped by on-the-job experience acquired while working in fund management. In contrast, our study

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[24] We say that this "might" be valuable because identifying all managers with industry experience and classifying their holdings by industry requires effort and resources (as was the case for the authors). The costs that this entails, in combination with transaction costs, might erode the returns we document.

[25] This raises the question why so few sample funds are run by managers with industry experience. A possible explanation is that we focus on single-managed diversified funds to be able to isolate the investment value of industry-specific human capital. Fund families might already include individuals with industry experience in their investment teams, something which is advertised in promotional materials or fund company websites to signal robust investment processes to potential investors. This was best illustrated in Sykora's interview of Foster, a portfolio manager with VanEck Mutual Funds, who worked previously as a geologist. Specific to this point, Foster (2008) said that "We try to set ourselves apart in our fund-management style, and one of the ways we do [so] is that we've always had an industry professional or industry experience on our staff."

[26] Other evidence supporting optimal deployment of managers' human capital by fund families comes from Fang, Kempf, and Trapp (2014), who show that fund families optimally assign more skilled managers to the least efficient market segments.

[27] There is also another strand of literature that looks at learning by trading among retail investors. Examples are Mahani and Bernhardt (2007); Pastor and Veronesi (2009); Seru, Shumway, and Stoffman (2009); Barber, Lee, Liu, and Odean (2010); Linnainmaa (2011); Huang, Wei, and Yan (2012); and Campbell, Ramadorai, and Ranish (2014).

examines experience that fund managers acquired while working within a specific non-investment industry before their fund management career. More broadly, our paper supports earlier findings from the economics literature that part of industry-specific human capital is transferrable to other industries (see e.g., Neal (1995)) by showing that employees can benefit from their industry-specific human capital when switching to the fund industry.[28]

Our paper is also related to Doskeland and Hvide (2011) who analyze whether industry-specific human capital of retail investors allows them to make outperforming investments in the industries where they work. They find no evidence of such outperformance. When looking at fund managers, we find the opposite. We believe that this discrepancy in findings can be explained by the main difference between fund managers and retail investors: While both have industry experience, fund managers also have investment experience they have acquired as professional investors. This could suggest that investors need to combine their industry experience with a certain level of investment literacy in order to translate their industry experience into better investment performance.

Our findings also support the key premise of many theoretical models that asymmetric information can lead to disparate returns among market participants (see, e.g., Grossman and Stiglitz (1976)). Information asymmetries that place institutional investors at an informational advantage have been examined in several studies. They appear to arise when institutional investors: engage in local investing (see Coval and Moskowitz (1999, 2001))[29]; are connected via shared education networks with board members of companies (see Cohen, Frazzini, and Malloy (2008)); exploit information related to FDA approvals obtained under the Freedom of Information Act (see Gargano, Rossi, and Wermers (2016) and Klein and Li (2015)); and receive SEC filings prior to them becoming public (see Rogers, Skinner, Zechman (2016)). Our contribution is that we document a new venue

[28] One can easily find other settings where prior work experience is useful after switching industry. For example, Bradley, Gokkaya, and Liu (2016) document that sell-side analysts with prior industry experience generate more accurate earnings forecasts for companies from their experience industries. Such experience is also highly valued by hedge funds who often seek advice from industry professionals belonging to expert networks when they trade outside their realm of expertise (see, e.g., Economist (2011)). Besides hedge funds, activist investors also appear to value such experience among corporate board members, as documented by a recent push to increase representation of board members with same-industry experience (see, e.g., Lublin (2014)). Outside the realm of finance, other examples where skills acquired in previous occupations can transfer to new occupations include individuals joining security or defense contracting firms after having served in the military, individuals joining lobbying organizations after careers as legislators, or individuals joining headhunting firms that specialize in certain industries after careers in those same industries.

[29] Pool, Stoffman, and Yonker (2012) examine the performance of investments made by mutual fund managers in companies from their homes states but find no evidence of related informed investing.

through which fund managers can obtain an informational advantage. This information advantage is costly, however, since considerable time and effort are needed to acquire the industry-specific human capital that we analyze.

Finally, our paper is related to a growing literature that examines various decisions undertaken by fund families. Among others, these papers look at product policies (e.g., Mamaysky and Spiegel (2002); Siggelkow (2003)); centralization of decision making (e.g., Kacperczyk and Seru (2012); advertising (e.g. Gallaher, Kaniel, and Starks (2006); introduction of new funds (e.g., Khorana and Serveas (1999)) and closure of existing funds (e.g., Zhao (2004); performance transfers across family funds (e.g., Gaspar, Massa, and Matos (2006)); outsourcing versus in-sourcing portfolio management (e.g., Chen, Hong, Jiang, and Kubik (2013)); choosing single versus teams of portfolio managers (e.g., Huang, Qiu, Tang, and Xu (2016)); choosing the type of distribution channel (e.g., Del Guercio and Reuter (2014)); and optimally allocating fund managers to mutual funds (e.g., Fang, Kempf, and Trapp (2014)). Our paper complements this literature by showing that fund families tend to exploit the industry-specific informational advantages of their managers with industry experience across a large number of family funds.

The rest of the paper is organized as follows. In Section 2.2 we discuss our sample selection approach and present descriptive statistics. Section 2.3 examines the investment value of industry experience. In Section 2.4 we show that investors can benefit from the industry experience of fund managers by replicating their investments in their experience industries. We show that fund families utilize the information generated by their managers with industry experience among other member funds in Section 2.5. Section 2.6 concludes.

2.2 Data

2.2.1 Data selection

To construct our sample, we identify diversified, domestic U.S. equity mutual funds managed by single managers. We impose three restrictions introduced sequentially to the mutual fund universe in the Center for Research in Security Prices Mutual Fund (CRSP MF) database. First, we limit the universe to include only diversified, domestic U.S. equity funds, thus excluding index, balanced, bond, money market, international, and sector funds. Second, we drop all funds that are not covered by Mutual Fund Links database (MFLINKS) because we later use MFLINKS to link fund characteristics from the CRSP MF database with fund holdings from the Thomson Reuters Mutual Fund database. Finally, we further restrict our sample to include funds that are managed by single portfolio managers. The rationale for this restriction is that our subsequent tests would be less precise for funds managed by multiple managers, especially if some managers have industry experience while some others do not.

To identify the names of fund managers and the time periods during which they managed individual funds, we use Morningstar Principia.[30] We match the manager information obtained from Morningstar to CRSP fund data. We also manually screen manager names for different spellings and/or abbreviations and assign a distinct identification number to each manager. Overall, we identify 1,495 managers who single managed at least one of 1,619 diversified U.S. domestic equity funds between 1996 and 2009.

To construct career profiles for fund managers, we hand-collect biographical information for each fund manager from various sources including fund company websites, morningstar.com, SEC filings (485APOS), newspaper articles, and websites like zoominfo.com or linkedin.com. We use this information to construct the career path of the manager until she started in the fund management industry by recording the names of her employers, the time periods she worked for them, and her job description.

Our industry categorization is based on the Fama-French 48 industry groupings.[31] We categorize a fund manager as having prior work experience in a particular industry if a company she worked for prior to joining the fund management industry belongs to that particular industry. Using the names of companies a fund manager worked for, we first determine whether those companies are publicly listed or privately held. When the company is publicly listed, we use the Standard Industrial Classification Code from the CRSP stock database to determine the industry to which it belongs. For companies that are not publicly listed, we manually search information about their business objective, which we then use to assign them to one of the Fama-French industry groupings.[32]

[30] Our choice of Morningstar Principia over the CRSP MF database to obtain this information was motivated by previous research showing that reported manager information is more accurate in the Morningstar database than in the CRSP MF database (see, e.g., Patel and Sarkissian (2013)).

[31] The Fama-French industry classifications were obtained from Ken French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#HistBenchmarks.

[32] Fund managers who worked as medical doctors are categorized as having experience in the Fama-French industries 11, 12, and 13, the main industries followed by health care sector funds.

Since we are interested in fund managers with prior work experience outside the financial sector, we exclude all managers who worked only for investment management firms or whose prior jobs were in banking. We also exclude managers whose prior work experience was limited to military service or educational institutions because of lack of additional information needed to assign these particular work experiences to specific industries. Our final sample consists of 130 managers (hereafter, sample managers) who are responsible for 199 single-managed funds (hereafter, sample funds). They have industry experience in 29 of the Fama-French 48 industry groupings.

2.2.2 Sample description

Panel A of Table 2.1 provides biographical information for the sample managers and sole managers without industry experience that manage funds with the same investment objectives (hereafter, peer managers and peer funds).

Table 2.1: Manager and fund characteristics

Panel A: Manager characteristics

Manager characteristic	Sample Managers	Peer Managers	Difference	t-statistic
Length of industry experience [years]	5.26	-		
Age of manager when managing first single fund [years]	39.37	37.67	1.70	1.41
MBA [%]	70.00	53.30	16.70	3.86
CFA [%]	46.92	49.85	-2.93	-0.63
PhD [%]	3.07	5.62	-2.55	-1.51
Business/Economics major [%]	54.81	75.07	-20.26	-3.93
Engineering/ Natural science major [%]	43.27	11.52	31.75	6.32
Other major [%]	11.54	21.00	-9.46	-2.71

(continued)

Table 2.1: Manager and fund characteristics - continued

Panel B: Fund characteristics

Fund characteristic	Sample Funds	Peer Funds	Difference	t-statistic
Fund size [in $ millions]	1,705.19	890.90	814.29	6.87
Expense ratio [%]	1.34	1.37	-0.03	-1.67
Turnover ratio [%]	109.62	99.85	9.77	1.28
Weight FF48 Exp. Industry [%]	6.42	3.27	3.16	30.81

Notes: This table reports manager and fund characteristics. Panel A reports characteristics for our sample of fund managers with prior industry work experience and for the peer managers who do not have such experience. Both groups of funds include fund managers who solely managed U.S. domestic diversified equity fund (excluding balanced, bond, money market, index, international, and sector funds) at some point between 1996 and 2009. The first row reports the average length of prior industry experience. In the second row, we report the average age of a manager when she first appears as single manager of a U.S. domestic diversified equity fund in the Morningstar Principia database. The table also reports the fraction of managers that hold an MBA, CFA, or PhD, followed by information on the fraction of managers with a major in a certain discipline. The cumulative fraction for the majors sums up to more than 100 percent because some managers have more than one declared major. Panel B reports characteristics for our sample funds and the peer funds. Our sample consists of 199 diversified, domestic U.S. equity funds single-managed during 1996-2009 by 130 fund managers with prior industry work experience. The peer group consists of 1,420 funds that have the same investment objectives as our sample but are managed by single managers with no prior industry experience. The reported fund characteristics include: fund size in $ millions, expense ratio measured in percentage points per year, turnover ratio measured in percentage points per year, and portfolio weights of Fama-French 48 industries in which our sample managers have experience. Variables are measured for each report date, we then calculate the average per fund and year.

Sample managers have an average industry experience of more than five years and appear to be slightly older than their peers, which is to be expected given that they worked somewhere else prior to joining the mutual fund industry. The fact that the average manager is almost forty years old when first recorded to be sole manager of a diversified fund is consistent with the average manager having worked before in a fund company perhaps as an analyst or member of a portfolio management team.

A further comparison of the two groups shows that our sample managers have disproportionately more undergraduate degrees with majors in engineering and natural sciences but less in business management and economics. They seem to compensate for this lack of business education by enrolling in an MBA program as part of their strategy to switch to a business career. This is supported by the fact that a significantly higher fraction of sample managers hold MBA degrees.[33]

Panel B of Table 2.1 compares the sample funds with their peer fund group, which consists of 1,420 single-managed funds. The average sample fund is larger than the average peer fund. However, the median sample fund (not reported in the table) is about the same size as the median fund in the peer group. A comparison of expense ratios and turnovers shows that they are of a similar order of magnitude across the two groups.

The last row of Panel B compares the fraction of the portfolio that our sample funds hold in their experience industries with the average weights that peer funds hold in those same industries. This comparison suggests that our sample funds tend to overweight their experience industries relative to the peer funds.[34] This is consistent either with a rational strategy to exploit an informational advantage in these industries or with a familiarity bias, i.e., fund managers overweight their experience industries simply because they are familiar with them. Our subsequent analysis will show that the former effect dominates.

2.3 The investment value of industry experience

This section examines the investment value of fund managers’ industry experience. Our main analysis presented in Section 2.3.1 investigates whether fund managers pick stocks from their experience industries that outperform stocks they pick from other industries. Documenting that this is indeed the case, we then proceed with two validation exercises in Section 2.3.2. Finally, in Section 2.3.3 we examine whether industry experience provides managers also with a timing advantage.

[33] Specifically, 70 percent of the sample managers have an MBA degree, compared to 53 percent for the peer group. The fraction of managers with MBA degrees in the peer group is similar in magnitude to evidence from Cohen, Frazzini, and Malloy (2008).

[34] In additional tests, we compared the weights of our sample funds in their experience industries to the weights of peer funds matched by investment objective in the same industries. We also compared the weights of our sample funds in their experience industries to the industry weights in the market portfolio, which is based on the CRSP stock universe. In both cases, we find significant relative overweighting of experience industries by our sample funds by 1.05 (t-statistic = 2.48) and 1.56 percentage points (t-statistic = 3.60), respectively.

2.3.1 Performance differences between experience and non-experience portfolios

To compare the performance of each manager's stocks from the experience and non-experience industries, we use that manager's holdings to construct a value-weighted experience portfolio and non-experience portfolio.[35] We compute buy-and-hold returns for each portfolio until the next holdings report date, at which the portfolios are then updated to reflect any changes in holdings. We do so for each manager each period and treat the performance of the experience portfolio and the non-experience portfolio over the corresponding holding period as distinct observations.

We employ five performance measures: raw returns, risk-adjusted returns, and three versions of characteristic-adjusted returns. Our risk-adjusted returns are based on the four-factor model of Carhart (1997).[36] We compute monthly Carhart alphas for each stock held in the experience and non-experience portfolios of each manager and use them to estimate risk-adjusted portfolio returns.[37] The three versions of characteristic-adjusted returns follow the idea of Daniel, Grinblatt, Titman, and Wermers (1997). We compute a stock's DGTW-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio to which that stock belongs. Each stock's benchmark portfolio is a value-weighted portfolio that includes all stocks that are part of the same size, book-to-market, and one-year past return quintile. Our fourth measure, intended to adjust for industry-related effects, is constructed by benchmarking the DGTW-adjusted performance of each held stock against that of a portfolio of stocks from the same industry not held in the portfolio (hereafter referred to as industry-adjusted DGTW return). Our last performance measure is constructed by benchmarking the DGTW-adjusted performance of each held stock against that of a portfolio of stocks from the same industry held by peer funds (matched by investment objective) but not held in the portfolio (hereafter referred to as peer-adjusted DGTW return).

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[35] In order for a fund manager to be included in the analysis in a given period, that manager must have at least one stock holding in both her experience and non-experience portfolios.

[36] Results are qualitatively similar for the three-factor model of Fama and French (1993) and the one-factor model of Jensen (1968).

[37] We compute the risk-adjusted return of a stock in a given month as its actual excess return for that month minus its expected excess return based on the Carhart (1997) model. A stock's expected excess return in a given month is computed by summing the products of the realized common factor values and the respective factor loadings estimated using the stock's returns from the previous 36 months.

This measure accounts for the possibility that managers that follow certain investment objectives are more skilled at picking stocks from certain industries.[38]

Table 2.2: Performance of experience portfolio vs. non-experience portfolio

Performance Measures	**Experience**		**Non-Experience**		**Difference**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Return	0.1005	2.00	0.0776	1.65	0.0229	1.51
Carhart	0.0598	2.99	0.0102	1.12	0.0496	2.39
DGTW	0.0271	2.25	0.0009	0.10	0.0262	2.38
Ind.-adj. DGTW	0.0215	2.02	0.0026	0.41	0.0189	2.06
Peer-adj. DGTW	0.0268	2.85	0.0024	0.43	0.0244	2.60

Notes: This table reports performance results for the managers' experience portfolios and non-experience portfolios. We determine whether a stock belongs to a manager's experience or non-experience portfolio by comparing the issuing company's Fama-French 48 industry to the industries in which the manager has worked prior to the beginning of her career as a fund manager. Following stock assignments into experience and non-experience sub-portfolios, we keep the stocks in the sub-portfolios until the next report date, when the composition of the sub-portfolios is updated again, to reflect changes in holdings. Our performance measures include: The raw return (Return), Carhart alpha (Carhart), DGTW-adjusted return (DGTW), industry-adjusted DGTW return (Ind.-adj. DGTW), and peer fund adjusted DGTW return (Peer-adj. DGTW). Carhart alpha is computed for a given stock each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns on the four risk factors. DGTW-adjusted returns are estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. Industry-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry but not held in the portfolio. Peer-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry held by peer funds (matched by investment objective), but not held in the portfolio. We compute buy-and-hold returns for each fund and each sub-portfolio, with the holding period determined by the distance between report dates. The buy-and hold returns are computed by value-weighting the buy-and-hold returns of the underlying portfolio stocks, with weights based on the market value of the positions at the beginning of the holding period. Estimates are averages across time and portfolios, and t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized. The number of observations is 2,188.

Table 2.2 analyzes the value of experience gained outside the investment industry for fund managers. It reports the average annualized performance for the experience and

[38] For example, growth managers might be better at picking tech stocks, regardless of whether they have industry experience.

non-experience portfolio along with their performance differences. To assess statistical significance, standard errors are clustered by both manager and report date.

Comparisons based on Carhart alphas and DGTW-adjusted returns suggest that the stocks that managers select from their experience industries outperform stocks they select from their non-experience industries, controlling for differences in risk or stock characteristics. This is consistent with our sample managers enjoying an informational advantage in their experience industries. In other words, human capital acquired outside the investment industry helps managers pick superior stocks in their respective experience industries. More broadly speaking, our results imply that such industry-specific human capital is valuable after switching to the fund industry. This evidence also suggests that the overweighting of experience industries by our sample managers documented in Table 2.1 is predominantly caused by an informational advantage, not by a familiarity bias.

A possible concern is that the experience industries of our managers are less informationally efficient making it easier for all managers to pick superior stocks in these industries. If this was the case, our main result would not reflect the value of industry-specific human capital acquired by fund managers in their previous careers but the characteristics of the industries they worked in before becoming fund managers. However, results from the fourth and fifth row rule this possibility out since our key result holds even after we control for industry and peer effects. All in all, the evidence from this analysis suggests that industry experience has investment value. This investment value is economically significant as documented by the performance difference between the experience and non-experience portfolios of the managers, which ranges from 1.9 to 5 percent annually across the performance measures.

When focusing on the performance of the two portfolios separately, we observe that the experience portfolio generates significant positive adjusted returns in a consistent manner across the performance measures, while the non-experience portfolio generates adjusted returns that are never statistically significant. Thus, portfolio managers are able to beat the market when they pick stocks from industries where they have the advantage associated with prior work experience, but are unable to do so when they pick stocks from other industries, where this advantage is missing. This suggests that while the general investment expertise that managers with industry experience acquired on-the-job during their careers in fund management is average, its combination with their industry-specific human capital from outside the investment industry can create a performance advantage.

After having documented in Table 2.2 that industry-specific human capital acquired outside the investment industry puts a fund manager at an informational advantage in her experience industry, we next examine how long this informational advantage lasts. To do so, we extend the holding periods of the experience and non-experience portfolios to 12, 24, and 36 months.

Table 2.3: Performance over longer holding periods

Performance Measures	**Experience**		**Non-Experience**		**Difference**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
			12 months			
Return	0.1154	4.16	0.0812	3.20	0.0342	3.45
Carhart	0.0596	4.58	0.0127	1.90	0.0469	3.51
DGTW	0.0298	3.16	-0.0029	-0.63	0.0328	3.74
Ind.- adj. DGTW	0.0217	2.68	-0.0051	-1.65	0.0268	3.34
Peer-adj. DGTW	0.0300	3.59	-0.0017	-0.55	0.0317	3.83
			24 months			
Return	0.2210	5.51	0.1629	4.50	0.0581	3.49
Carhart	0.0826	4.73	0.0194	2.14	0.0632	3.31
DGTW	0.0456	3.21	-0.0032	-0.47	0.0488	3.47
Ind.- adj. DGTW	0.0327	2.52	-0.0084	-1.61	0.0411	3.12
Peer-adj. DGTW	0.0447	3.32	-0.0041	-0.77	0.0488	3.71
			36 months			
Return	0.2791	6.01	0.2244	5.56	0.0547	2.06
Carhart	0.0935	4.39	0.0296	2.39	0.0639	2.60
DGTW	0.0455	2.23	-0.0006	-0.08	0.0462	2.19
Ind.- adj. DGTW	0.0233	1.21	-0.0079	-1.25	0.0312	1.57
Peer-adj. DGTW	0.0367	1.90	-0.0037	-0.60	0.0404	2.04

Notes: This table reports performance results for the managers' experience portfolios and non-experience portfolios over longer holding periods. The experience and non-experience portfolios are constructed as described in Table 2.2. Our performance measures, described in more detail in Table 2.2, include: the raw return (Return), Carhart alpha (Carhart), DGTW-adjusted return (DGTW), industry-adjusted DGTW return (Ind.-adj. DGTW), and peer fund adjusted DGTW return (Peer-adj. DGTW). We value-weight the performance of stocks making up each portfolio by the market value of each position at the beginning of portfolio formation. We compute buy-and-hold returns for each fund and each sub-portfolio over holding intervals of different lengths that range from 12 to 36 months. Estimates are averages across time and portfolios, and t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized. The number of observations is 2,188.

The reported returns over these longer horizons in Table 2.3 suggest that the informational advantage that managers enjoy in stocks from their experience industries is not short-lived. Instead, it appears to gradually materialize in the underlying stock returns over a longer period, leading to an outperformance peak of the experience portfolio relative to the non-experience portfolio roughly after 24 months. This suggests that it takes time for the other market participants to eliminate the informational disadvantage that they have relative to managers with industry experience, who have skills and contacts in their experience industries that are hard to replicate without such experience.

2.3.2 Validation exercises

In this section, we conduct two tests intended to validate our identification strategy. Our first test examines whether the investment value of industry experience increases with the length of experience, which is to be expected if our approach is indeed capturing the effect of industry-specific human capital acquired outside the investment industry. Our second test conducts a bootstrap analysis with random assignment of pseudo experience industries to rule out the possibility that our methodology gives rise to a spurious performance difference between the experience and non-experience portfolios.

2.3.2.1 Length of experience and investment value of industry experience

To validate our identification strategy, we employ length of experience as part of a validation exercise. Longer experience is intuitively expected to be more valuable because a manager who worked in an industry for a longer period of time is likely to have gained a deeper understanding of that industry and developed more contacts that she can consult than another manager who worked in an industry only for a shorter period. If our identification strategy is not capturing the effect of industry experience, then more industry experience resulting from a longer tenure in a particular industry ought to be unrelated with the performance differences between the two sub-portfolios.

To test this, we proceed as follows. We take the time between the first date when a manager was employed in a given industry and the date when the manager left the industry as a measure of the length of experience in that industry. Based on this information, we classify a manager as having long experience if that manager has industry experience with a length of more than five years, which is the cross-manager average; the rest of managers are classified as having short industry experience. We replicate the analysis of Table 2.2 but now for the two subsets of managers categorized by length of their industry experience.

In Table 2.4 we report the performance differences between the experience and non-experience portfolios for the subset of managers with long experience, for the subset of managers with short experience, and most importantly, compare the performance differences between the two. Results show that length of experience matters for the performance difference between the experience and non-experience portfolios. Fund managers with long experience generate performance differentials that are significantly larger than those generated by managers with short experience. The difference is up to seven percentage points. Thus, the evidence that the investment value of industry experience increases with the length of experience rejects the null hypothesis that our identification approach does not capture the effect of industry work experience.

Table 2.4: Performance differences and length of experience

Performance Measures	**Managers with long experience**		**Managers with short experience**		**Difference**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-stat
Return	0.0734	2.69	0.0143	0.92	0.0590	2.14
Carhart	0.1105	3.62	0.0393	1.86	0.0712	2.55
DGTW	0.0757	3.42	0.0178	1.61	0.0579	2.62
Ind.-adj. DGTW	0.0636	3.29	0.0114	1.35	0.0522	3.14
Peer-adj. DGTW	0.0728	4.63	0.0161	1.75	0.0566	4.05
Observations	318		1,870		2,188	

Notes: This table reports performance differences between experience and non-experience portfolios for two groups of managers categorized by length of prior industry experience. The performance differences between experience portfolio and non-experience portfolio are calculated as in Table 2.2. We determine whether a manager has long or short experience using the length of the manager's experience in the industry prior to becoming a fund manager. We categorize managers as having long experience if they have more than five years of experience, the mean length of experience in our sample. The remaining managers are categorized as managers with short experience. All t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized.

2.3.2.2 Bootstrap analysis with random assignment of pseudo experience industries

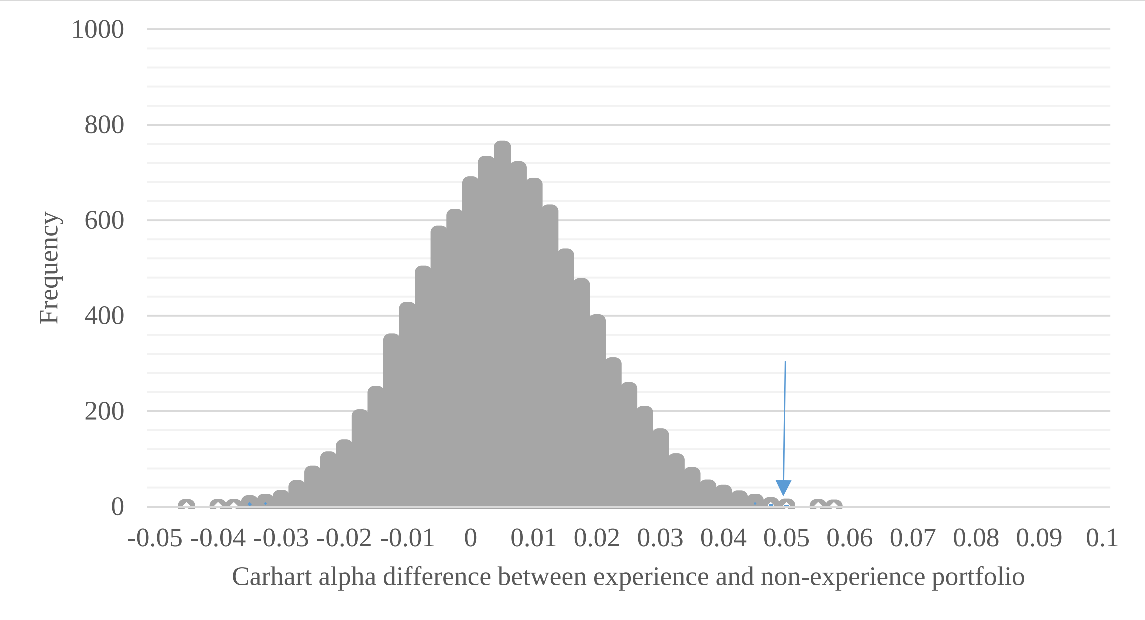
There is also the possibility that our methodology might give rise to a spurious performance difference between the experience and non-experience portfolios. For example, the experience portfolio of a fund manager is likely to have more idiosyncratic risk than the larger, more diversified non-experience portfolio. This could favor the risk-adjusted performance of the experience portfolio in a way that does not reflect industry-specific skill.

To address this concern, we perform a bootstrap procedure where each manager is assigned random pseudo experience industries, i.e., industries in which the manager has in fact no experience. This sampling approach imposes the null hypothesis of no stock picking effect due to industry experience. To replicate our original setup as closely as possible, the random experience industries must fulfill two conditions. First, the number of random pseudo experience industries assigned to a manager has to equal the number of her actual experience industries in our original sample. Second, these industries are represented in the manager's portfolio by at least one stock holding on one report date. We repeat this random draw 10,000 times for all managers and implement the measurement approach of Table 2.2.

In Figure 1, we display the distribution of Carhart alpha differences between the managers' random pseudo experience portfolios and remaining non-experience portfolios. We observe that the actual performance difference of Table 2.2 is positioned at the right-hand tail of the bootstrap distribution, such that it is significantly greater than the mean of the empirical distribution resulting under the null of no stock-picking effect due to industry experience (p-value=0.0004).[39] This result rejects the null in favor of our hypothesis that industry experience provides a stock picking advantage.

[39] Bootstrap results from the other risk- and characteristics-adjusted performance measures are not reported in the interest of brevity, but they all reject the null at conventional levels of significance.

Fig 2.1: Bootstrap analysis



Notes: The figure displays the average Carhart alpha difference between managers' randomly drawn pseudo experience portfolio and their remaining non-experience portfolio. We test the null hypothesis of no stock picking effect due to experience by randomly choosing one industry in which the manager has no experience as her pseudo experience industry. For managers with experience in multiple industries, we randomly draw the same number of industries. We then compute the Carhart alpha difference as described in Table 2.2. We do this for each manager and report date, and estimate the performance difference as the average across all managers and report dates. We repeat this procedure 10,000 times, and display the distribution of the estimates. The x-axis displays the upper interval limit, the y-axis the number of estimates which fall into a given interval. The interval width equals 0.025 in all panels. For comparison, we also indicate the estimate from Table 2.2.

2.3.3 Industry timing

In this section, we explore whether industry experience provides fund managers with a timing advantage. The basic hypothesis is that managers can time industry returns better when they have prior work experience in those industries. Thus, the empirical prediction is that the managers' tendency to increase (decrease) their portfolio exposure to an industry prior to strong (weak) industry returns should be more pronounced for their experience industries than for their non-experience industries.

To test for this hypothesized effect, we relate future industry returns to changes in industry portfolio weights of fund managers in a regression framework:

$$
\begin{aligned}
r_{t,fut}^{j} = {} & \alpha_0 + \alpha_1 \Delta w_t^{j,f} + \alpha_2 D_{Exp}^{j,f} + \alpha_3 \Delta w_t^{j,f} D_{Exp}^{j,f} + \alpha_4 \Delta w_t^{j,peer} + \alpha_5 r_{t,past}^{j} \\
& + \alpha_6 \hat{\beta}_t^{j,Mkt} + \alpha_7 \hat{\beta}_t^{j,\mathrm{SMB}} + \alpha_8 \hat{\beta}_t^{j,\mathrm{HML}} + \varepsilon_t^{j}.
\end{aligned}
\tag{2.1}
$$

The dependent variable $r_{t,fut}^{j}$ is the future return of a given industry *j*, which is computed as the compounded return of a value-weighted portfolio consisting of all stocks from that industry over a 12-month period – starting from the first month after each report date *t*.

The key independent variable is the change in the weight, $\Delta w_t^{j,f}$, that the manager of a given fund *f* has in a particular industry *j* from *t-1* to *t*. The weight is determined each report date by summing the market values of all stock positions that belong to a given industry and dividing the resulting sum by the sum of the market values of all stock positions of the fund. $D_{Exp}^{j,f}$ is a dummy variable that equals one if the manager of fund f has experience in industry j. Our key test is based on the interaction term, which tests whether a fund manager has better timing ability in her experience industries than in other industries.

We control for investment patterns of a typical fund with a particular investment objective in an industry by utilizing the change in average weight in that industry across all peer funds $\left(\Delta w_t^{j,\text{peer}}\right)$. Furthermore, we control for possible industry momentum (see, e.g., Grinblatt and Moskowitz (1999)) by adding the previous year's industry return $\left(r_{t,past}^{j}\right)$ as an additional control variable. Other controls, intended to control for differences in stock characteristics across different industries, are the factor loadings on the market, HML, and SMB factors, estimated for industry *j* and report date *t*. We obtain these factor loadings by estimating the Fama and French (1993) three-factor model over the last 36 months for each industry's value weighted return. Using these variables, we perform a pooled regression and use standard errors clustered by manager and report date to determine significance of the individual estimates.

Table 2.5 reports regression results for specifications with and without control variables. All specifications show that increases in industry weights predict higher industry returns only if the manager has prior work experience in that industry. This result supports the hypothesis that managers can time industry returns better when they have prior work experience, suggesting another venue through which industry-specific human capital outside the investment industry is useful for fund managers.

Table 2.5: Fund industry weight changes and future returns

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Constant	0.0996	3.16	0.1137	3.10	0.0772	2.54
Industry weight change	0.0286	0.37	0.1282	1.71	0.1147	1.50
Manager with experience	-0.0055	-0.52	-0.0059	-0.53	0.0120	1.11
Industry weight change * Manager with experience	0.3660	2.00	0.3212	2.11	0.3438	2.20
Peer fund weight change			0.2162	0.25	0.1892	0.22
Lagged return			-0.1624	-1.35	-0.1673	-1.42
Market beta					0.0223	0.93
SMB beta					0.0120	0.55
HML beta					0.0511	2.13
R-squared	0.0001		0.0242		0.0391	

Notes: This table reports results from a regression of future industry returns on funds' industry weight changes, a dummy variable indicating whether a manager has work experience in the industry prior to becoming a fund manager, and the interaction of these two variables. The dependent variable is the compounded 12-month-ahead industry return from a value-weighted industry portfolio consisting of all stocks belonging to a given Fama-French industry. Control variables include: the change of average industry weight of peer funds, the industry return over the previous year, the industry's market beta, the small minus big (SMB) beta, and the high minus low (HML) beta. Betas are measured as factor loadings from a rolling regression of an industry's excess return on the CRSP market index return, the HML factor, and the SMB factor. The average industry weight of peer funds is computed as the average portfolio weight in a given industry at the same reporting date for peer funds, i.e., funds with the same investment objective (Micro Cap, Small Cap, Mid Cap, Growth, Income, Growth & Income). The number of observations is 123,024. All t-statistics are computed using standard errors clustered by manager and date.

Although our key result that managers are better at timing their experience industries is highly significant in a statistical sense, from this analysis alone it is hard to get a sense for how much timing ability contributes to the overall return of the experience portfolio. Thus, to assess its economic importance, we perform an additional analysis. Since managers appear to have no ability to time their non-experience industries, we focus on the experience portfolio and decompose its gross return into components that measure contribution from selectivity (CS) and timing skills (CT) using the decomposition of Daniel, Grinblatt, Titman, and Wermers (1997). The decomposition of the experience portfolio generates an annual CT measure of 2.60 percent (t-statistic=2.36) and an annual CS measure of 3.87 percent (t-statistic=3.19). This suggests that timing ability provides roughly 40 percent of the active return component of the experience portfolio and is thus important in an economic sense.[40]

2.4 Can investors profitably exploit the industry experience of fund managers?

Having established that industry experience has investment value, we now employ an investors' perspective to determine whether investors might be able to benefit from the industry experience of fund managers. An obvious way to do so would be to buy funds run by managers with industry experience. However, our sample managers run diversified funds and hold, on average, only about 8.6 percent of the portfolio in their experience industries. This means that overall fund performance is mainly determined by the part of the fund portfolio invested in non-experience industries,[41] suggesting that investors might be better off mimicking only the part of the fund portfolio invested in managers' experience industries.

Table 2.3 showed that the stocks picked in the managers' experience portfolios generate returns materializing over a period of time that extends beyond the 60-day grace period after the report date, during which funds are mandated to file their holdings with the SEC.[42] This could suggest that investors can profitably replicate the positions of fund managers' experience portfolios even though holdings information is available to them with a delay.

To test whether investors can profitably mimic the experience portfolios of fund managers, we evaluate a simple replication strategy. We assume that, after observing the stock positions of a given manager's portfolio, an investor mimics the experience portfolio of the manager by replicating its weights. The investor then changes the weights when new portfolio holdings are disclosed. Based on this procedure, a series of monthly returns is

[40] We also tried a slightly revised version of the decomposition, whereby we modify the DGTW approach by replacing the DGTW 125 stock benchmarks with the 48 FF industry portfolios. The resulting decomposition provided qualitatively similar results, with a CT measure of 3.06 percent (t-statistic=2.81) and a CS measure of 3.47 percent (t-statistic=2.52).

[41] This is corroborated by finding that our sample funds typically generate a positive but not statistically significant outperformance relative to peer funds.

[42] The report date is the actual reporting date of the mutual fund holdings while the filing date is the date when mutual funds actually file their reports with the SEC. Mutual funds are required to file their holdings with the SEC not later than 60 days after the report date.

constructed from replicating the experience portfolio of each manager. Finally, we assume that the investor invests equally across the experience portfolios of all managers. The time series of monthly returns from investing in this aggregate experience portfolio are evaluated using the same performance measures as in Table 2.2.

Table 2.6: Performance of investment strategies that mimic experience portfolios

	No lag		**1-month lag**		**2-month lag**		**3-month lag**	
	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
Return	0.1288	2.00	0.1273	2.00	0.1238	1.95	0.1160	1.83
Carhart	0.0533	2.67	0.0529	2.69	0.0498	2.68	0.0420	2.22
DGTW	0.0355	2.10	0.0334	2.06	0.0304	1.93	0.0236	1.44
Ind.-adj. DGTW	0.0287	2.08	0.0255	1.77	0.0190	1.33	0.0121	0.80
Peer-adj. DGTW	0.0353	2.76	0.0309	2.35	0.0265	2.14	0.0124	0.93

Notes: This table reports performance results for investment strategies that mimic the experience portfolios of our sample managers. Using the most recently reported holdings, we construct the experience portfolio at the end of the report date (No lag) or up to three months after the report date (3-month lag). Our performance measures include: the raw return (Return), Carhart alpha (Carhart), DGTW-adjusted return (DGTW), industry-adjusted DGTW return (Ind.-adj. DGTW), and peer fund adjusted DGTW return (Peer-adj. DGTW). With the exception of Carhart alpha, for each fund and experience portfolio, we compute a monthly series of value-weighted performance measures, with weights determined by the market value of each position at the date of the portfolio formation. The performance measures of these portfolios are equally-weighted across all funds each month to construct an aggregate monthly return. This generates a series of monthly performance measures for the aggregate experience portfolio. Carhart alpha is estimated as the intercept from a regression of the monthly excess returns of the aggregate experience portfolio on the four Carhart risk-factors. DGTW-adjusted returns are estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. Industry-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry but not held in the portfolio. Peer-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry held by peer funds (matched by investment objective), but not held in the portfolio. The characteristic-adjusted performance measures are valued-weighted each month at the portfolio level across all portfolio stocks. From left to right, we shift the date of portfolio constructions by one month. Estimates are from the time series of aggregate returns and t-statistics are computed using Newey-West standard errors. All performance measures are annualized. The number of observations is 168.

Table 2.6 presents annualized performance numbers for the replicating strategy described above separately for scenarios assuming that the holdings information is available to investors immediately on the report date (time t), or with a delay of one, two, and three months. Since mutual funds are required to make their holdings publicly available by filing no later than 60 days after the report date, only the replicating strategy from the third and fourth scenarios would be feasible. Returns from the first two scenarios are hypothetical, however, as investors have access to holdings data for all funds only at the end of the 60-days grace period. Nevertheless, we include the first two scenarios for comparison.

Results from Table 2.6 show that uninformed investor can benefit from the industry experience of managers by mimicking their experience portfolios. Even when investors get to know the portfolio positions with a delay of two months, they are able to generate significant risk-, and characteristic-adjusted returns from the mimicking strategy. Both the Carhart alpha and DGTW-adjusted return deliver a significant outperformance of 4.98 percent and 3.04 percent, respectively. However, there is some evidence to suggest that earlier the investors learns about the portfolio composition, the more valuable this information is. Raw, risk- and characteristic-adjusted returns decline as the delay with which holdings data are made available for portfolio construction increases. Specifically, annualized Carhart alphas drop from 5.33 percent (t-statistic=2.67) in the first replicating scenario with no information delay to 4.20 percent (t-statistic=2.22) in the last scenario with a three-month information delay. Similarly, DGTW-adjusted returns drop from 3.55 percent (t-statistic=2.10) to 2.36 percent (t-statistic=1.44).

At first blush, this result seems to suggest the presence of a valuable trading strategy based on publicly available information which would constitute a violation of semi-strong market efficiency. That might well be the case, however, it is also possible that the needed information to implement the strategy is burdensome for investors to collect from SEC filing reports and other sources. Moreover, the trading strategy might be hard to implement due to transactions costs or investment restrictions. Thus, the performance of the mimicking strategy would just compensate for these efforts without necessarily indicating a violation of market efficiency.

2.5 Do fund families scale up the industry experience of fund managers?

The fact that industry experience enables certain fund managers to identify superior investments in their experience industries suggests that a rational strategy for fund families would be to extend the benefits of this advantage to a larger asset base encompassing other funds in the family (hereafter, affiliated funds). If fund families are acting in such a fashion, we would expect affiliated funds to utilize the investment ideas from a colleague's experience industry while paying little or no attention to their colleague's ideas in other industries where no clear advantage is evident.

To test this prediction, we employ pooled regressions where the dependent variable reflects individual stock weights in the portfolios of affiliated funds. The regression specification is as follows:

$$w_t^{i,f} = a_0 + a_1 shared_t^{i,f} + a_2 expindustry_t^{i,f} + a_3 shared_t^{i,f} \times expindustry_t^{i,f} + \sum_{k=1}^{6} \gamma_k control_t^{i,f} + \varepsilon_t^{i,f}, \tag{2.2}$$

where $w_t^{i,f}$ is the weight of affiliated fund *f* in stock *i* at time *t*, $shared_t^{i,f}$ is an indicator variable that equals one if stock *i* in the portfolio of affiliated fund *f* is concurrently held by a manager with industry experience within the same family, $expindustry_t^{i,f}$ is an indicator variable that equals one if the stock is from an industry where at least one manager from the family has prior work experience. Our key test is based on the interaction term. It helps us determine whether an affiliated fund manager weights an investment idea of a colleague with prior work experience more when that idea is from the colleague's experience industry than when it is from other industries.

We control for the following stock characteristics: natural log of market capitalization of a stock, past 12-month compounded stock return, past 12-month stock return volatility, and book-to-market ratio. We also control for the natural logarithm of the total net assets managed by the fund family and the average stock weight in peer funds outside the given fund families. To focus on intra-fund variation and thus effectively control for fund characteristics, in one of the specification we employ fund-by-report date fixed effects. We set all report dates to the nearest quarter and cluster standard errors by fund family.

Results are reported in Table 2.7. Panel A shows results considering all affiliated funds. In Panel B we restrict the analysis to a sub-sample of affiliated funds that share at least one stock with the manager that has industry experience. The reason for this restriction is to ensure that the funds of managers with industry experience and their affiliated managers are not subject to investment restrictions that would automatically prohibit them from keeping any stocks in common.

Table 2.7: Commonality in holdings and industry experience

Panel A: All affiliated funds

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Constant	0.0095	5.83	-0.0194	-4.84		
Shared	0.0004	0.74	0.0007	1.25	0.0006	1.27
Experience industry	-0.0026	-7.23	-0.0003	-1.16	0.0000	0.22
Shared in experience industry	0.0035	7.25	0.0012	4.83	0.0007	2.22
Firm size			0.0017	9.27	0.0021	22.61
Past return			0.0005	2.15	0.0008	4.99
Past volatility			0.0005	0.13	-0.0036	-1.20
Book-to-market ratio			-0.0000	-0.08	-0.0000	-0.53
Family size			-0.0010	-8.30	0.0005	27.96
Peer fund weight			0.1132	5.00	0.0984	6.98
Fund by report date FE	No		No		Yes	
R-squared	0.0058		0.1996		0.4836	
Observations	273,810		246,461		246,461	

(continued)

The insignificant coefficient on the *shared* variable is consistent with affiliated funds paying no attention to the investment ideas of our sample managers in their non-experience industries where they are not known to have an informational advantage. In contrast, the sign and significance of the interaction term is consistent with affiliated funds putting larger weights on investment ideas of their colleague in her experience industry. A reasonable interpretation of this evidence is that affiliated managers pay greater attention to the investment ideas coming from the experience industries of their colleagues and accordingly put greater portfolio weights on those ideas.

Given that the analysis above examines concurrent overlaps in holdings, we employ an additional test to provide further support for a causal interpretation of this evidence. We argue that new ideas that appear for the first time in the portfolio of a manager with industry experience but not in the portfolios of affiliated managers are most likely to have been produced by the former manager. Under this premise, in line with our interpretation of Table 2.7 results, we would expect affiliated funds to exhibit a higher likelihood of following the new ideas that come from their colleague's experience industry than those that come from their non-experience industries.

Table 2.7: Commonality in holdings and industry experience - continued

Panel B: Affiliated funds sharing at least one stock with the manager with industry experience

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Constant	0.0086	5.33	-0.0186	-4.54		
Shared	0.0009	1.56	0.0011	1.75	0.0005	1.15
Experience industry	-0.0018	-6.19	0.0001	0.51	0.0000	0.09
Shared in experience industry	0.0032	7.90	0.0011	3.52	0.0007	2.51
Firm size			0.0016	9.33	0.0021	23.76
Past return			0.0004	2.00	0.00065	6.48
Past volatility			-0.0012	-0.35	-0.0029	-1.04
Book-to-market ratio			0.0000	0.11	-0.0000	-0.53
Family size			-0.001	-8.04	-0.0023	-34.32
Peer fund weight			0.1076	5.09	0.0953	7.08
Fund by report date FE	No		No		Yes	
R-squared	0.68		20.89		46.98	
Observations	245,346		223,195		223,195	

Notes: This table reports results from a regression of portfolio weights of affiliated fund managers that do not have industry experience on multiple independent variables. The key independent variables are: shared, an indicator variable that equals one if the stock is concurrently held by a manager with industry experience within the same family; Experience industry, an indicator variable that equals one if a stock is from an industry where a manager from the family has gained work experience; and Shared in experience industry, the interaction of the first two variables. We control for: firm size, measured as the natural log of market capitalization of a stock (shares outstanding multiplied by stock price at the report date); past 12 month compounded stock return; past 12-month stock return volatility; and book-to-market ratio. We also control for the natural logarithm of the total net assets managed by the fund family and the average stock weight in peer funds outside the given fund families. To exploit intra-fund variation, we use fund-by-report-date fixed effects in one of the specifications. Panel A shows results considering all affiliated funds. Panel B shows results for a sub-sample of affiliated funds that share at least one stock with the manager that has industry experience. All report dates are set to the nearest quarter. Standard errors are clustered by fund family.

To test this prediction, we employ a linear probability model. The unit of observation is a stock corresponding to an initiating buy of a manager with industry experience as of the end of the quarter when it happened, i.e., a stock held for the first time by that manager but not held concurrently by an affiliated fund.

$$inbuy\_shared_t^{i,f} = a_0 + a_1 expindustry_t^{i,f} + \sum_{k=1}^{5} \gamma_k control_t^{i,f} + \varepsilon_t^{i,f} \tag{2.3}$$

The dependent variable $inbuy\_shared_t^{i,f}$ is an indicator variable, which equals one if an initiating buy of a manager of fund *f* with industry experience in stock *i* is held by at least one other fund within the same family subsequently at quarter *t*+1 or *t*+2 but not at quarter *t*, and zero otherwise. The key independent variable is experience industry ($expindustry_t^{i,f}$), an indicator variable that equals one when the initiating buy of the manager with industry experience is from her experience industry. If affiliated managers are more likely to follow the new ideas that come from their colleague's experience industry than those that come from their non-experience industries, then the coefficient on this variable is expected to be positive.

We control for firm size, the natural logarithm of market capitalization (stocks outstanding multiplied with stock price at the end of the report date), past 12-month compounded stock return, past 12-month stock return volatility, and book-to-market ratio. We also control for the natural logarithm of the total net assets managed by the fund family. Since the analysis is at the family level and we want to use within-family variation in order to control for family differences, we employ family-by-report date fixed effects. Standard errors are clustered by fund family.

Results are reported in Table 2.8. Panel A shows results considering all affiliated funds, while Panel B restricts the analysis to a sub-sample of affiliated funds that hold at least one stock in the experience industry. As before, the reason for this restriction is to ensure that affiliated managers are not precluded from investing in the experience industries due to possible investment restrictions.

The coefficient on the experience industry dummy is positive, ranging from five to seven percentage points, and statistically significant at the five percent level.[43] Thus, the probability that the new ideas of managers with industry experience are subsequently utilized by the family's other funds is more than 5 percentage points higher when the new ideas are from the experience industry than when they are from other industries. This is economically significant because it constitutes more than a 50 percent increase in probability relative to the baseline probability that family's other funds follow the ideas of

[43] Most likely, this underestimates the size of the economic effect because this test only considers fund managers following their experienced colleagues with a time lag of one or two quarters. Many fund managers will be able to observe the trades of their experience colleagues within the same quarter and thus adopt the ideas of their experience colleagues within the same quarter. Cici, Jaspersen, and Kempf (2016) document that the performance effect is the stronger, the earlier information is shared across managers of a fund family.

their colleagues from their non-experience industries. This evidence is consistent with family's other managers paying greater attention to the investment ideas coming from the experience industries of their colleagues with industry experience and being more likely to act on those ideas.

Table 2.8: Utilization of ideas and industry experience

Panel A: All affiliated funds

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Constant	0.1060	2.49	-1.1059	-4.96		
Experience industry	0.0719	1.97	0.0661	2.28	0.0500	2.29
Firm size			0.0457	4.92	0.0428	4.01
Past return			-0.0021	-0.72	-0.0008	-0.51
Past volatility			-0.0186	-0.23	0.0199	0.37
Book-to-market ratio			-0.0140	-2.16	-0.0030	-0.44
Family size			0.0379	3.97	0.3007	3.31
Family by report date FE	No		No		Yes	
R-squared	0.0051		0.1187		0.2767	
Observations	13,345		9,205		9,205	

Panel B: Affiliated funds holding at least one stock from the experience industry

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Constant	0.1105	2.50	-1.1516	-5.19		
Experience industry	0.0691	1.87	0.0649	2.16	0.0502	2.23
Firm size			0.0481	5.18	0.0447	4.06
Past return			-0.0025	-0.81	-0.0010	-0.56
Past volatility			-0.0193	-0.24	0.0185	0.34
Book-to-market ratio			-0.0140	-2.15	-0.0032	-0.45
Family size			0.0378	4.02	0.3030	3.33
Family by report date FE	No		No		Yes	
R-squared	0.0047		0.1183		0.2749	
Observations	12,840		8,794		8,794	

(continued)

Table 2.8: Utilization of ideas and industry experience - continued

Notes: This table reports results from a linear regression modeling the probability that an idea initiated by a manager with industry experience is utilized subsequently by affiliated managers without industry experience. The observations include the initiating buys of managers with industry experience, which are identified as stocks that are held for the first time by such a manager and not held concurrently by an affiliated fund at t. The dependent variable is an indicator variable that equals one if an initiating buy of a manager with industry experience is held by at least one other fund within the same family at t+1 or t+2 and zero otherwise. The key independent variable, Experience industry, is an indicator variable that equals one when a stock is from an industry where a manager from the family has gained work experience. We control for: firm size, measured as the natural logarithm of market capitalization at the end of the report date; past 12 month compounded stock return; past 12 month stock return volatility; and book-to-market ratio. We also control for the natural logarithm of the total net assets managed by the fund family. Panel A shows results considering all affiliated funds. Panel B shows results for a sub-sample of affiliated funds that hold at least one stock in the experience industry. Standard errors are clustered by fund family.

All in all, results from this section imply that fund families utilize the industry-specific human capital of their managers with prior industry work experience by applying it to a larger asset base, which goes beyond funds managed by the managers with industry experience themselves. These findings have yet another implication for fund families, suggesting that a fund family might increase its overall performance by hiring more fund managers with prior industry experience across a broader spectrum of industries.

2.6 Conclusion

In this paper we show that industry-specific human capital acquired outside the investment industry is transferrable to the investment industry and is valuable from an investment perspective. Identifying industries in which portfolio managers had prior work experience, we split managers' portfolios into two subsets that reflect, respectively, managers' experience and non-experience industries. We find that managers' stock picks from their experience industries generate significant risk- and characteristic-adjusted performance of up to five percent per year. In contrast, their stock picks from their non-experience industries generate performance that is indistinguishable from zero.

The investment value of prior work experience also manifests itself when managers make industry timing decisions, in that they exhibit superior timing ability in their experience industries relative to their non-experience industries. Specifically, managers' tendency to increase (decrease) their portfolio exposure to an industry prior to strong (weak) industry returns is significantly more pronounced for their experience industries than for their non-experience industries.

Besides documenting the value of prior industry experience from the prism of fund managers, our analysis has implications for investors and fund families. Our results suggest that investors might benefit from the prior industry experience of fund managers by mimicking the stocks holdings of these managers in their experience industries. While we show that fund families utilize the industry experience of their managers with prior industry work experience by applying it to a larger asset base, we think that fund families could benefit from hiring more fund managers with prior industry experience across a broader spectrum of industries. Such a strategy could increase overall family performance and benefit investors in the end.

Chapter 3

Do Generalists Profit from the Fund Families’ Specialists? Evidence from Mutual Fund Families Offering Sector Funds*

3.1 Introduction

Investments in active mutual equity funds are only justified when they outperform their passive benchmarks. To justify their existence, active fund managers are heavily reliant on superior price relevant information. Mutual fund managers often oversee hundreds of stocks. As attention and time are limited resources, portfolio managers might not always be able to monitor stocks, industries and their overall portfolio decomposition adequately. However, their funds mostly belong to larger business entities, commonly referred to as mutual fund families. The fund family provides research, trading desks, distribution externalities and other resources to its member funds.

In this study, I focus on a mutual fund family characteristic that has been widely ignored by empirical asset management studies: offering sector funds.

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* This chapter is based on Göricke (2016).

While there are a few studies focusing on the skill of sector fund managers (see Khorana and Nelling (1997); Dellva, Demaskey, and Smith (2001); and recently Kostovetsky and Ratushny (2016)), the role of sector funds within fund families has not been studied. Past research has shown that fund family organization has an effect on member fund performance.[44] I focus on how the existence of skilled sector fund managers affects the performance and investment behavior of affiliated funds. To the best of my knowledge, this is the first study to address this question.

In addition to satisfying investor demand and increasing assets under management by offering exposure to certain sectors, sector funds could be an advantage for mutual fund families in a different way: I assume that sector or specialist funds are, by definition, linked to experts for certain industries in the stock market. Having access to these specialists might help generalists (diversified funds) select stocks for specific industry sub-portfolios.

The access to sector specialists is only valuable if they have superior skill. There are two reasons why sector managers should be able to select undervalued stocks. First, in this paper, a specialist focuses on a narrow selection of industries, whereas the generalist has to pick stocks from far more industries.[45] When time and attention are limited resources of the manager, concentrating on fewer industries makes it easier to pick undervalued stocks. Second, while all families may have access to research on different industry sectors, offering sector funds might provide fund families with a competitive advantage in evaluating information. In many fund families, a fund manager starts her career as an analyst, providing research for the funds of the family. From the perspective of an analyst, running a sector fund might provide a stronger incentive to do good research because results of her work are observable and linked to compensation. According to Wiley (1997), “good wages” (here: pay is linked to assets under management), “appreciation for work done” (here: performance of stock picks) and “promotion” (here: being a manager instead of an analyst) are key factors for employee motivation and highly motivated employees could help their employers gain a competitive advantage. In addition, it might be more attractive for good analysts to work as a sector fund manager, enabling sector fund families to attract more talented people.

[44] See, e.g., Gaspar, Massa, and Matos (2006); Kacperzcyk and Seru (2012); and Chen, Hong, Jiang, and Kubik (2013).

[45] My definition of specialists and generalists is related to the categorization applied by Zambrana and Zapatero (2015). In their paper, a generalist runs multiple diversified funds with different investment objectives, whereas a specialist just has one diversified fund with one investment objective.

Finally, there is a difference in providing data to fund managers and selecting stocks yourself.[46]

Following these arguments, I hypothesize that sector funds have stock picking skill. I show that they have positive net three- and four-factor alphas, which are up to 207 basis points p.a. higher than the alphas of comparable diversified funds with respect to size, turnover, costs, etc. I also show that the stocks sector funds share with affiliated diversified funds outperform the stocks from the same industries that are uniquely held by diversified funds by up to 240 basis points p.a. This is in line with my argument that families attract talent with sector funds instead of setting up sector funds as a result of existing superior research in certain sectors.

To understand how generalists profit from specialists, it is important to understand how information flows between generalists and specialists. Following the argument that specialists have stock picking skills, I hypothesize that rational diversified fund managers implement ideas of sector managers. I show that the quality of both the diversified and the sector fund are important drivers of how much information they share. Diversified funds that underperform the passive portfolio in a certain sector in the previous year share more information with sector funds in this given sector. Moreover, more information is shared with superior sector funds. Generalists also seem to value specialist experience because they share more information with longer tenured specialists. Finally, managers who control a diversified fund and a sector fund at the same time have higher overlap. This is in line with families not following a centralized research approach. Taken together, my results imply that information is flowing from specialists to generalists.

Even though sector fund families do not seem to follow a centralized research approach, generalists should clearly share information with specialists. Selecting a stock for a sector fund is a strong signal about the quality of the issuing firm. For this reason, I hypothesize that on average, stocks held by sector funds should appear in more portfolios than stocks not held by sector funds. Accordingly, I find significant evidence that stocks held by sector funds have an up to 78.55 percent higher chance to appear in more than two diversified fund portfolios of the family than other stocks.

[46] Voss (2014) points out that the most crucial difference between investment managers and analysts is decisiveness.

Following the aforementioned results, I hypothesize that as more sectors are covered, the more expertise is available to be shared in the family. In other words, the more sectors covered, the better it is for the affiliated diversified fund's performance. I show that the number of sectors covered is significantly and positively related to unadjusted and risk-adjusted measures of fund-level performance. Diversified funds belonging to families that cover at least three sectors show up to 127 basis points better performance p.a. than comparable peer funds from similar families that do not offer sector funds.

If managers can rely on part of the stock selection being made by affiliated sector funds, they can spend more time covering the rest of their portfolios. Following this argument,[47] more efficient attention allocation allows managers to focus on (and thus give more weight to) stocks with alpha-generating potential; this generally refers to stocks that are hard to value. According to Peng (2005), allocating more information acquisition effort to assets with uncertain payoffs is beneficial.[48] Also, when managers implement more ideas they should trade more, as measured by higher turnover. I document a strong positive correlation between the number of sectors covered in the fund family and the amount of hard-to-value stocks held by affiliated funds. The same holds true for fund turnover. Taken together, these results support the finding of an outperformance on the fund level for diversified funds from sector fund families.

With this paper, I contribute to the extensive literature on mutual fund manager skills. Apart from Dellva, DeMaskey, and Smith (2001), the study most closely related to this paper is Cici and Rosenfeld (2016). Both papers find that sector funds respectively buy-side analysts do have investment value. The latter focuses on analyst-run funds without a focus on specialized sector funds and their role in 14 fund families. My paper takes a wider approach by analyzing 154 families with a deeper focus on the effect of industry/sector specific expertise. I examine the influence of sector specialists on affiliated generalists and compare them to generalists from families without sector funds.

In addition, this paper adds to the literature looking at information sharing within large business entities like mutual fund families. Augustiani, Casavecchia, and Gray (2015) look at the link between interconnection of mutual funds and fund performance. Cici, Jaspersen, and Kempf (2016) analyze how the speed of information diffusion within a fund

[47] See the idea brought forth by Gupta-Mukherjee and Pareek (2015).

[48] See also Mondria (2010); Gabaix and Laibson (2005); and Gabaix, Laibson, Moloche, and Weinberg (2006).

family affects performance. I add to the literature by showing which fund and manager characteristics influence sub-portfolio overlap of different funds in a family. In contrast to other studies, I show how quality (performance and tenure) affects information sharing, indicating a direction of information flow. I also document that sector fund held stocks appear in more portfolios than other stocks in the family.

Finally, I further contribute to the literature by analyzing how strategy or the organizational structure of mutual fund families affect the performance outcomes and investment behavior of affiliated funds. Chen, Hong, Huang, and Kubik (2004) show that funds from larger families outperform. Siggelkow (2003) shows that funds from families that put their focus on particular investment objectives outperform. Cici, Dahm, and Kempf (2016) show that families with more efficient trading desks have better performing funds. In these and other examples, being part of a fund family seems to allow member funds to exploit economies of scale and scope. In the present study, it is the ability to attract and build high quality research in certain sectors that is available to other funds. Documenting this family characteristic and its impact on performance is my contribution. I add to the literature by showing that establishing an in-house source of high quality research that is available to affiliated funds affects performance in a positive way.

The remainder of this paper is organized as follows. In section 3.2, I present the data used for this study and sample summary statistics. I provide a first understanding on how families offering sector funds are different and what is special about sector funds. In section 3.3, I analyze the performance of sector funds and their stock picks. Section 3.4 presents evidence on how generalists share information with specialists by analyzing portfolio overlap between sector funds and diversified funds from the same family. Section 3.5 analyzes how the availability of sector expertise affects fund level performance, stock selection and trading behavior of generalists. Section 3.6 concludes.

3.2 Data

3.2.1 Data selection

I obtain fund data from the mutual fund database compiled by the Center for Research in Security Prices and combine it with the Thomson Mutual Fund Holdings Database using Mutual Fund Links (MFLINKS). Holding information is supplemented by information from the CRSP stock database. The CRSP mutual fund database contains information about funds' investment objectives and a family identifier, which allows me to assign each active equity fund to a distinct fund family. For diversified funds, I select funds with the CRSP fund objective codes EDCI (Micro Cap), EDCM (Mid Cap), EDCS (Small Cap), EDYB (Growth & Income), EDYG (Growth); and EDYI (Income). Sector funds with the codes EDSA (Telecom), EDSF (Financial), EDSG (Consumer Goods), EDSH (Health), EDSI (Industrials), EDSN (Natural Resources), EDSM (Materials), EDSS (Consumer Services), EDST (Technology), and EDSU (Utilities) are included.[49]

I additionally check the fund names to make sure they are assigned to the right category. I drop all index and foreign funds. If a fund offers multiple share classes, I aggregate information like fund return, fees, etc. to the fund level by weighing the information by the total net assets of the related share classes in the prior month. To sort stocks into industry sub-portfolios I use the Fama and French 48 industry definition based on historical SIC codes. The main sample comprises the years from 2000 to 2014. For Tables 3.5 and 3.6, I use Morningstar Principia to obtain information on the managers responsible for the funds in my sample. This data is only available to me until 2009. My choice of Morningstar Principia over the CRSP mutual fund database to obtain this information was motivated in large part by previous research showing that reported manager information is more accurate in the Morningstar database than in the CRSP mutual fund database (see, e.g., Patel and Sarkissian (2013)).

I match the manager information obtained from Morningstar to CRSP fund data. I also manually screen manager names for different spellings and/or abbreviations and assign a distinct identification number to each manager.

[49] I select only equity sector funds and thus drop gold and commodity sector funds. Since gold funds have the code EDSG, I manually check fund names and holdings to separate them from consumer goods funds, which received the same code by CRSP.

3.2.2 Sample description

I classify fund families into sector fund families that offer at least one active U.S. sector equity fund in a given calendar year and non-sector-fund families that only offer actively managed U.S. domestic diversified equity funds. Table 3.1 presents summary statistics for characteristics for both types of families and their affiliated diversified funds.

There are 154 distinct families offering sector funds in the sample period. 1,444 distinct diversified funds belong to these families. Sector fund families are larger and offer more domestic equity funds than non-sector fund families.[50] Sector fund families offer 20.9 diversified funds, on average. This is consistent with Khorana and Servaes' (1999) finding that large families have more experience in opening funds and are more likely to open new funds. These families are also most likely to benefit from economies of scale and scope. Fittingly, diversified funds offered by sector fund families are on average older than diversified funds from non-sector fund families and almost twice as large regarding assets under management. Since smaller funds have higher returns on average, it is not surprising that the average net return is lower for funds belonging to sector fund families.[51] There is no difference, on average, regarding total expense ratios.

I define the variable sectors covered as the number of distinct investment objectives in the category sector funds within a family in a given calendar year. Sector fund families cover 2.5 sectors on average, while a small group of families covers all available sectors. Table 3.2 shows the characteristics of the 350 sector funds I identified. Panel A shows that they are considerably smaller, younger and have higher flows than affiliated diversified funds, on average. They hold 8.1 (diversified funds: 28.6) Fama-French 48 sub-portfolios.[52] Panel B shows that most funds are offered in the sectors Health/Biotechnology, Technology, and Financial Services.

[50] Family size comprises all family funds covered by MFLINKS.
[51] See Chen, Hong, Huang, and Kubik (2004).
[52] Taking Health/Biotech funds as an example, only 3 of the 48 industries seem to be important at first sight: 11(Healthcare), 12(Medical Equipment), 13 (Pharmaceutical Products). However, they also hold stocks related to the medicine field in industries 35 (Computers), 41(Wholesale), and 45 (Insurance), for example.

Table 3.1: Summary statistics sector vs. non-sector fund families

	Sector Fund Families					Non Sector Fund Families					Diff.
Variable	Mean	Stdev.	50%	1%	99%	Mean	Stdev.	50%	1%	99%	
Net-of-fee return	0.0582	0.2232	0.0958	-0.4705	0.5230	0.0690	0.2199	0.0978	-0.4684	0.5258	***
OAR	-0.0006	0.0794	0.0004	-0.2355	0.2266	0.0026	0.0873	0.0001	-0.2283	0.2717	***
Fama-French alpha	-0.0120	0.0824	-0.0155	-0.2132	0.2466	-0.0118	0.0817	-0.0148	-0.2099	0.2588	
Carhart alpha	-0.0146	0.0741	-0.0159	-0.2161	0.2082	-0.0117	0.0781	-0.0135	-0.2156	0.2376	***
DGTW Return	-0.0014	0.0673	-0.0006	-0.2042	0.1876	-0.0000	0.0734	-0.0006	-0.2062	0.2139	
Total expense ratio	0.0128	0.0044	0.0123	0.0040	0.0243	0.0127	0.0049	0.0121	0.0027	0.0299	
# Sectors covered	2.48	2.07	2.00	1.00	9.00						
# Sector funds	5.15	9.87	2.00	1.00	42.00						
# Diversified funds	20.87	15.48	17.00	2.00	68.00	6.93	6.77	4.00	1.00	28.00	***
Family size in $ mio.	123,052.50	244,798.80	36,522.70	127,10	977,863.80	40,123.77	222,884.40	2,829.10	3.70	983,248.60	***
Family focus	0.22	0.14	0.17	0.09	0.77	0.44	0.30	0.33	0.10	1.00	***
Fund size in $ mio.	1,696.14	5,047.64	359.90	2.20	23,514.60	938.36	4,274.61	138.00	1.30	11,669.40	***
Fund turnover	1.00	1.61	0.73	0.04	4.25	0.85	1.19	0.61	0.03	4.58	***
Fund age	13.96	13.76	10.00	0.40	70.75	12.66	12.26	9.33	0.51	65.50	***
Fund flow	0.26	3.24	-0.05	-0.59	5.02	0.33	8.49	-0.03	-0.66	4.80	

(continued)

Table 3.1: Summary statistics sector vs. non-sector fund families - continued

Notes: This table reports summary statistics on the major variables for the sample of actively managed U.S. domestic equity funds and the fund families they belong to between the years 2000 and 2014. Each year funds are classified into funds belonging to fund families offering sector funds or to families not offering any sector funds. There are 1,444 diversified funds belonging to 154 sector fund families and 2,005 diversified funds belonging to 699 non-sector fund families. Performance measures are on a yearly basis. Net-of-fee return is the cumulated monthly net fund return for a given year. OAR is the cumulated monthly excess return over the mean investment objective return. Fama-French (1993) and Carhart (1997) alphas are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the respective factor returns. DGTW return measures the cumulated monthly value weighted excess return of the fund's holdings over the respective value weighted benchmark as defined in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004). Total expense ratio represents the fund's fees charged for total services. # Sectors covered measures the number of different sectors that sector funds covered within a fund family in a given year. # Sector and # diversified funds is the number of different U.S. domestic equity sector funds or, respectively, diversified funds offered in a given year. Family Size is the total net assets under management by the fund family in $ millions. Family focus is the concentration of a fund family across investment objectives as defined in Siggelkow (2003). Fund size is the funds' total net assets under management in $ millions. Fund turnover is the fund's yearly turnover. Fund age is the fund's age in years. Fund flow is the fund's yearly growth rate adjusted for internal growth as in Sirri and Tuffano (1998). ***,**,* denote statistically significant differences in the means at the 1%, 5%, and 10% significance level, respectively.

Table 3.2: Summary statistics for sector funds

Panel A: Sector fund characteristics

Variable	Mean	Stdev.	50%	1%	99%
Net-of-fee return	0.0541	0.2931	0.0883	-0.5706	0.7452
Fama French alpha	0.0001	0.1056	-0.0013	-0.2766	0.3179
Carhart alpha	0.0050	0.10121	0.0005	-0.2471	0.3566
Total expense ratio	0.0155	0.0057	0.0150	0.0068	0.0319
Fund size in $ mio.	585.86	1,524.92	151.60	0.70	5,208.60
Fund turnover	1.97	3.77	0.91	0.06	18.67
Fund age	11.88	10.10	9.75	0.08	59.32
Fund flow	2.80	66.73	-0.06	-0.65	10.34
# Industry sub-PF	8.10	4.17	8.00	1.00	20.00

Panel B: Distribution of sectors

Health/Biotech	18.60%
Financial services	11.10%
Natural resources	9.70%
Technology	39.70%
Utilities	8.90%
Consumer goods/services	3.90%
Industrials	3.10%
Basic materials	1.10%
Telecommunication	4.00%
Sector funds	350

Notes: This table reports summary statistic for U.S. domestic equity sector funds between the years 2000 and 2014. Net-of-fee Return is the cumulated monthly net fund return for a given year. Fama-French (1993) and Carhart (1997) alphas are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the respective factor returns. Total expense ratio represents the fund's fees charged for total services. Fund size is the funds' total net assets under management in $ millions. Fund turnover is the fund's yearly turnover. Fund age is the fund's age in years. Fund flow is the fund's yearly growth rate adjusted for internal growth as in Sirri and Tuffano (1998). # Industry sub-PF is the average number of Fama-French 48 industry sub-portfolios held at a report date. Panel B describes to which sectors the different sector funds belong.

3.3 Sector fund manager skill

Specialists are only valuable to generalists of the fund family if they have superior stock picking skills. For this reason, I analyze sector fund alphas in section 3.3.1. In order to show that it is specialist knowledge and not fund family expertise in certain sectors leading to positive alphas, I analyze the performance difference between stocks that sector and diversified managers share and stocks from the same industries uniquely held by diversified managers in section 3.3.2.

3.3.1 Sector fund level performance

To assess the stock picking ability of sector fund managers I use modified Fama and French (1993) three- and Carhart (1997) four-factor models. Since sector fund portfolios comprise only a few industries of the market, it is appropriate to modify the factor return for the market. Dellva, DeMaskey, and Smith (2001) highlight the importance of using the right benchmark for assessing sector funds' stock picking skills. I therefore construct a sector benchmark index for each of the nine sectors. First, I identify which industries are held with a weight of more than ten percent by any fund in the sector over time. I then construct a passive market capitalization weighted benchmark using all stocks from the identified industries. Finally, I replace the excess market return with the fitting excess sector index return in the regressions with three and four factors. To put the performance of sector funds into perspective, I also compute regular three- and four-factor alphas for the diversified funds in the sample.

For all funds, I first compute the fund performance for each performance measure per month and then compound it over the 12 monthly observations to get the performance per year. A funds monthly alpha is the difference between the realized and expected excess fund return. The expected net return in a given month is computed using factor loadings estimated over the previous 36 months and factor returns in that month.

The average stock picking performance is shown in Tables 3.1 and 3.2. While diversified funds have a gross alpha of around zero, sector funds have a gross alpha that is positive. It can also be seen that sector funds have, for instance, less assets under management, on average. Smaller funds might find it easier to invest in small, unknown firms. This could make it easier to identify undervalued stocks. This is why I run the following pooled regression to control for fund characteristics:

$$\begin{aligned} Perf_{i,t} &= \alpha + \beta_1 Sectorfund_{i,t} + \gamma_1 FundSize_{i,t-1} + \gamma_2 FundTO_{i,t-1} + \gamma_3 FundTER_{i,t-1} \\ &+ \gamma_4 FundAge_{i,t-1} + \gamma_5 FundFlow_{i,t-1} + \gamma_6 FundPerf_{i,t-1} + a_t + \varepsilon_{i,t}. \end{aligned} \tag{3.1}$$

My key independent variable is $Sectorfund_{i,t}$. This is an indicator variable equal to one, if the observation belongs to a sector fund or zero if it does not. Since diversified funds and sector funds are different, I include widely used fund characteristics as controls. I control for the logarithm of the fund's total net assets at the end of the past year, the fund's yearly turnover and total expense ratio, the fund's age in years, fund flows as defined in Sirri and Tufano (1998) for the past year, and fund performance for the past year. As discussed in Berk and Green (2004), skilled managers might charge higher fees to extract rents. Since I focus on a comparison of skills, I need to compare gross returns. This is why I use the total expense ratio as a control variable in all regressions. To control for differences in performance over time I include year fixed effects denoted by a_t. Standard errors are clustered at the fund level.

Table 3.3: Stock picking skills of sector fund managers compared to diversified fund managers

Dependent variable	Return	Fama French	Carhart
Sector fund	0.0081***	0.0181***	0.0207***
	(2.76)	(7.22)	(9.15)
Fund size	-0.0032***	-0.0014***	-0.0013***
	(-7.12)	(-4.14)	(-4.10)
Fund turnover	-0.0040***	-0.0032***	-0.0029***
	(-6.20)	(-5.42)	(-4.96)
Total expense ratio	-1.1065***	-1.2259***	-1.0649***
	(-5.08)	(-7.37)	(-6.61)
Fund age	0.0034***	-0.0004	-0.0002
	(3.45)	(-0.48)	(-0.35)
Past flow	-0.0002***	0.0000	0.0000
	(-3.88)	(0.67)	(0.22)
Past return	0.1433***	-0.0623***	0.0177
	(12.69)	(-5.06)	(1.35)
Observations	19,160	19,160	19,160
R-squared	0.8307	0.1068	0.0972

(continued)

Table 3.3: Stock picking skills of sector fund managers compared to diversified fund managers - continued

Notes: This table presents results from pooled OLS regressions that analyze the stock picking skills of sector funds compared to diversified funds. I include U.S. domestic sector funds having the following CRSP Objective Codes: EDSH (Health/Biotechnology), EDSF (Financial Services), EDSN (Natural Resources), EDST (Science & Technology), EDSU (Utilities), EDSG (Consumer Goods)/EDSS(Consumer Services), EDSI (Industrials), EDSM (Basic Materials), EDSA (Telecommunication). Only diversified funds having the investment objectives EDCI (Micro Cap), EDCS (Small Cap), EDCM (Mid Cap), EDYB (Growth & Income), EDYG (Growth), and EDYI (Income) are included. For each fund, I measure monthly net alphas by regressing funds' net-of-fee excess returns on the Fama French (1993) and Carhart (1997) factor returns using 36-month rolling-window regressions. I compound monthly returns and alphas for every year and fund. For sector funds the market factor return is replaced with a sector specific index return. I compute this index return by value-weighting returns of stocks belonging to Fama-French 48 industries usually covered by the respective sector funds in the sample period. The key independent variable is sector fund, which is equal to one if the fund is a sector fund and zero otherwise. Additional independent controls include fund size, fund turnover, total expense ratio, fund age, past flow, and past return. Fund size is the logarithm of the fund's total net assets under management. Fund turnover is the fund's yearly turnover ratio, defined as the minimum of aggregated security purchases and sales divided by the average total net assets under management during the calendar year. Total expense ratio represents the fund's fees charged for total services. Fund age is the logarithm of the fund's age in years. Past flow is the net fund flow of the past year. Past return is the relevant return measure for the past year. All other independent variables are also lagged by one year. Regressions are run with year fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 3.3 shows that even after controlling for standard fund characteristics, sector fund managers have higher alphas than diversified fund managers. Their alphas are up to 207 basis points p.a. higher. This is a clear indication that sector fund managers possess skill.

3.3.2 Comparison of specialist's and generalist's stock picks

My hypothesis is that sector fund managers are skilled rather than the family having skill in certain sectors and consequently offering matching funds. To test this hypothesis, I form one aggregate family stock portfolio at each report date. Report dates are all set to the nearest quarter. The resulting portfolio contains all stocks held by the diversified funds of the family. I then drop stocks from industries where no affiliated sector fund concurrently holds more than 10 percent of his portfolio. I calculate risk-adjusted stock returns based on 36-month rolling window regressions and characteristic benchmark adjusted returns as defined in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004). I compound all return measures until the next report date (three months). If the whole family has skill in the industries covered by the specialists there should be no difference in performance for stocks diversified funds share with sector funds and stocks uniquely held by diversified funds. I run the following pooled regression:

$$\begin{aligned} Perf_{j,m,t} = \alpha + \beta_1 Shared_{j,m,t} + \gamma_1 Size_{j,t} + \gamma_2 Pastret_{j,t} + \gamma_3 Paststd_{j,t} \\ + \gamma_4 Btm_{j,t} + a_{m,t} + a_{i,t} + \varepsilon_{j,m,t}. \end{aligned} \tag{3.2}$$

$Shared_{j,m,t}$ is the key independent variable in the regression. It is an indicator variable equal to one if stock *j* was also held by at least one sector fund of family *m* at report date *t* and zero if it was only held by diversified funds of the family. In order to control for differences between the two groups I include the natural log of the market capitalization at the beginning of the holding period, the past 12 month compounded return, the standard deviation of the past 12 month return and the ratio of book equity to market equity at the end of the last fiscal year. I add report date by family ($a_{m,t}$) and report date by industry fixed ($a_{i,t}$) effects to control for unobserved industry and family characteristics affecting the results. Standard errors are clustered at the fund family level.

Table 3.4: Performance of stocks diversified funds share with sector funds in covered industries

Dependent variable	Return	Fama French	Carhart	DGTW
Shared with SF	0.0027**	0.0059***	0.0060***	0.0037***
	(2.24)	(6.32)	(5.62)	(3.59)
Market capitalization	-0.0091***	-0.0032***	-0.0037***	-0.0051***
	(-14.92)	(-8.56)	(-7.58)	(-11.77)
Past return	-0.0096***	-0.0028	-0.0085***	-0.0049***
	(-5.86)	(-1.44)	(-3.18)	(-3.41)
Past return volatility	-0.1028***	0.0681***	0.0773**	-0.0850***
	(-3.19)	(3.39)	(2.42)	(-5.17)
Book-to-market ratio	-0.0358***	-0.0335***	-0.0310***	-0.0359***
	(-18.80)	(-19.89)	(-17.55)	(-18.55)
Observations	332,817	332,638	332,638	332,817
R-squared	0.3316	0.0838	0.0785	0.0827

(continued)

Table 3.4: Performance of stocks diversified funds share with sector funds in covered industries - continued

Notes: This table presents results from pooled OLS regressions that analyze the performance of stocks that diversified funds share with affiliated sector funds. I set all report dates to the nearest quarter. For each fund family, I select all stocks that were held by the diversified funds of the family. I then drop stocks from industries that have a maximum weight of less than 10 percent in affiliated sector fund portfolios at the same report date. Industry definitions are based on Fama and French's 48 industry groupings. For each stock, I measure the compounded performance until the next report date. Abnormal returns are based on rolling 36-month rolling window regressions and the DGTW adjustment approach. The key independent variable is an indicator variable that equals one if a stock is concurrently held by a sector fund and zero otherwise. Additional controls include the natural logarithm of the stock market capitalization, the compounded stock return in the past 12 months, monthly return volatility over the past 12 months, and the ratio of book equity to market equity at the end of the previous year. Regressions are run with report date by family and report date by industry fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund family.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 3.4 shows that the stocks sector fund managers share with diversified fund managers have a strong outperformance of up to ca. 240 basis points p.a. This result is consistent with specialists sharing good ideas with generalists and inconsistent with the idea that the family has superior overall research in certain sectors.

3.4 Dissemination of specialist information within sector fund families

After showing that sector funds have stock picking skills, I go on to analyze how valuable information created by fund family specialists is disseminated within the fund family organization. In section 3.4.1, I ask the question on how quality-related individual manager characteristics influence information sharing between pairs of diversified and sector funds within a family. This sheds light on which direction valuable information flows within the family. It is also related to the question of whether fund families force ideas into portfolios or whether they provide information from specialists and let their managers decide if they want to trade on it. Having shown that generalist managers share more information with specialists with more experience and a good track record, in section 3.4.2, I analyze if sector manager ideas are held by more managers in the family than other ideas.

3.4.1 Individual overlap between diversified funds and sector funds

My main hypothesis regarding information sharing is that families offering sector funds provide access to specialist information rather than centralizing the decision on which stocks have to be bought or sold. This is in line with valuable sector-ideas being created by the specialists of the family. However, it is impossible to see from the data who had the idea in the first place. Therefore, I test several hypotheses related to individual portfolio overlap between generalists and specialists that are closely linked to my main hypothesis.

First, a manager that is responsible for a diversified fund and a sector fund at the same time should share more information. If research is centralized within the family, this link between two funds should not matter.

I further add manager and fund related information that undermine the specialist idea hypothesis. I expect manager tenure to have an impact on portfolio overlap. I assume that tenure is related to skill. This is in line with Kempf, Manconi, and Spalt (2016) who find that managers become better at analyzing an industry after they have experienced turbulent times in this industry. Thus, it is more likely for managers with longer tenure to know industries well. For instance, young generalist managers have probably not been around the block as many times and therefore seek assistance. Hence, the overlap should be higher the younger the generalist and the older the specialist is.

As an alternative indicator for skill, which is more directly linked to a certain sector, I measure the past average value weighted performance in a sub-portfolio based on reported holdings and compare it to the performance of a passive value weighted benchmark of all CRSP stocks in this industry. I do this for the diversified and the sector fund. On the one side, I expect managers to share more with experts who excelled in a sector. On the other side, I assume managers who performed poorly in the last year to rely more on specialist ideas in the next year.

I also control for the size of both funds. The size of the fund can be a sign for its quality, importance, and visibility. In addition to being explanatory variables of their own right, they are important control variables because variables of interest like manager tenure are probably correlated with fund size.

I further add a dummy variable that indicates whether the paired funds are similar regarding their stock universe. I again run a multivariate regression to analyze the drivers of portfolio overlap between pairs of generalist and specialist funds. The pooled regression model is specified as follows:

$$\begin{aligned}Overlap_{i,f,s,t} = \alpha &+ \beta_1 MgrLink_{f,s,t} + \beta_2 MgrTen_{f,t} + \beta_3 MgrTen_{s,t}\\ &+ \beta_4 PastPerf_{i,f,t} + \beta_5 PastPerf_{i,s,t} + \beta_6 FundSize_{f,t}\\ &+ \beta_7 FundSize_{s,t} + \beta_8 Fit_{f,s,t} + a_t + a_m + \varepsilon_{i,f,s,t}.\end{aligned} \tag{3.3}$$

$Overlap_{i,f,s,t}$ measures the weight of stocks that are shared with the matched sector fund *s* in an industry sub-portfolio *i* of diversified fund *f* at a report date *t*. There are up to 48 sub-portfolios, but I consider only those industries in which the matched sector fund holds at least one stock. All report dates are set to the nearest quarter in order not to miss any overlaps, because of cases where the diversified fund reports in February and the sector fund reports in March. $MgrLink_{f,s,t}$ is an indicator variable which is equal to one if a manager is managing both funds at the observed report date (as single manager or team member). $MgrTen_{f,t}$ and $MgrTen_{s,t}$ measure the average time the manager or management team of the diversified fund *f* or sector fund *s*, respectively, has spent managing funds in years.

$PastPerf_{i,f,t}$ and $PastPerf_{i,s,t}$ are indicator variables measuring the track record in an industry for the past year. The average monthly performance of the active industry sub-portfolio is compared to the passive industry sub-portfolio return for each fund. The active portfolio is value weighted and based on reported holdings of the past year's report dates. The passive portfolio is value weighted using returns and market capitalizations of all stocks in the CRSP stock universe in the past year. The indicator variable for the diversified fund is equal to one if the fund's industry portfolio underperformed the passive portfolio in the past year or if the industry was not held. It is equal to zero if the fund outperformed the passive portfolio in that industry. The indicator variable for sector funds is equal to one if the sector fund's industry sub-portfolio outperformed the passive industry portfolio, on average. It is equal to zero if the industry was not held or if the sub-portfolio performed worse than the passive portfolio.

$FundSize_{f,t}$ and $FundSize_{s,t}$ measures the natural logarithm of asset under management at the report date. $Fit_{f,s,t}$ is a variable indicating if both funds hold similar stocks on average regarding size and book-to-market ratio. For both characteristics, all stocks in the market are divided in quintiles. Then, for both characteristics, fund and report date, I calculate the average of the quintile assigned to the stocks held. This gives the fund's score for size and book-to-market ratio at each report date. $Fit_{f,s,t}$ is equal to one if the absolute deviation for both scores of a pair of funds is lower than one. I add report date (a_t) and family fixed effects (a_m) to control for unobserved time and family characteristics affecting the results. Standard errors are clustered at the fund level.

Table 3.5 shows strong support for my hypotheses. Managers have higher overlap with sector funds they manage themselves. On average, they share around 11 percent more. Also, diversified manager tenure has a negative, albeit small, impact on overlap in all specifications. The standard deviation of diversified manager tenure is 4.24. A one standard deviation increase in tenure thus leads to 38 basis points lower overlap. Sector manager tenure has the expected positive sign. The standard deviation of sector manager tenure is 3.15. A one standard deviation increase in sector manager tenure thus leads to up to 50 basis points higher overlap.

When a diversified fund underperformed in an industry in the past year, overlap is higher in this industry in the following year. Congruously, there is more overlap in industries where the sector fund performed well. The coefficient for the dummy variable indicating an outperformance of the sector fund in an industry is 2.5 percent. The average sub-portfolio overlap of 11.29 percent thus implies a 22 percent higher overlap in these cases. This is an indication for managers knowing when they need assistance and that they take notice of sector specialists who stood out in the past year. The result is in line with the analysis of Rebello and Wei (2014) who find that buy-side analysts with a good track-record have a stronger impact on mutual funds' trades. All of these findings strengthen the hypothesis that sector fund families do not follow a centralized approach where affiliated funds have to hold specialist ideas. Since all skill measures of specialists positively affect overlap, results are in line with ideas being created by specialists.

Table 3.5: Determinants of pairwise overlap between affiliated diversified and sector fund

Dependent Variable:	Overlap	Overlap	Overlap
Managerlink	0.1129***	0.1132***	0.1136***
	(9.17)	(9.23)	(9.24)
Managertenure DF	-0.0009*		-0.0009*
	(-1.73)		(-1.68)
Managertenure SF	0.0016***		0.0013**
	(2.58)		(2.15)
Past ind.perf. DF		0.0072***	0.0034***
		(4.78)	(3.09)
Past ind. perf. SF		0.0250***	0.0023**
		(13.73)	(2.52)
Size DF	0.0033***	0.0024**	0.0707***
	(3.05)	(2.50)	(14.87)
Size SF	0.0028***	0.0026***	0.0079***
	(3.09)	(3.13)	(4.97)
Fit	0.0706***	0.0693***	0.0268***
	(14.83)	(15.55)	(13.86)
Observations	456,726	507,966	456,726
R-squared	0.1439	0.1462	0.1463

Notes: This table presents results from pooled OLS regressions that analyze the pairwise overlap in industry sub-portfolios between diversified funds (DF) and sector funds (SF) in a given fund family. Each diversified fund in a sector fund family is matched to each available sector fund in the same family at every report date. I set report dates to the nearest quarter. Overlap measures the weight of shared stocks within a Fama-French 48 industry sub-portfolio. Only Fama-French 48 industries that are concurrently covered by the matched sector fund are considered. Managerlink is an indicator variable, which is equal to one if a manager is responsible for both the diversified fund and the matched sector fund and zero otherwise. Managertenure measures the (for teams: average) tenure as a fund manager in years. Past industry performance is an indicator variable based on the fund's average monthly performance in an industry relative to the passive CRSP stock universe performance in that industry in the past year. For diversified funds the indicator variable is equal to one if the fund underperformed the passive industry return or did not hold the industry in the past year and zero otherwise. For sectors funds the indicator variable is equal to one if the fund outperformed the passive industry return and zero otherwise. Fit is an indicator variable, which is equal to one if the diversified fund and sector fund have similar scores for the size and the book-to-market ratios for the average stock in their portfolios. My manager database covers the years between 2000 and 2009 so this analysis comprises only this period. Regressions are run with fund family and report date fixed effects. Robust standard errors reported in parentheses are clustered by the diversified fund. ***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

3.4.2 Dissemination of sector fund stock picks within the fund family

My second hypothesis related to dissemination of information is that fund families behave rationally by fostering the sharing of information where superior information is available. I hypothesize that stocks picked by sector funds should appear in more portfolios than other stocks, even though I have documented that managers have autonomy of decision.

I assume that it is a strong signal about a stock's quality if the manager selects a stock for her portfolio. In contrast to a simple analyst recommendation, a specialist managing a fund thereby shows a higher commitment to a stock, because its performance is directly linked to her performance, which is linked to her compensation and reputation. I thus count the number of diversified funds that hold a stock within a family at a report date. To account for possible differences in the publishing dates of reports across funds, I set all report dates to the nearest quarter. I run a multivariate regression to test the dissemination of specialist ideas. The pooled regression model is specified as follows:

$$\begin{aligned} Appearance_{j,m,t} = \alpha + \beta_1 Sectorstock_{j,m,t} + \gamma_1 MCap_{j,t} + \gamma_2 Pastret_{j,t} \\ + \gamma_3 Paststd_{j,t} + \gamma_4 Btm_{j,t} + \gamma_5 \# Analysts_{j,t} \\ + a_t + a_m + \varepsilon_{j,m,t}. \end{aligned} \tag{3.4}$$

For each stock j, I count the $Appearance$ within a fund family m at report date t as the number of diversified funds holding the stock. In the second column of Table 3.6, I divide the number of funds holding a stock by the number of diversified funds within the family at report date t. In the last column, $Appearance$ is replaced by an indicator variable, which is equal to one if the stock is held by at least two funds within the family at the report date.

The key independent variable is $Sectorstock_{j,m,t}$. It is a dummy variable indicating whether a stock j is held by a sector fund of the same family m at report date t. I control for stock specific characteristics as the stock's market capitalization, past year stock return, past stock return standard deviation, stock book-to-market ratio, and the number of analysts covering a stock. I also add report date and family fixed effects to control for unobserved time and family characteristics affecting the results. Standard errors are clustered at the fund family level.

Table 3.6 shows that all three specifications strongly support the hypothesis that families make sure generalist funds can profit from specialist information. The first column shows that stocks concurrently held by sector funds are on average held by one diversified fund more than other stocks. The last column presents results from a logit model, where probabilities are transformed into logarithmic odds. The logistic regression implies that, holding the other variables at fixed values, the odds for sector fund stock picks to be held by more than one diversified fund in the family are 78.55 percent higher than the odds for other stock picks in the family.

Table 3.6: Dissemination of sector fund stock picks within the fund family

Panel A:

Dependent Variable:	Appearance	Appearance ratio	Appearance dummy
Sector stock	1.0056**	0.0365***	0.5797***
	(2.17)	(7.46)	(5.59)
Firm size	0.2980***	0.0215***	0.4004***
	(4.89)	(14.93)	(10.74)
Past return	0.0130	-0.0005	0.0290
	(1.32)	(-0.65)	(1.48)
Past standard deviation	0.1714	0.0295***	0.3649
	(1.49)	(2.77)	(1.15)
Book-to-market ratio	0.0335*	0.0030***	0.0238
	(1.80)	(2.78)	(1.08)
# of analysts	0.0086***	0.0006***	0.0121***
	(4.37)	(5.01)	(8.34)
Observations	1,364,959	1,364,959	1,364,804
R-squared/Pseudo R-squared	0.2880	0.4226	0.1743

Panel B:

Dependent Variable:	Appearance	Appearance ratio	Appearance dummy
Sector stock	0.8322**	0.0338***	0.4742***
	(2.44)	(4.63)	(5.02)
Firm size	0.2781***	0.0212***	0.4058***
	(5.06)	(10.59)	(7.99)
Past return	-0.0028	-0.0009	0.0182
	(-0.25)	(-0.81)	(0.79)
Past standard deviation	0.1714	0.0239*	0.5122
	(1.34)	(1.92)	(1.42)
Book-to-market ratio	0.0348**	0.0031***	0.0196
	(2.42)	(2.76)	(1.11)
# of analysts	0.0062***	0.0006***	0.0131***
	(3.76)	(5.15)	(5.82)
Observations	863,611	863,611	863,494
R-squared/Pseudo R-squared	0.2703	0.4001	0.1852

(continued)

Table 3.6: Dissemination of sector fund stock picks within the whole fund family – cont.

Notes: This table presents results from pooled OLS and logistic regressions that analyze the impact of sector funds within their fund families. Appearance measures the number of diversified funds holding a specific stock at a report date. Appearance ratio is the number of diversified funds holding a specific stock at a report date scaled by the number of affiliated diversified funds existing at a report date. Appearance dummy is an indicator variable, which is equal to one if the stock is held by more than one diversified fund at a report date. Sector stock is an indicator variable, which is equal to one if the stock is concurrently held by a sector fund and zero otherwise. Firm size is the natural logarithm of the stock market capitalization, past return is the stock return in the last year, past standard deviation is the standard deviation of the stock's monthly returns in the past 12 months, book-to-market is the book-to-market ratio at the end of the past year. # Analysts is the number of analysts covering a stock at a report date. Regressions are run with fund family and report date fixed effects. The third column presents results of a logistic regression. The analysis in panel A comprises all family funds, when measuring the appearance of a stock at a given report date. The analysis in panel B does not take observations into account where the fund management of a diversified fund is also managing an affiliated sector fund at the same report date. My manager database covers the years between 2000 and 2009, therefore the analysis in panel B comprises only this period. t-statistics are reported in parentheses and computed using standard errors clustered by fund family.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Falkenstein (1996) finds that stocks with low costs and high visibility are popular. In this paper, the number of analysts covering a stock seems to be working as a visibility measure. Market capitalization comprises both visibility and low costs. The signs of the regression coefficients of all three variables are in line with Falkenstein's (1996) results.

I have shown in Table 3.5 that in some cases sector and diversified funds are managed by the same person and those funds have higher overlap. Thus, in Panel B, observations where the diversified manager is also managing a sector fund are not considered. Panel B results show that although the coefficients are slightly lower compared to Panel A, the results are not entirely driven by these observations.

3.5 Access to specialists and its effect on fund level performance and investment behavior of generalists

In section 3.4, I have documented that generalists make vast use of specialist ideas. In section 3.5, I analyze how the existence of specialist knowledge affects performance and investment behavior of affiliated funds. Section 3.5.1 analyzes the effect on fund level performance. Section 3.5.2. shows how access to specialists affects investment behavior.

3.5.1 Sector coverage and fund level performance

Having documented that sector specific knowledge is utilized by generalists, I examine how this might translate into overall fund performance. The more sector funds are available the better, since there is high research quality for more industries in the family. This is especially valuable when a sector is unlikely to perform well. In this case, ideas from a sector with better prospects can be shared. Moreover, if the family only has a source of superior information for one sector, outperformance is unlikely to be observable at the fund level because the portfolio weight of this sector is too low. When a sufficient proportion of the portfolio is covered by sector funds, it is more likely to translate into superior performance at the fund level.

I compare the performance of sector family funds and non-sector family funds using multivariate regressions. The pooled regression model is specified as follows:

$$\begin{aligned} Perf_{f,t} &= \alpha + \beta_1 \#Sectors_{f,t} + \beta_2 FamSize_{f,t-1} + \beta_3 FamFocus_{f,t-1} \\ &+ \gamma_1 FundSize_{f,t-1} + \gamma_2 FundTO_{f,t-1} + \gamma_3 FundTER_{f,t-1} + \gamma_4 FundAge_{f,t-1} \\ &+ \gamma_5 FundFlow_{f,t-1} + \gamma_6 FundPerf_{f,t-1} + a_t + a_o + \varepsilon_{f,t}. \end{aligned} \tag{3.5}$$

I use five fund-level performance measures as dependent variables: net-of-fee fund return, objective adjusted return (OAR), Fama French (1993) alpha, Carhart (1997) alpha, and characteristic benchmark adjusted returns as defined in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004). I first compute the fund performance for each performance measure per month and then compound it over the 12 monthly observations to get the performance per year *t*. Objective adjusted return is the fund's return minus the average return in its investment segment. A funds monthly alpha is the difference between the realized and expected excess fund return. The expected net return in a given month is computed using factor loadings estimated over the previous 36 months and factor returns in that month. DGTW returns are based on the reported holdings. For each stock, I subtract from its return the return of the DGTW benchmark portfolio to which it belongs. I use the adjusted shares reported to value weight these excess returns and hold the portfolio until the next report date at which it is rebalanced. This gives me a time series of monthly DGTW adjusted returns.

My key independent variable is the number of sectors covered by the family behind fund f in year t ($\#Sectors_{f,t}$). This is the number of distinct CRSP objective codes for the category sector funds within a family in a given year. For example, if a fund family offers two utility and three technology sector funds, it covers two sectors. To control for possible other family characteristics that have been documented to impact the performance of affiliated funds, I include the logarithm of the fund family's total net assets under management (in $ millions) and the concentration of the fund family across investment segments at the end of the past year ($FamFocus_{f,t-1}$). Since diversified funds from sector fund families are different, especially in size, I include widely used fund characteristics as controls. I control for the logarithm of the fund's total net assets at the end of the past year, the fund's yearly turnover and total expense ratio, the fund's age in years, fund flows as defined in Sirri and Tufano (1998) for the past year, and fund performance for the past year. As discussed in Berk and Green (2004), skilled managers might charge higher fees to extract rents. I focus on a comparison of skills, so I need to compare gross returns. Accordingly, I add the total expense ratio as a control variable in all regressions, except for the one with the DGTW measure since this is a gross-measure by construction. To control for unobservable year and investment objective effects on performance, I include year and objective fixed effects denoted by a_t and a_o. Standard errors are clustered at the fund level.

Table 3.7 confirms the hypothesis that the more expertise available, the better it is for affiliated funds' performances. The relation between the number of sectors covered and performance is positive and significant at the one percent level in four out of five specifications. The standard deviation of sectors covered over all observations is 1.8. A one-standard deviation increase thus leads to an increase in performance of up to 23 basis points p.a. Consistent with Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004) I find a negative impact of fund size on performance. Results also confirm the negative performance impact of turnover documented by Carhart (1997) in all specifications. In line with Sapp and Tiwari (2004), there does not seem to be a smart money effect since flow has no significant loading in the Carhart alpha specification of the model. Return and objective adjusted return seem to be short-term correlated, defining the short-term as one year. Results on short-term persistence are shown by Hendricks, Patel, and Zeckhauser (1993), Bollen and Busse (2004), and Busse and Irvine (2006). In these studies, persistence is very short-lived (less than one year) and partly driven by consistently bad performing funds. I cannot confirm any positive persistence in alphas which is in line with Carhart's (1997) finding.

I additionally employ a matched sample analysis whereby I compare the performance of funds from sector fund families and funds from families not offering any sector funds. This approach allows me to control reasonably well for fund or family characteristics that might affect fund performance in a non-linear way. I select the group of funds belonging to families that cover more sectors than the median sector fund family and match each fund of this group with an equally weighted portfolio of funds belonging to families without sector funds sharing similar characteristics (this means they belong to the same quintile regarding the characteristic in the past year). To be consistent with Table 3.7, I add the total expense ratio to net returns. To obtain a sufficient number of matches for each year, I match on the most consistently significant variables shown in Table 3.7: family size, family focus, fund size, fund age, fund turnover and fund objective. I use the performance measures from Table 3.7 since I match on objective, raw returns corresponding to objective adjusted returns.

Table 3.7: Impact of number of sectors covered on performance of diversified equity funds

Dependent variable:	Return	OAR	Fama French	Carhart	DGTW
# Sectors	0.0013***	0.0009***	0.0006**	0.0008***	0.0012***
	(3.36)	(2.66)	(2.07)	(2.81)	(4.72)
Family size	0.0013***	0.0012***	0.0006	0.0004	-0.0003
	(2.95)	(3.17)	(1.60)	(1.18)	(-0.91)
Family focus	0.0080**	0.0103***	0.0054*	0.0063**	-0.0003
	(2.36)	(3.33)	(1.76)	(2.17)	(-0.10)
Fund size	-0.0035***	-0.0033***	-0.0017***	-0.0017***	-0.0013***
	(-7.36)	(-7.56)	(-4.32)	(-4.51)	(-4.15)
Fund turnover	-0.0060***	-0.0063***	-0.0049***	-0.0048***	-0.0030***
	(-6.36)	(-6.89)	(-4.63)	(-4.23)	(-3.69)
Total expense ratio	-1.1226***	-0.9943***	-1.2656***	-1.1775***	
	(-5.09)	(-4.96)	(-7.02)	(-6.63)	
Fund age	0.0026***	0.0023***	0.0001	0.0006	0.0015**
	(2.81)	(2.71)	(0.10)	(0.87)	(2.14)
Past flow	-0.0001***	-0.0001*	0.0000	0.0000	0.0000
	(-3.03)	(-1.85)	(0.88)	(0.61)	(0.35)
Past return	0.1241***	0.1146***	-0.0847***	-0.0024	0.0138
	(9.69)	(8.37)	(-6.56)	(-0.17)	(1.09)
Objective fixed effects	Yes	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	16,957	16,957	16,957	16,957	16,957
R-squared	0.8567	0.0339	0.1178	0.1043	0.1280

(continued)

Table 3.7: Impact of number of sectors covered on performance of diversified equity funds - continued

Notes: This table presents results from pooled OLS regressions that analyze the impact of sector fund expertise available to other affiliated diversified funds within the same fund family using five different performance measures: net-of-fee fund return (Return), objective-adjusted Return (OAR), Fama and French (1993) three-factor alpha, Carhart (1997) four-factor alpha, and the holding based DGTW fund return following Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004). All performance measures except DGTW are net-of-fees. Only funds having the investment objectives EDCI (Micro Cap), EDCS (Small Cap), EDCM (Mid Cap), EDYB (Growth & Income), EDYG (Growth), and EDYI (Income) are included. The main independent variable is the number of sectors covered by a fund family within the same year. I include U.S. domestic sector funds having the following CRSP Objective Codes: EDSH (Health/Biotechnology), EDSF (Financial Services), EDSN (Natural Resources), EDST (Science & Technology), EDSU (Utilities), EDSG (Consumer Goods)/EDSS(Consumer Services), EDSI (Industrials), EDSM (Basic Materials), EDSA (Telecommunication). Additional independent controls include family size, family focus, fund size, fund turnover, total expense ratio, fund age, past flow, and past return. Family size is the logarithm of the fund family's assets under management. Family focus, represents the concentration of a fund family across objectives, defined as in Siggelkow (2003). Fund size is the logarithm of the fund's total net assets under management. Fund turnover is the fund's yearly turnover ratio, defined as the minimum of aggregated security purchases and sales divided by the average total net assets under management during the calendar year. Total expense ratio represents the fund's fees charged for total services. Fund age is the logarithm of the fund's age in years. Past flow is the net fund flow of the past year. Past return is the relevant return measure for the past year. All other independent variables are also lagged by one year. Regressions are run with year and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 3.8: Matched sample performance comparison

	Sector family funds	Peer funds	Difference
Return	0.0840***	0.0713***	0.0127***
	(9.93)	(8.90)	(3.91)
Fama French	0.0009	-0.0049***	0.0058**
	(0.40)	(-2.76)	(2.38)
Carhart	0.0010	-0.0057***	0.0069***
	(0.54)	(-3.28)	(2.85)
DGTW	-0.0015	-0.0010***	0.0085***
	(-0.77)	(-5.61)	(3.73)

Notes: This table reports results from a matched sample analysis where each fund from families covering more than two sectors is matched with an equally weighted portfolio of funds from families which do not offer sector funds using the following matching criteria: year, family size, family focus, fund age, fund size, fund objective and fund turnover. The performance measures are gross-of-fees. The matching variables are defined as in Table 3.7. One-year-lagged values of these variables are used to rank funds into quintiles independent of their family affiliation. Sector family funds are then matched to non-sector family peer funds that belong to the same quintiles for the matching criteria. t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively. There are 728 observations.

Table 3.8 clearly shows that funds belonging to families covering more than two sectors deliver a significantly higher gross performance than comparable funds from comparable families not offering any sector funds. The estimated outperformance ranges from 58 to 127 basis points p.a.

3.5.2 Sector coverage and investment behavior

My first hypothesis is that funds trade more when they have access to superior research because more investment ideas can be implemented. If generalist managers rely on (some) stock picks made by specialists, there is more time remaining to spend on creating own ideas for these and other sectors. This is why I expect to find a turnover effect on the fund level.

To test this hypothesis, I study the impact of sectors covered on two measures of portfolio turnover. First, I use the fund turnover ratio reported in CRSP. Since fund's trading activities have a different price impact due to differences in fund size, I also calculate the position-adjusted turnover as suggested by Edelen, Evans, and Kadlec (2013). It is defined as the turnover ratio from CRSP adjusted for the average size of the fund's holding position.

Table 3.9: Impact of number of sectors covered on diversified fund turnover

Dependent variable:	Fund turnover	Position adj. turnover
# Sectors	0.0590***	0.1868***
	(4.45)	(4.13)
Family size	-0.0184	-0.0836*
	(-1.46)	(-1.66)
Family focus	-0.1601*	-0.3612
	(-1.76)	(-1.17)
Fund size	-0.0776***	-0.6060***
	(-7.47)	(-15.10)
Fund age	-0.0332	-0.2179***
	(-1.38)	(-2.73)
Past flow	0.0004	-0.0021
	(0.60)	(-1.35)
Past return	-1.1503***	-3.7494***
	(-6.08)	(-5.15)
Observations	16,950	16,907
R-squared	0.0713	0.1465

Notes: This table presents results from pooled OLS regressions that analyze the impact of number of sectors covered on turnover of affiliated diversified funds. Fund turnover is the fund's yearly turnover ratio, defined as the minimum of security purchases and sales divided by the fund's average TNA during the year. Position adjusted turnover is defined in Edelen (2013), it adjusts the total turnover ratio for the average size of the fund's holding positions. Independent variables are described in Table 3.7. Regressions are run with year and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund. ***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 3.9 shows that the number of sectors covered is positively related to the trading activity of affiliated diversified funds. Not surprisingly, the coefficient on fund size is negative since it is harder and costlier for larger funds to turn over their entire portfolio. The mainly negative coefficient of past return is an indication for funds reacting to bad performance in the last year by changing part of their portfolio. This result is not inconsistent with the findings of Puetz and Ruenzi (2011). They use a piecewise linear regression and find that the relation between turnover and past returns is only positive for funds in the top performance quintile.

My second hypothesis related to investment behavior is that funds from families with more sectors covered hold more hard-to-value stocks. Hard-to-value stocks are those that offer more alpha generating potential. To asses this potential, managers need superior skill or time. I assume that affiliated generalists have more time than their peers. Due to information sharing with specialists they can allocate more attention to the remaining portfolio. I follow Gupta-Mukherjee and Pareek (2015) with this argumentation.

Following Kumar (2009), my first measure for the fraction of hard-to-value stocks is the fund's weight in stocks that belong to the top three deciles of stock idiosyncratic volatility for a given month. Idiosyncratic volatility is measured as the standard deviation of the residuals from a 36-month rolling window regression of stock excess return on the Carhart (1997) factors. If the movement of a firm's stock price is strongly driven by idiosyncratic factors, I assume that analyzing the firm is relatively difficult. Accordingly, I also measure the fund's weight in the bottom three idiosyncratic volatility deciles which I assume to be easy to value.

Complementary, the number of analysts covering a stock should also be associated with how hard-to-value a stock is. I therefore calculate the average number of analysts covering a stock for a fund portfolio at a given date. The last measures are based on the analyst earnings forecast dispersion for a stock. A high analyst forecast dispersion is a sign for a hard-to-value stock because it indicates high insecurity about future firm earnings. To be consistent with the idiosyncratic volatility measure, I again measure the weight in the top three and the bottom three deciles of stock's analyst dispersion measure at a given date.[53]

Table 3.10 strongly confirms my hypothesis that more sector expertise in families is associated with affiliated funds holding more hard-to-value stocks. They give a higher weight to stocks with high idiosyncratic volatility and less weight to those with low idiosyncratic volatility. The average number of analysts covering stocks held decreases with more sector funds. They hold more stocks with higher analyst dispersion and less stocks with low analyst dispersion. The coefficient for the other family specialization measure, family focus, has the same sign as the sector covered measure for every specification and is always significant. Specialization on less investment segments seems to allow managers to pick more hard-to-value stocks. This is in line with Siggelkow (2003) finding an outperformance for these funds.

In order to address any issues with independent variables possibly affecting dependent variables in a non-linear way, I again use a matched sample approach. The principle is the same as in Table 3.8, except for the dependent variables being the ones presented in Tables 3.9 and 3.10.

[53] See Abarnell, Lanen, and Verrechia (1995); Diether, Malloy, and Scherbina (2002); and Garfinkel and Sokobin (2006) for the relation between differences in opinion and hard-to-value stocks.

Table 3.10: Impact of number of sectors covered on hard-to-value stocks in diversified fund's holdings

Dependent Variable:	High idiosyncratic vola	Low idiosyncratic vola	# of analysts	High analyst dispersion	Low analyst dispersion
# Sectors	0.0022***	-0.0035**	-0.0476*	0.0024***	-0.0042***
	(2.63)	(-2.29)	(-1.89)	(4.04)	(-3.70)
Family size	-0.0005	-0.0017	0.0026	0.0010	0.0008
	(-0.54)	(-0.98)	(0.09)	(1.59)	(0.62)
Family focus	0.0310***	-0.0489***	-1.6835***	0.0256***	-0.0677***
	(3.67)	(-3.09)	(-6.34)	(4.64)	(-5.52)
Fund size	-0.0035***	0.0049**	-0.0634*	0.0016**	-0.0035**
	(-3.34)	(2.47)	(-1.89)	(2.26)	(-2.34)
Fund age	-0.0000	-0.0013	0.4626***	-0.0050***	0.0149***
	(-0.02)	(-0.31)	(6.46)	(-3.63)	(5.28)
Fund turnover	0.0185***	-0.0295***	-0.0934	0.0050***	-0.0147***
	(6.01)	(-5.96)	(-1.63)	(4.01)	(-5.66)
Past flow	-0.0000	0.0000	0.0017*	-0.0001	0.0000
	(-0.12)	(0.88)	(1.66)	(-1.28)	(1.09)
Past return	-0.0290**	0.0100	-4.1582***	0.0267***	-0.1544***
	(-2.19)	(0.53)	(-14.11)	(2.87)	(-10.20)
Observations	16,950	16,950	16,950	16,950	16,950
R-squared	0.4499	0.5728	0.6248	0.2089	0.3199

Notes: This table presents results from pooled OLS regressions that analyze the impact of sectors covered by a fund family on the stock selection by the affiliated diversified funds. High (Low) idiosyncratic vola is the fund's weight in stocks that belong to the top (bottom) three deciles of stocks regarding idiosyncratic stock volatility in a given report month.# Analysts is the average of the number of analysts covering a stock. High (Low) analyst dispersion is the fund's weight in stocks that belong to the top (bottom) three deciles of stocks regarding stock's analyst dispersion in a given report month. All dependent variables are averages per fund and year. Independent variables are described in Table 3.7. Regressions are run with year and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 3.11: Matched sample holdings and turnover comparison

	Sector family funds	Peer funds	Difference
High idiosyncratic vola	0.0910***	0.0823***	0.0088**
	(28.66)	(21.42)	(2.36)
Low idiosyncratic vola	0.5471***	0.5753***	-0.0281***
	(74.68)	(74.26)	(-4.41)
# Analysts	12.0861***	12.3235***	-0.2374**
	(95.56)	(92.35)	(-2.20)
High analyst dispersion	0.1224***	0.1008***	0.0216***
	(48.30)	(46.08)	(7.49)
Low analyst dispersion	0.5548***	0.5879***	-0.0332***
	(122.47)	(138.40)	(-6.61)
Turnover	0.9598***	0.7949***	0.1646***
	(23.35)	(75.63)	(3.91)

Notes: This table reports results from a matched sample analysis where each fund from families covering more than two sectors is matched with an equally weighted portfolio of funds from families which do not offer sector funds using the following matching criteria: year, family size, family focus, fund age, fund size, fund objective and fund turnover (except for turnover comparison). The independent variables are described in Tables 3.9 and 3.10. The matching variables are defined as in Table 3.7. One-year-lagged values of these variables are used to rank funds into quintiles independent of their family affiliation. Sector family funds are then matched to non-sector family peer funds that belong to the same quintiles for the matching criteria. t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively. There are 728 and 1,676 (turnover comparison) observations.

Table 3.11 confirms that sector family generalists on average have an up to 21 percent higher portfolio weight for hard-to-value stocks and have 25 percent higher turnover relative to comparable peer funds from comparable families. The fund-level performance results taken together with the results on hard-to-value stocks and turnover, respectively, are in line with generalists with access to specialists being able to do a better job than their peers.

3.6 Conclusion

My study presents new findings considering the role of sector-funds within mutual fund families. First, I find that sector fund managers generate positive alphas, on average. Second, stocks that specialists share with generalists have higher alphas than comparable stocks that are uniquely held by generalists. Consequently, the skill for certain sectors can be attributed to the managers of sector funds in the family. Additionally, I identify several drivers of individual overlap between diversified and sector funds of a family. Specialists seem to provide assistance to relatively unexperienced generalist managers. Additionally, generalists seem to pay attention on how specialists performed with their stock selections in the past and seem to acknowledge their own missing expertise in some sectors. This is in line with sector fund families not following a centralized research approach and information flowing from specialists to generalists. I also show that generalists make vast use of specialists' ideas since sector fund held stocks can be found in more portfolios than other stocks. Finally, I find that diversified funds from sector fund families perform better than comparable peer funds regarding fund level performance. Complementary, I find evidence that the availability of high quality specialist research comes with a reduction in workload for generalists since they seem to have more time to put effort in selecting more hard-to-value stocks.

This paper has implications for fund families and investors. It pays off for fund families to invest in their research facilities. Creating sector funds can be a valuable strategy with a multiplier effect within a fund family. Sector funds attract flows from investors and, seemingly, more talented specialists. The latter benefits fund families' generalists through cooperation and these funds are thus more attractive to investors. Nevertheless, the benefits of opening new sector funds might only outweigh the costs for relatively large families. In small families, there are probably not enough economies of scale and scope. In any case, labor division among employees is an important issue to address for fund families. Time and attention are scarce resources and generalists seem to make sensible use of released capacities. Fund investors should pay attention to the research quality of the fund family when they consider investing in active mutual funds. Sector funds offered by the family can be a signal for this.

Chapter 4

Does Economic University Education Matter for Fund Performance?*

4.1 Introduction

Does mutual fund manager university education matter for fund performance? Among others, Gottesman and Morey (2006) have addressed this question. Like most prior research in this field they study the effect of postgraduate MBA or CFA degrees and consider undergraduate institution quality. They conclude that an MBA degree is the only aspect of education relevant for diversified equity mutual fund performance. However, none of the studies on manager education has looked at the field of undergraduate studies. The present paper fills this gap in the literature by analyzing the fit of the field of study with the job as a diversified equity mutual fund manager. There are several reasons why this should matter for fund performance.

First, since fund managers analyze the economy at the macro and the micro level, the obvious field of theoretical education for a manager is business or economics. In addition to having the best fit regarding their theoretical background, managers with an economic background (henceforth: economists) might know far earlier that they want to work in the

* This chapter is based on Göricke (2017).

financial industry later, thus getting in contact with capital markets much earlier. This is something impossible to capture by using observable industry or fund tenure.

Second, managers that studied business or economics have (and know) probably more former fellow students that work in firms that belong to their investment universe than managers with a degree in, e.g., medicine or human sciences.[54] Third, starting with Marwell and Ames (1981), there is wide literature arguing that economist are different in their behavior, some even argue they are born different (see Cipriani, Lubian, and Zago (2009)). Zhou (2010) shows that academic experience in economics reduces risk aversion and irrationality. Less irrationality, for instance, could be of advantage in market phases where sentiment is high.

Following these arguments, I hypothesize that economists outperform managers that studied something else (henceforth: non-economists). I find strong evidence that managers with a fitting theoretical background outperform managers without a comparable background. Risk-adjusted, the performance is up to 168 basis points p.a. higher.

Similar to an undergraduate degree in an economic field, an MBA degree can give fund managers an edge. It is intuitive to assume that MBA degrees have a stronger impact on performance in the group of managers that have not studied economics before, as compared to their peers that did. Besides providing access to a new network, MBA programs teach economic theory as well as management and analytical skills. Managers with an undergraduate degree in an economics related field already have a large fraction of the knowledge and a network. They should thus profit only from part of the MBA program, while managers with no economic background should fully profit from the program. I hypothesize that the performance impact of an MBA should be stronger for managers that have a non-economics background.

I find strong support for my hypothesis. I show that the positive effect of an MBA is generally stronger for observations belonging to managers that do not have an undergraduate degree in economics or a similar type of study.

Finding a positive relation between manager characteristics and fund performance is an indication for the importance of the manager. However, in recent years, a growing strand of the literature has documented that the fund family is an important factor to consider

[54] This could be different for sector funds, which are not analyzed in this study. See, e.g., Kostovetsky and Ratushny (2016).

when assessing fund performance. For instance, studies show that structural differences of families affect fund performance (see, e.g., Kacperczyk and Seru (2012); Chen, Hong, Jiang, and Kubik (2013); Cici, Dahm, and Kempf (2016); and Göricke (2016)). Older studies on manager education do not address the issue of fund family heterogeneity when analyzing the effect of manager education on performance. Gottesman and Morey (2006) admit that funds that disproportionally hire MBAs might have better support staff and in-house research instead of their managers being more skilled than others. Due to insufficient data, they do not test this hypothesis.

In this context, the present paper analyses whether managers with different academic backgrounds work for different fund families. On the one side, managers might prefer to work for large companies since they provide the chance to manage more assets and accordingly, earn a higher salary. Given that managers compete for jobs at large fund families, they might be willing to earn extra postgraduate degrees or attend top universities for their undergraduate studies to signal their abilities (see, e.g., Spence (1973); Weiss (1983); and Hvide (2003)). On the other side, large families can do cherry-picking and select the most talented managers. Rivera (2011) shows that elite employers in law, consulting, and investment banking do indeed favor candidates with elite university affiliations.

My tests show convincing evidence that the largest fund families seem to have a strong preference for managers with MBA degrees and undergraduate degrees from top-tier institutions. The field of undergraduate studies seems to be less important in the hiring process for large fund families. However, it is significantly less likely that a manager with an economic background works for one of the smallest companies.

If managers with different graduate and postgraduate backgrounds do indeed get jobs at fund families that differ in their size, it is important not to confuse manager skills with the quality of the resources provided by the family. For instance, Chen, Hong, Huang, and Kubik (2004) argue that small families could have disadvantages regarding trading commissions and lending fees, which effectively leads to a lower performance of their funds.

I can show that the effect of the SAT (formerly: Scholastic Assessment Test) score on performance vanishes once I add fund family control variables as well as family fixed effects to the regression. The effect of MBA and an economics undergraduate degree remain positive and significant. This is evidence that a family effect is at work for some manager and fund characteristics. Nevertheless, fund family heterogeneity does not explain return differences related to economic education. Following my argumentation, this result points to managers being either different by character, better connected, educated or a combination thereof.

If managers that have chosen to study an economic field are born different, there should be a persistent difference between economists and non-economists if this is the only reason for performance differences. In contrast to earlier studies, I have sufficient data to split my sample into a sub-sample of managers with relatively long and a sub-sample of managers with relatively short tenure in the asset management industry. I find a significant difference between economists and non-economists as well as an effect for an MBA degree only for the group consisting of managers with relatively short industry tenure. This means that non-economists are either able to make up for their disadvantages over time, or bad managers being eliminated by competition. It is also an indication for economist managers not being born different.

Further, my sample allows analyzing the effect of economic education in different states of the market. The skills associated with economic education could matter more in certain market periods. If insecurity in the market is high, economists could profit most because they have a broader network. This could reduce uncertainty due to access to more information. Additionally, economists are possibly less risk averse and irrational. For identification, I choose market phases with extreme sentiment (fear) and relatively low sentiment. I use the CBOE Volatility index data and compare years that follow peaks in the VIX (fear) with years that follow constantly low VIX values.

I find strong performance differences between economists and non-economists in the periods following peaks in the VIX index. This is intuitive since peaks are usually associated with sharp market declines followed by steep increases of market prices. A perfect example is the VIX peak at the end of 2008 and the following increase in market prices starting in march 2009.

With this paper, I contribute to two strands of literature. First, it is related to the literature concentrating on educational mutual fund manager characteristics and performance. Golec (1996) studies the effect of tenure, age and MBA degree on mutual fund performance. He finds that an MBA and tenure positively affect performance and young managers outperform older managers. Chevalier and Ellison (1999) show that the quality of the undergraduate institution, as measured by the average SAT score, is positively related to higher returns, but that an MBA is generally unrelated to returns. Gottesman and Morey (2006) show that in the period from 2000 until 2003, managers with MBAs from highly ranked institutions outperform. Andreu and Pütz (2016) show funds with managers holding both an MBA and a CFA degree have more stable risk levels.

Second, this paper is related to the literature on economic credentials and employment in a highly prestigious sector.[55] Khorana (1996) and Chevalier and Ellison (1999) study how managers are hired and fired. Fang, Kempf, and Trapp (2014) show that fund families assign their most skilled managers to the least efficient bond market segments. Del Guercio and Reuter (2014) show that funds directly distributed to investors employ more managers from prestigious universities than funds sold via brokers.

All in all, this paper identifies a new characteristic related to fund performance and reconciles contradictory evidence on the impact of MBA degrees by showing who benefits most from such a degree and in which markets phases the outperformance is strongest. Additionally, this paper fills the gap of analyzing whether these characteristics are pure signs of manager skill or whether they are prerequisites for finding jobs at fund families that are able to offer unobservable high quality support to the manager.

4.2 Data

4.2.1 Data selection

I obtain fund data from the mutual fund database compiled by the Center of Research in Security Prices (CRSP). The CRSP mutual fund database contains information about funds' investment objectives and a family identifier which allows me to assign each active equity fund to a distinct fund family. I select funds with the CRSP fund objective codes EDCI (Micro Cap), EDCM (Mid Cap), EDCS (Small Cap), EDYB (Growth & Income), EDYG (Growth), and EDYI (Income). I drop index funds and foreign funds. If a fund offers multiple share classes, I aggregate information as returns, fees, etc. to the fund level by weighing the information by the total net assets of the related share classes in the prior

[55] For social and economic studies on employer hiring outside the asset management industry see, e.g., Neckermann and Kirschenman (1991); Holzer (1996); Bills (1999); and Rivera (2011).

month using the Wharton Financial Institution Center Number provided by Mutual Fund Links.

I use Morningstar Principia to obtain information on the managers responsible for the funds in my sample. My choice of Morningstar Principia over the CRSP mutual fund database to obtain this information was motivated in large part by previous research showing that reported manager information is more accurate in the Morningstar database than in the CRSP mutual fund database (see, e.g., Patel and Sarkissian (2013)).

I match the manager information obtained from Morningstar to the CRSP fund data. I also manually screen manager names for different spellings and/or abbreviations and assign a distinct identification number to each manager. I focus on single managed funds since Bär, Kempf, and Ruenzi (2011) show that team managed funds and single managed funds behave differently and it is unclear how the qualities of individual managers affect fund behavior and performance in a team. However, if a fund is only intermittently team managed, I assign the fund to the previous manager (lead manager). Managers have to be managing a fund alone for at least twelve months to be in the sample.

For each manager, I manually collect biographical information from sources like zoominfo.com, Morningstar, linkedin.com, mutual fund company websites or fund filings from SEC Edgar. I collect the field of the bachelor and master degree, the graduation year, the graduate institution, whether the manager has an MBA, and from which institution the MBA is attained.[56] I get information on the graduate institution matriculates' SAT scores from the websites collegeapps.about.com, businessweek.com, entrepreneur.com, and the schools' websites. I use the 25 percent and 75 percent SAT score percentiles in mathematics and critical reading for the class entering in 2010 because historical information about the SAT score is not available. For managers with degrees from multiple institutions, I select the best institution according to its average SAT score. I drop observations linked with managers where I do not have the field of graduate education. I further obtain data on the Volatility index from the official website of the Chicago Board Options Exchange.

[56] I do not use information on CFA degrees. The reason is that the year of CFA designation is not always available. For managers where it is available, in many cases this year lies after the year when the manager was first responsible for a fund. This is clearly not the case for undergraduate degrees. My data also points to the conclusion that this is not the case for MBA degrees.

4.2.2 Sample description

The final sample comprises the years between 1996 and 2009 and contains 784 managers and 886 diversified funds. Table 4.1 presents summary statistics for the overall sample.

Table 4.1: Summary statistics

Variable	Mean	Stdev.	50%	1%	99%
Net-of-fee return	0.0631	0.2524	0.0875	-0.4766	0.6697
Fama-French alpha	-0.0087	0.1069	-0.0158	-0.2638	0.3555
Carhart alpha	-0.0103	0.1012	-0.0159	-0.2549	0.3155
Total expense ratio	0.0135	0.0053	0.0127	0.0030	0.0318
Fund size in $ mio.	1,172.27	3,274.13	191.60	2.10	17,945.40
Fund turnover	1.04	1.94	0.70	0.03	5.99
Fund age	12.92	13.71	8.25	1.29	70.67
Fund flow	0.36	2.31	-0.01	-0.54	7.28

Notes: This table reports summary statistics on the major variables for the sample of actively single-managed U.S. domestic equity funds between the years 1996 and 2009. Performance measures are on a yearly basis. Net-of-fee return is the cumulated monthly net fund return for a given year. Fama-French (1993) and Carhart (1997) alphas are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the respective factor returns. Total expense ratio represents the fund's fees charged for total services. Fund size is the funds' total net assets under management in $ millions. Fund turnover is the fund's yearly turnover. Fund age is the fund's age in years. Fund flow is the fund's yearly growth rate adjusted for internal growth as in Sirri and Tuffano (1998).

For each fund, I measure monthly net alphas by regressing funds' net-of-fee excess returns on the Fama French (1993) and Carhart (1997) factor returns using 36-month rolling-window regressions. I compound monthly returns and alphas for every year and fund. The average fund in the sample has total net assets of around $ 1.2 billion and is 12.9 years old. There is a strong positive skewness in the distribution of fund size as the median fund size is only around $ 192 million.

To get a better understanding for the differences in funds associated with managers who received economic undergraduate education and other managers, I divide the sample into two groups. The first group comprises all fund observations associated with managers having an economic background (economists). This comprises all managers with at least one degree or minor in: accounting, banking, business administration, economics, finance, and marketing.[57] The other group consists of funds with managers, which have a clear non-economics background (non-economists). The first group accounts for 73 percent of distinct managers and 74.8 percent of all observations.

Table 4.2 shows that funds and managers of both groups are different. Funds associated with economists have lower turnover ratios and lower total expense ratios. Also, economist managers are associated with older funds, on average. The average manager in the sample has received undergraduate education from highly ranked institutions. There are 278 distinct undergraduate schools with available SAT scores in the sample and a score of 655 is the threshold for the top 25 percent of these schools. This is an indication for the asset management industry being very competitive. The average non-economist manager seems to have received education from even higher ranked schools. This is a lead for families using the ranking of the undergraduate institution as a signal for intelligence of the manager when they consider hiring non-economists. Economist managers are younger and have longer industry tenure. The reason might be that the non-economist group contains, among others, engineers and medical doctors who most likely spent several years of their career outside the financial industry. There is also a significant difference in the fraction of managers with MBA degrees between the two groups. Anecdotal evidence shows a large fraction of MBA students are career-switchers.[58] It is therefore likely that non-economist managers decide to earn an MBA degree when they want to switch into asset management.

The differences in total expense ratios and age could be a first indication towards managers with different backgrounds being selected by different fund families. I investigate performance differences in section 4.3. I then look at fund family heterogeneity related to manager education in section 4.4.

[57] In the rare cases where a manager also reports his field of study for his master's degree, I consider bachelor and master degree to define whether the manager is an economist.
[58] http://www.darden.virginia.edu/mba/career/counseling-support/switchers/

Table 4.2: Summary statistics economists vs. non-economists

	Business/Economics Graduates				Other Graduates				Difference
Variable	Mean	50%	1%	99%	Mean	50%	1%	99%	
Net-of-fee return	0.0649	0.0877	-0.4759	0.6698	0.0576	0.0852	-0.4766	0.644	0.0072
Fama French alpha	-0.0075	-0.0147	-0.2542	0.3558	-0.012	-0.0202	-0.2867	0.3394	0.0045
Carhart alpha	-0.0089	-0.015	-0.2528	0.3295	-0.0143	-0.0184	-0.2707	0.3065	0.0054
Total expense ratio	0.0132	0.0125	0.0028	0.0324	0.0142	0.0139	0.0034	0.0264	0.0010***
Fund size in $ mio.	1,126.35	202.30	2.70	15,658.20	1,308.71	155.40	0.80	22,311.70	-182.36
Fund turnover	0.97	0.67	0.03	5.4	1.26	0.78	0.04	7.31	-0.29***
Fund age	13.13	8.32	1.32	71.91	12.29	8.16	1.2	62.23	0.84*
Flow	0.36	-0.01	-0.54	4.1	0.37	-0.01	-0.54	5.75	-0.01
Manager age (non miss.)	44.93	43	28	74	46.75	44.94	28	76	-1.80***
SAT score (non missing)	643.85	645	485	750	673.52	685	453.25	750	-33.12***
Industry tenure	9.85	9	1	34	9.36	8	1	31	0.49**
MBA	0.59	1	0	1	0.68	1	0	1	-0.09***

Notes: This table reports summary statistics on the main fund related variables from Table 4.1 grouped by degrees attained by fund managers. One group contains all managers that have at least one economic degree or minor (accounting, banking, business administration, economics, finance, or marketing). The other group contains all managers that have degrees unrelated to economics or business. Additionally, this table presents variables describing the managers. Manager age is calculated assuming that a manager was 21 years old when receiving her first degree. SAT Score is the average of the 25% and 75% SAT Score percentiles in reading and math of the class entering in 2010 of the school where a manager received her undergraduate degree. Industry tenure measures the time since the manager first appeared as a fund manager. ***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

4.3 Fund manager education and performance

In this section, I test my main hypotheses: Managers with an economic background outperform managers with a non-economic background. In addition, I test the hypothesis that an MBA degree should be more valuable for managers without undergraduate degrees in economics.

To test my hypotheses, I use three different net-of-fee performance measures as independent variables: net-of-fee fund return, Fama-French (1993) three-factor alpha, and Carhart (1997) four-factor alpha. All performance measures are net-of-fees. For all funds, I first compute the fund performance for each performance measure per month and then compound it over the 12 monthly observations to get the performance per year. A fund's monthly alpha is the difference between the realized and expected excess fund return. The expected net return in a given month is computed using factor loadings estimated over the previous 36 months and factor returns in that month.

I run the following pooled regression to control for differences in fund and manager characteristics:

$$\begin{aligned} Perf_{i,t} &= \alpha + \beta_1 Economist_{i,t} + \beta_2 MBA_{i,t} + \beta_3 SAT/100_{i,t} + \beta_4 SATmiss_{i,t} \\ &+ \beta_5 Tenure_{i,t} + \gamma_1 FundSize_{i,t-1} + \gamma_2 FundTO_{i,t-1} + \gamma_3 FundTER_{i,t-1} \\ &+ \gamma_4 FundAge_{i,t-1} + \gamma_5 FundFlow_{i,t-1} + \gamma_6 FundPerf_{i,t-1} + a_t + a_o + \varepsilon_{i,t}. \end{aligned} \tag{4.1}$$

My key independent variable is $Economist_{i,t}$. This is an indicator variable equal to one if fund *i* is managed by a person with an economics degree in year *t*. I also add an indicator variable equal to one if the manager of the fund holds a postgraduate *MBA* degree. The variable $SAT/100_{i,t}$ measures the quality of the undergraduate institution as described in section 4.2 divided by 100. $SATmiss_{i,t}$ indicates that the SAT score was not available. $Tenure_{i,t}$ is the natural logarithm of the difference between the present year *t* and the date the manager first appeared in Morningstar principia in years. I assume that this measure of industry tenure sufficiently captures differences in experience. I do thus not control for manager age, as both variables are highly correlated.[59]

At the fund level, I control for the logarithm of the fund's size, yearly turnover ratio, total expense ratio, logarithm of fund age (in years), fund flow, and fund performance. As I

[59] When I add the age of the manager as a control variable, results remain almost unchanged.

focus on fund manager skills, I need to control for the total expense ratio in order to capture differences in gross returns.[60] In order to control for unobservable time or fund investment objective effects affecting my results, I include year and objective fixed effects in all regressions. All fund related controls are lagged by one year.

Table 4.3 shows that funds managed by economists have higher returns. In columns (1)-(3), I compare managers with different undergraduate backgrounds irrespective of whether they hold a postgraduate degree or not. It is intuitive that holding an MBA degree mitigates the difference between both groups if qualities associated with an economic undergraduate degree can be acquired via postgraduate education. In columns (4)-(6), I modify the regression described in equation (4.1) by adding an interaction term of economist and MBA. Accordingly, *Economist* measures the performance difference for managers without postgraduate degrees. Economists show a large outperformance compared to peer managers without economics undergraduate or postgraduate degrees. The difference in performance ranges between 158 and 301 basis points p.a.

MBA measures the difference between non-economist managers with an MBA degree and non-economist managers without MBA degree. The difference between both groups has the same magnitude as the difference between economists and non-economists without MBA degrees. The coefficient of the interaction variable, *MBA*Economist*, shows that the MBA-effect visible in columns (1)-(3) is driven by the performance difference between non-economists with and without MBA degrees. The add-on of an MBA degree is significantly smaller for economists. The results imply that managers with an economics university background are better than comparable managers without this background. An MBA degree almost completely offsets the difference between the two groups. Economists with MBA degrees have on average a 205 basis points higher Carhart (1997) alpha p.a. than non-economist without MBA degrees. Non-economists with an MBA have a 187 basis points outperformance for Carhart (1997) alpha p.a. as compared to managers without any economic university education.

[60] As discussed in Berk and Green (2004), skilled managers might charge higher fees to extract rents.

Table 4.3: Fund manager education and performance

Dependent variable	Return	Fama French	Carhart	Return	Fama French	Carhart
Economist	0.0103**	0.0069*	0.0065*	0.0301***	0.0168***	0.0158***
	(2.21)	(1.92)	(1.94)	(3.52)	(2.90)	(2.65)
MBA	0.0163***	0.0068**	0.0079***	0.0394***	0.0182***	0.0187***
	(3.71)	(2.16)	(2.62)	(4.25)	(2.79)	(2.94)
MBA*Economist				-0.0301***	-0.0150**	-0.0140**
				(-2.89)	(-2.00)	(-1.98)
SAT/100	0.0074**	0.0040*	0.0052**	0.0077**	0.0042*	0.0054**
	(2.26)	(1.76)	(2.30)	(2.37)	(1.84)	(2.38)
SAT missing	0.0295	0.0243	0.0301*	0.0315	0.0253	0.0311*
	(1.25)	(1.43)	(1.81)	(1.34)	(1.49)	(1.87)
Industry tenure	-0.0035	-0.0047	-0.0010	-0.0035	-0.0046	-0.0010
	(-0.98)	(-1.64)	(-0.46)	(-0.98)	(-1.64)	(-0.46)
Fund size	-0.0046***	-0.0007	-0.0025***	-0.0046***	-0.0007	-0.0025***
	(-3.78)	(-0.73)	(-2.96)	(-3.77)	(-0.72)	(-2.94)
Turnover ratio	-0.0038***	-0.0016	-0.0023*	-0.0037***	-0.0016	-0.0022*
	(-3.53)	(-1.40)	(-1.86)	(-3.37)	(-1.40)	(-1.87)
Total expense ratio	-0.8246*	-0.6867*	-0.7163**	-0.7911	-0.6700*	-0.7007*
	(-1.70)	(-1.89)	(-1.97)	(-1.62)	(-1.85)	(-1.94)
Fund age	-0.0009	-0.0016	-0.0007	-0.0011	-0.0016	-0.0008
	(-0.32)	(-0.72)	(-0.39)	(-0.37)	(-0.76)	(-0.42)
Flow	-0.0039***	0.0031	0.0003	-0.0040***	0.0030	0.0002
	(-3.22)	(1.57)	(0.31)	(-3.24)	(1.55)	(0.27)
Past return	0.0639***	0.0633*	0.1376***	0.0636***	0.0632*	0.1373***
	(3.03)	(1.81)	(3.30)	(3.03)	(1.80)	(3.29)
Observations	3,928	3,928	3,928	3,928	3,928	3,928
R-squared	0.6778	0.1168	0.1361	0.6784	0.1176	0.1369

(continued)

Table 4.3: Fund manager education and performance - continued

Notes: This table presents results from pooled OLS regressions that analyze the relation between manager education and yearly fund performance using three different performance measures: net-of-fee fund return (Return), Fama and French (1993) three-factor alpha, and Carhart (1997) four-factor alpha. For each fund, I measure monthly net alphas by regressing funds' net-of-fee excess returns on the Fama French (1993) and Carhart (1997) factor returns using 36-month rolling-window regressions. I compound monthly returns and alphas for every year and fund. The key independent variables are: Economist, MBA, and SAT/100. Economist is an indicator variable which is equal to one if the manager responsible for a fund has at least one economic degree or minor (accounting, banking, business administration, economics, finance, or marketing) and zero otherwise. MBA is an indicator variable indicating whether the manager attained a Master of Business Administration degree. SAT/100 is the average of the 25% and 75% SAT score percentiles in reading and math of the class entering in 2010 of the school where a manager received her undergraduate degree divided by 100. SAT missing is a variable indicating the SAT score of the undergraduate institution is not available. The remaining control variables are described in Tables 4.1 and 4.2. All fund variables are lagged by one year. Regressions are run with year and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Furthermore, I find a positive effect for the quality of the graduate institution as in Chevalier and Ellison (1999). The positive loading on the dummy variable indicating a missing SAT score might be due to the fact that it comprises, among others, high quality foreign universities like Oxford and Cambridge. Fund size has a negative impact on performance which is consistent with the findings of Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004). Also, the negative loading of the fund turnover variable is in line with Carhart (1997). Return and risk-adjusted returns seem to be short-term correlated, defining the short-term as one year. Results on short-term persistence are shown by Hendricks, Patel, and Zeckhauser (1993); Bollen and Busse (2004); and Busse and Irvine (2006).

4.4 Fund manager education and family allocation

To better differentiate between the observable characteristics of the fund manager and the unobservable characteristics of the organization behind the fund, I first test whether there are differences in the allocation of managers with different backgrounds to different families in section 4.4.1. In section 4.4.2, I then look whether differences in fund performance related to manager education still hold when I add time varying fund family characteristics and family fixed effects to the performance analysis from section 4.3.

4.4.1 Fund family and manager education matching

In this section, I test whether managers with different education work for different fund families. Generally, one could argue that the career achievements of a manager also matter for the selection as a fund manager. Nevertheless, I assume that fund families hire people as analysts and later promote them to fund managers. Therefore, educational characteristics should be sufficient to signal managerial qualities to employers.

On the one hand, it is plausible to assume that mutual fund families that have the largest funds can cherry-pick among managers. For managers, it is attractive to manage large funds because managing more assets means higher salaries for them. On the other hand, very small families can probably not be as selective. Accordingly, I define differences in fund families by the total net assets managed by the organization.[61] Each year, I define big families as the families belonging to the top quarter of families according to total net assets managed across all funds affiliated to the family. Small families belong to the bottom quarter. The rest of the families are defined as middle families. This simple categorization is also a straightforward measure of family prestige.[62] I model the probability that certain managers are employed by certain families by running the following pooled logistic regression[63]:

$$\begin{aligned}\Pr(D_{i,t}^{Big}=1)=F(&\alpha+\beta_1 Economist_{i,t}+\beta_2 MBA_{i,t}+\beta_3 TopSchool_{i,t}\\&+\beta_4 Tenure_{i,t}+\beta_5 MgrAge_{i,t}+\beta_6 Agemiss_{i,t}\\&+a_t+a_o+\varepsilon_{i,t}).\end{aligned} \tag{4.2}$$

$D_{i,t}^{Big}$ is an indicator variable which is equal to one if fund *i* belongs to a big family in year *t*. $F(z)=e^z/(1+e^z)$ is the cumulative logistic distribution. $TopSchool_{i,t}$ is an indicator variable if the SAT score of the undergraduate institution is higher than 655 (the 75th percentile of the 278 institutions where the SAT score is available). $MgrAge_{i,t}$ is the age of the manager responsible for fund *i* in year *t*. It is calculated based on the assumption that the manager was 21 when receiving her undergraduate degree. $Agemiss_{i,t}$ indicates that age data is not available for the manager of fund *i*. To control for time trends and fund investment objective effects affecting the allocation of managers to different families, I add time and fund objective fixed effects to the regression.

The results in Table 4.4 confirm that the probability of being assigned to a big fund family depends on the education attained by the manager. While the probability is not significantly higher for economists to work for large companies, large companies are more likely to employ managers with postgraduate degrees and managers with undergraduate degrees from top institutions. For instance, the odds are 101 percent higher for managers with a graduate degree from one of the best universities to work for a large fund company.

Also, large families are associated with younger managers. One reason is that large families are possibly stricter regarding manager’s retiring age than smaller families. Alternatively, anecdotal evidence shows that Fidelity, as one of the largest families,

[61] I use the total net assets of all funds covered by MFLINKS.
[62] For hiring policies of prestigious employers see Rivera (2011).
[63] Using a probit-model instead yields very similar results.

promotes young analysts to fund managers quickly.[64] The age is more likely to be missing for older managers in the data, since younger managers more frequently use linkedin.com where data is usually most complete. This is why both coefficients have the same sign. In columns (2) and (3) I replace $D_{i,t}^{Big}$ with $D_{i,t}^{Mid}$ and $D_{i,t}^{Small}$, indicating a fund belongs to a medium or small fund family, respectively.

Table 4.4: Family allocation of fund managers

Dependent variable	Large	Middle	Small
Economist	0.2689	0.1000	-0.8618***
	(1.32)	(0.47)	(-2.99)
MBA	0.4108**	0.0157	-1.1025***
	(2.24)	(0.08)	(-4.18)
Topschool	0.6985***	-0.5156***	-0.6650**
	(3.66)	(-2.66)	(-2.29)
Industry tenure	0.1193	-0.0118	-0.1403
	(0.82)	(-0.08)	(-0.80)
Manager age	-1.4341**	0.8299*	0.9069**
	(-2.18)	(1.71)	(2.31)
Age missing	-5.9048**	3.5255*	3.8569***
	(-2.39)	(1.94)	(2.61)
Observations	4,024	4,024	4,024
Pseudo R-squared	0.0639	0.0398	0.0887

Notes: This table presents results from pooled logistic regressions that analyze the allocation of mutual fund managers to different fund families. I rank fund families by their total net assets managed. The dependent variable is an indicator variable which is equal to one if the family a fund belongs to in year t is (Large) above the 75th percentile of fund families regarding total net assets managed, (Middle) between the 25th to 75th percentile, or (Small) in the bottom 1st to 25th percentile. Economist is an indicator variable which is equal to one if the manager responsible for a fund has at least one economic degree (accounting, banking, business administration, economics, finance, or marketing) or minor and zero otherwise. MBA is an indicator variable indicating whether the manager attained a Master of Business Administration degree. Topschool is an indicator variable which is equal to one if the SAT of the manager's undergraduate institution is above 655 and zero otherwise (also if the SAT score is missing). The SAT score is the average of the 25% and 75% SAT score percentiles in reading and math of the class entering in 2010 of the school where a manager received her undergraduate degree divided by 100. Manager age is calculated assuming that a manager was 21 years old when receiving her first degree. Age missing is a variable indicating that the age of the manager is not available. Regressions are run with year and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

[64] See Maiello (2009).

Generally, I find that small fund families are very different compared to big fund families with respect to the educational qualities of their managers. The probability is significantly lower for economists to work there. The same holds true for managers with postgraduate degrees and graduates from top institutions.

4.4.2 Manager education, performance, and the impact of the fund family

As shown in section 4.4.1, there are size differences in the families associated with managers with different educational characteristics. It is possible that fund families not only differ with respect to their size, but also in the quality of the support they provide to their managers. This is why I repeat the regression from section 4.3 and add time varying family control variables in Table 4.5.

I add the lagged logarithm of fund family size and the lagged family focus as defined in Siggelkow (2003). Additionally, I use family fixed effects. Family fixed effects control for heterogeneity in fund families. This way I capture variation of fund manager education characteristics within a fund family.

Table 4.5 shows that the main results still hold when controlling for family characteristics and unobservable family heterogeneity. However, the loading of SAT score is not significant in this specification. According to the results in Table 4.4, there seems to be less variation in SAT scores within different kinds of fund families resulting in a non-significant loading. As it seems, a degree from a highly-ranked university is a prerequisite for being employed by a big family. Put differently, the result for SAT score in Table 4.3 is driven by variation across families and not variation across managers.

However, there is still enough variation in funds with managers differing with regard to their undergraduate and postgraduate degrees. The results for the specification presented in Table 4.5 allow me to rule out the possibility that the finding in section 4.3 is solely based on poorly managed mutual fund families not screening the skills of the managers they hire adequately, or alternatively that the best mutual fund families simply attract all the talented managers.[65]

[65] Results still hold when I exclude very small funds (< 5 $ mio. in total net assets) and funds belonging to the small families.

Table 4.5: Fund manager education and performance with family controls

Dependent variable:	Return	Fama French	Carhart
Economist	0.0280**	0.0142*	0.0185**
	(2.37)	(1.96)	(2.53)
MBA	0.0373***	0.0154**	0.0200***
	(2.86)	(2.00)	(2.66)
MBA*Economist	-0.0167	-0.0104	-0.0143*
	(-1.17)	(-1.17)	(-1.68)
SAT/100	0.0044	0.0004	0.0027
	(1.05)	(0.13)	(1.00)
SAT missing	0.0031	-0.0171	-0.0062
	(0.11)	(-0.88)	(-0.34)
Industry tenure	-0.0063	-0.0024	-0.0015
	(-1.42)	(-0.69)	(-0.50)
Fund size	-0.0086***	-0.0018	-0.0040***
	(-3.75)	(-1.19)	(-2.63)
Turnover ratio	-0.0042***	-0.0013	-0.0017
	(-3.21)	(-0.95)	(-1.43)
Total expense ratio	-1.2198	-1.2599	-1.4787
	(-0.97)	(-1.52)	(-1.60)
Fund age	0.0059	0.0012	0.0026
	(1.26)	(0.35)	(0.83)
Flow	-0.0033***	0.0036	0.0008
	(-2.63)	(1.53)	(0.74)
Past return	0.0379**	-0.0209	0.0551
	(2.23)	(-0.55)	(1.12)
Family size	-0.0230***	-0.0123***	-0.0126***
	(-3.59)	(-2.64)	(-3.02)
Family focus	0.0294	0.0295	0.0422
	(0.62)	(1.16)	(1.61)
Observations	3,871	3,871	3,871
R-squared	0.7166	0.2232	0.2390

Notes: This table presents results from pooled OLS regressions that analyze the relation between manager education and yearly fund performance using three different performance measures: net-of-fee fund return (Return), Fama and French (1993) three-factor alpha, and Carhart (1997) four-factor alpha. For each fund, I measure monthly net alphas by regressing funds' net-of-fee excess returns on the Fama French (1993) and Carhart (1997) factor returns using 36-month rolling-window regressions. I compound monthly returns and alphas for every year and fund. The key independent variables are: Economist, MBA, and SAT/100. Economist is an indicator variable which is equal to one if the manager responsible for a fund has at least one economic degree (accounting, banking, business administration, economics, finance, marketing) or minor and zero otherwise. MBA is an indicator variable indicating whether the manager attained a Master of Business Administration degree. SAT/100 is the average of the 25% and 75% SAT score percentiles in reading and math of the class entering in 2010 of the school where a manager received her undergraduate degree divided by 100. SAT missing is a variable indicating the SAT score of the undergraduate institution is not available. The remaining control variables are described in Tables 4.1 and 4.2. Family size is the logarithm of the fund family's assets under management. Family focus, represents the concentration of a fund family across objectives, defined as in Siggelkow (2003). All fund and family variables are lagged by one year. Regressions are run with fund family, year, and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

4.5 Manager education conditional on experience

Following the arguments that managers with economic degrees are possibly better connected or might have studied the markets for a longer period of time, this effect should become less important the longer a manager is on the job. On the contrary, if managers are born different, the effect should persist even when managers without economic degrees gather more experience and connections.

In their first years, managers with undergraduate degrees in an economic field could be at an advantage. However, as time goes by, other managers will probably make up for their disadvantage by building connections and market experience themselves. Alternatively, competition could eliminate especially bad managers. I therefore repeat the analysis from section 4.4.2 conditioning on manager industry experience. The median industry tenure for my sample is 9 years. Accordingly, I split the sample into observations belonging to managers with above sample median industry tenure and managers with below sample median tenure. Columns (1)-(3) present results from the regressions for the sub-sample of managers with above median experience, columns (4)-(6) for managers with below median experience.

Table 4.6 shows that I only find a significant positive effect for graduate and postgraduate education for the sub-sample of observations belonging to relatively unexperienced fund managers. The effect is still positive for the remaining sub-sample but it is not statistically significant. Fund and family related control variables generally have the same sign in both sub-samples.[66] This finding is consistent with the education and social business network hypothesis, respectively, but inconsistent with the hypothesis that the outperformance is due to qualities economists are born with.

To better understand why economists excel in the subgroup of relatively unexperienced managers, I analyze their investment style. If economists outperform non-economists this can be due to skillful timing of different strategies. To capture differences in style, I use the funds' factor loadings from the Carhart (1997) model. I follow Bär, Kempf, and Ruenzi (2011) to calculate style extremity for fund *i* in a given year *t*:

[66] If I exclude past return and total expense ratio from the regressions, results remain qualitatively unchanged.

$$EM_{i,t}^{S} = \frac{\left|\beta_{i,t}^{S} - \overline{\beta}_{\mathrm{k},t}^{S}\right|}{\frac{1}{N^{k}} \cdot \sum_{j=1}^{N^{k}} \left|\beta_{j,t}^{S} - \overline{\beta}_{\mathrm{k},t}^{S}\right|}, \tag{4.3}$$

where *S* represents the investment style (Market, SMB, HML, WML, respectively) and N^k gives the number of funds in a specific market segment (defined by the CRSP objective code) *k* in year *t*. To normalize the extremity measure, I divide it by the average style deviation in the corresponding market segment and respective year. I use the absolute deviation from the average style in a given segment because skilled managers might not always have a higher exposure to the market for instance. They might reduce the exposure before markets go down. I analyze style differences by running the following pooled regression:

$$\begin{aligned} EM_{i,t}^{S} = {} & \alpha + \beta_1 Economist_{i,t} + \beta_2 MBA_{i,t} + \beta_3 SAT/100_{i,t} + \beta_4 SATmiss_{i,t} \\ & + \beta_5 Tenure_{i,t} + \gamma_1 FundSize_{i,t-1} + \gamma_2 FundTO_{i,t-1} + \gamma_3 FundTER_{i,t-1} \\ & + \gamma_4 FundAge_{i,t-1} + \gamma_5 FundFlow_{i,t-1} + \gamma_6 FundPerf_{i,t-1} \\ & + \delta_1 FamSize_{i,t-1} + \delta_2 FamFocus_{i,t-1} + a_m + a_t + a_o + \varepsilon_{i,t}. \end{aligned} \tag{4.4}$$

Table 4.7 shows that economists are more extreme regarding their investment style for two out of four styles. Since they have a better performance, the significant differences in extremity for the market exposure and the momentum exposure are an indication for superior style timing skills. In unreported results, I do not find a significant difference for the average factor loadings. Taken together these results imply that, for example, economist managers might be changing from a momentum to a contrarian strategy when it is the right time. Alternatively, economists have skilled momentum and contrarian managers among them. To investigate this further, I differentiate between different market phases in section 4.6.

Table 4.6: Performance conditional on manager experience

	Above median industry tenure			Below median industry tenure		
Dependent variables:	Return	Fama French	Carhart	Return	Fama French	Carhart
Economist	0.0071	0.0064	0.0097	0.0370*	0.0217**	0.0271**
	(0.51)	(0.56)	(0.78)	(1.88)	(1.97)	(2.49)
MBA	0.0028	0.0060	0.0020	0.0539***	0.0227**	0.0324***
	(0.20)	(0.59)	(0.17)	(2.60)	(2.01)	(2.94)
MBA*Economist	0.0047	-0.0055	0.0013	-0.0260	-0.0146	-0.0229*
	(0.29)	(-0.42)	(0.09)	(-1.12)	(-1.10)	(-1.81)
SAT/100	0.0058	0.0010	0.0009	-0.0006	0.0017	0.0053
	(1.08)	(0.25)	(0.24)	(-0.08)	(0.41)	(1.28)
SAT missing	-0.0090	-0.0266	-0.0364	-0.0229	0.0019	0.0184
	(-0.22)	(-0.90)	(-1.30)	(-0.47)	(0.06)	(0.66)
Industry tenure	0.0052	-0.0027	0.0127	-0.0002	0.0027	-0.0007
	(0.43)	(-0.28)	(1.34)	(-0.03)	(0.57)	(-0.16)
Fund size	-0.0066**	-0.0017	-0.0029*	-0.0094***	-0.0013	-0.0040*
	(-2.49)	(-0.93)	(-1.68)	(-2.61)	(-0.57)	(-1.76)
Turnover ratio	-0.0036***	-0.0002	-0.0004	-0.0035	-0.0048	-0.0070
	(-4.53)	(-0.43)	(-0.92)	(-0.34)	(-0.70)	(-1.34)
Total expense ratio	-0.9999	-1.4038*	-1.3632	2.3722*	1.0507	0.8408
	(-0.82)	(-1.69)	(-1.27)	(1.76)	(1.18)	(1.03)
Fund age	0.0074	0.0028	0.0024	0.0098	0.0017	0.0031
	(1.25)	(0.74)	(0.64)	(1.43)	(0.35)	(0.69)
Flow	-0.0007	0.0061	0.0028	-0.0037**	0.0023	-0.0003
	(-0.46)	(1.03)	(0.82)	(-2.05)	(0.93)	(-0.35)
Past return	-0.0080	-0.1462***	-0.1045***	-0.0391	-0.0292	0.0197
	(-0.34)	(-5.61)	(-2.88)	(-0.62)	(-0.58)	(0.36)
Family size	-0.0377***	-0.0229***	-0.0216***	-0.0256**	-0.0080	-0.0124**
	(-4.38)	(-4.35)	(-4.05)	(-2.31)	(-1.47)	(-2.42)
Family focus	0.0493	0.0221	0.0451	0.0143	-0.0093	0.0201
	(0.81)	(0.46)	(0.87)	(0.19)	(-0.25)	(0.65)
Observations	1,628	1,628	1,628	2,187	2,187	2,187
R-squared	0.8146	0.3125	0.3299	0.7020	0.3336	0.3665

(continued)

Table 4.6: Performance conditional on manager experience - continued

This table presents results from pooled OLS regressions that analyze the relation between manager education and yearly fund performance for two sub-samples using three different performance measures: net-of-fee fund return (Return), Fama and French (1993) three-factor alpha, and Carhart (1997) four-factor alpha. I split the sample into observations belonging to managers that have more than 9 years (sample median) of experience in managing portfolios (first three columns of the table), and observations belonging to managers that have less experience. For each fund, I measure monthly net alphas by regressing funds' net-of-fee excess returns on the Fama French (1993) and Carhart (1997) factor returns using 36-month rolling-window regressions. I compound monthly returns and alphas for every year and fund. The key independent variables are: Economist, MBA, and SAT/100. Economist is an indicator variable which is equal to one if the manager responsible for a fund has at least one economic degree (accounting, banking, business administration, economics, finance, marketing) or minor and zero otherwise. MBA is an indicator variable indicating whether the manager attained a Master of Business Administration degree. SAT/100 is the average of the 25% and 75% SAT score percentiles in reading and math of the class entering in 2010 of the school where a manager received her undergraduate degree divided by 100. SAT missing is a variable indicating the SAT score of the undergraduate institution is not available. The remaining control variables are described in Tables 4.1 and 4.2. Family size is the logarithm of the fund family's assets under management. Family focus, represents the concentration of a fund family across objectives, defined as in Siggelkow (2003). All fund and family variables are lagged by one year. Regressions are run with fund family, year, and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 4.7: Style extremity for sub-sample of less experienced managers

Dependent Variable	Market	SMB	HML	WML
Economist	0.2153**	0.0476	0.1341	0.2761**
	(2.31)	(0.48)	(1.47)	(2.33)
MBA	0.1058	0.0961	0.0584	0.2415**
	(1.06)	(0.89)	(0.55)	(2.05)
MBA*Economist	-0.2008*	-0.0643	-0.1008	-0.2648*
	(-1.76)	(-0.48)	(-0.79)	(-1.87)
SAT/100	0.0039	0.0442	0.0200	0.0161
	(0.11)	(0.71)	(0.38)	(0.26)
SAT missing	0.0548	0.0979	0.2885	0.0242
	(0.22)	(0.24)	(0.73)	(0.06)
Industry tenure	-0.0284	-0.0173	-0.0610	0.0966*
	(-0.70)	(-0.32)	(-1.19)	(1.69)
Fund size	0.0215	-0.0062	0.0468*	0.0153
	(1.11)	(-0.25)	(1.90)	(0.69)
Turnover ratio	0.0576*	0.0269	0.0212	0.0858*
	(1.78)	(0.71)	(0.45)	(1.89)
Total expense ratio	7.5702	16.5710*	4.3202	18.3863*
	(1.16)	(1.88)	(0.46)	(1.91)
Fund age	0.0046	0.0510	-0.0913**	-0.0307
	(0.13)	(0.94)	(-2.06)	(-0.68)
Flow	-0.0152*	-0.0088	-0.0085	-0.0158
	(-1.91)	(-0.72)	(-0.95)	(-1.64)
Past return	0.0666	0.0960	-0.0911	0.1885
	(0.37)	(0.48)	(-0.55)	(0.97)
Family size	-0.0881***	-0.1062***	-0.0395	-0.0671
	(-2.81)	(-3.16)	(-0.79)	(-1.65)
Family focus	0.2722	0.3841	0.4056	0.8861**
	(1.15)	(1.32)	(1.51)	(2.42)
Observations	2,187	2,187	2,187	2,187
R-squared	0.4277	0.3009	0.3074	0.3589

Notes: This table presents results from pooled OLS regressions that analyze the relation between manager education and style extremity for the sub-sample of managers that have below sample median industry tenure. To calculate style extremity, I follow the approach of Bär, Kempf, and Ruenzi (2011). Each year, I use the sensitivities (factor loadings) from the Carhart (1997) model to capture the investment style of a fund. I then calculate the extremity measure as follows:

$$EM_{i,t}^{S} = \frac{\left|\beta_{i,t}^{S} - \overline{\beta}_{\mathrm{k},t}^{S}\right|}{\frac{1}{N^{k}} \cdot \sum_{j=1}^{N^{k}} \left|\beta_{j,t}^{S} - \overline{\beta}_{\mathrm{k},t}^{S}\right|},$$

where *S* represents the investment style (Market, SMB, HML, WML, respectively) and N^k gives the number of funds in a specific market segment (defined by the CRSP objective code) *k* in year *t*. To normalize the extremity measure, I divide it by the average style deviation in the corresponding market segment and respective year. The independent control variables are the same as in Table 4.6. Regressions are run with fund family, year, and objective fixed effects. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

4.6 Manager education and market sentiment

To get a better understanding where performance differences originate from, I try to look at where economic education pays the most. If better educated managers can analyze the market and certain companies better or have superior contacts they should benefit more in certain market phases. The advantages of economists should payoff most when sentiment is high, since in these market phases stock prices deviate from fundamental values.[67] I use the CBOE Volatility index (VIX) to distinguish different market periods.

The volatility index is constructed from Black-Scholes implied volatilities of S&P index options. It tends to surge when investors sell-off stocks and hedge their equity portfolios by buying S&P index puts. Simon and Wiggins (2001) find that these periods of extreme fear have provided excellent buying opportunities.

This is why I hypothesize that managers with superior education are more successful when compared to their peers in these times. My approach is straightforward: I take the five highest values of the VIX in the period 1996-2009 and set a dummy variable for the years following these peaks (1998, 1999, 2002, 2003, and 2009). The reason is that the results of the buying opportunities should be measurable in the following year. On the contrary, I take the years in 1997 and 2004-2006 as years where the index was especially low before and set the dummy variable to zero in these years. I pool all those years and estimate the following multivariate regression:

$$\begin{aligned} Perf_{i,t} &= \alpha + \beta_1 Economist_{i,t} + \beta_2 Economist_{i,t} * Fear_t + \beta_3 MBA_{i,t} \\ &+ \beta_4 MBA_{i,t} * Fear_t + \beta_5 MBA_{i,t} * Economist_{i,t} \\ &+ \beta_6 MBA_{i,t} * Economist_{i,t} * Fear_t + \delta Y_{i,t} + \gamma X_{i,t-1} + a_t + a_o + a_m + \varepsilon_{i,t} \,. \end{aligned} \tag{4.5}$$

$Fear_t$ is an indicator variable that is equal to one if year t is following a spike in the VIX and zero if the VIX values where especially low in the preceding year.[68] $Y_{i,t}$ represents all manager related controls, $X_{i,t-1}$ stands for fund and family related controls used in the regression in section 4.4.2. For brevity, I only report the key independent variables.

[67] See Shleifer and Vishny (1997) or Baker and Wurgler (2006).
[68] Since the model uses year fixed effects, the main effect is not included in the regression.

Table 4.8: Manager education and performance in years following highly negative sentiment

Dependent variable:	Return	Fama French	Carhart
Economist	-0.0231	-0.0073	-0.0037
	(-1.62)	(-0.73)	(-0.35)
Economist*Fear	0.0697***	0.0438***	0.0383**
	(3.62)	(2.97)	(2.47)
MBA	-0.0119	-0.0019	-0.0031
	(-0.86)	(-0.19)	(-0.29)
MBA*Fear	0.0574***	0.0306*	0.0332**
	(2.94)	(1.93)	(1.99)
MBA*Economist	0.0360**	0.0066	0.0059
	(2.06)	(0.57)	(0.49)
MBA*Economist*Fear	-0.0714***	-0.0316*	-0.0324*
	(-2.81)	(-1.80)	(-1.76)
Observations	2,593	2,593	2,593
R-squared	0.6613	0.2506	0.2574

Notes: This table presents results from pooled OLS regressions that analyze the relation between manager education and yearly fund performance in years following peaks in the CBOE volatility index (VIX) versus years following low VIX levels using three different performance measures: net-of-fee fund return (Return), Fama and French (1993) three-factor alpha, and Carhart (1997) four-factor alpha. For each fund, I measure monthly net alphas by regressing funds' net-of-fee excess returns on the Fama French (1993) and Carhart (1997) factor returns using 36-month rolling-window regressions. I compound monthly returns and alphas for every year and fund. The key independent variables are: Economist and MBA. Economist is an indicator variable which is equal to one if the manager responsible for a fund has at least one economic degree (accounting, banking, business administration, economics, finance, marketing) or minor and zero otherwise. MBA is an indicator variable indicating whether the manager attained a Master of Business Administration degree. Fear is an indicator variable which is equal to one for the years 1998, 1999, 2002, 2003, and 2009. For the remaining years 1997, 2004, 2005, and 2006 it is zero. Control variables are described in Tables 4.1, 4.2, and 4.3. For brevity, results for the control variables are not reported in this table. Regressions are run with fund family, year, and objective fixed effects. For brevity, only the estimates for key variables are presented. t-statistics are reported in parentheses and computed using standard errors clustered by fund.***,**,* denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Results in Table 4.8 provide strong evidence for the hypothesis that managers with economic education can reap benefits especially in market phases with strong buying opportunities. The return differences between economists and non-economists without MBA degrees is much higher in years following peaks in the VIX index and insignificant in years where there are less extreme buying opportunities. The same is true for the difference between non-economists with MBA degrees and non-economists without MBA degrees. Also, like in results presented earlier, the add-on of an MBA degree is significantly lower for economists. The coefficients are comparatively high which points to a strong effect. This is an intuitive result since returns are extreme around the "fear periods". A perfect example for this are the years 2008 and 2009. Results are also in line with Zhou (2010) since these conditions should benefit managers who are less risk averse and irrational.

4.7 Conclusion

This paper presents new evidence on the importance of the fund manager, especially the effect of manager education quality, on fund performance. I show that higher performance is related to managers with undergraduate degrees in economic fields, an MBA degree, or an undergraduate degree from a highly-ranked institution. I also show that most of these characteristics matter for the mutual fund family a manager is allocated to. Large families seem to have a preference for managers from top undergraduate institutions and managers with MBA degrees. The field of undergraduate education seems to be unrelated to the allocation to a top tier family. The effect of economic undergraduate degree and MBA degree remains positive and significant even after controlling for family characteristics.

Clearly, this paper has the same limitations as previous papers in the field of manager characteristics. It is not entirely clear where the difference in returns between the groups of different managers originates from. To shed light on this issue, even more data would be needed. However, as I have a broader sample as previous studies, I show that the performance effect is stronger among managers that are relatively unexperienced. Additionally, returns on economic undergraduate degrees and MBA degrees are highest following market phases with strong buying opportunities. This leads to the conclusion that both variables capture qualities the manager has attained through earning the degrees instead of qualities that economists are born with (self-selection hypothesis).

The present study has implications for investors, fund families, and fund managers. Apart from assessing the quality of the fund family, reading the fund manager’s résumé can be fruitful for mutual fund investors seeking extra returns. This is also true for hiring new managers from the perspective of a mutual fund family, although diversity within the family might be valuable because of spillover effects between different funds. Lastly, for managers who do not already have theoretical economic education, earning an MBA degree seems to be valuable from a career (fund family allocation) and performance perspective. For managers who already have economic undergraduate education, an MBA degree seems to be more of a gate-opener for landing a job at more prestigious fund families.

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