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ABSTRACT

This paper analyzes how the existence of sector funds (specialists) within a mutual fund family affects the performance and investment behavior of affiliated diversified equity funds (generalists). First of all, I show that specialists have stock picking skills. Second, information flows from the specialist to the generalist. The overlap in specialist and generalist industry sub-portfolios is positively related to the past track-record of the specialist in this industry and specialist work experience and negatively related to the overall work experience and the industry track-record of the generalist. Generally, stocks held by specialists appear in more diversified funds of the family than other stocks. As a result, diversified funds from fund families with sector funds perform better, trade more, and hold more hard-to-value stocks than their peers from families without sector funds.

JEL classification: D23; D83; G23; G24

Keywords: Mutual funds, fund families, analyst skills, manager skills, information sharing, fund performance, investment behavior

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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: sector funds. While there are a few studies focusing on the skill of sector fund managers (see Khorana and Nelling (1997) or Dellva et al. (2001) and recently Kostovetsky and Ratushny (2016)), the role of sector funds within fund families has not been studied so far. Past research has shown that fund family organization has an effect on member fund performance.[1] 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 of 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) selecting 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

[1] See, e.g., Gaspar et al. (2006), Kacperzcyk and Seru (2012) and Chen et al. (2013).

paper a specialist focuses on a narrow selection of industries, whereas the generalist has to pick stocks from far more industries.[2] 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 higher motivated employees could gain their employers 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.

Following these arguments, I hypothesize that sector funds have stock picking skill. I can show that they have positive net three- and four-factor alphas, which are up to 207 basispoints p.a. higher than alphas of comparable diversified funds with respect to size, turnover, costs, etc. I also show that stocks sector funds share with affiliated diversified funds outperform stocks from the same industries that are uniquely held by diversified funds by up to 240 basispoints p.a. This is in line with my argumentation 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

[2] 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.

have stock picking skills, I hypothesize that rational diversified fund managers implement ideas of sector managers. Fittingly, I can show that the quality of both the diversified and the sector fund are important drivers of how much information they share. Diversified funds that underperformed the passive portfolio in a certain sector in the previous year share more information with sector funds in this sector, and more information is shared with sector funds that stood out compared to passive market performance in an industry. They also seem to value specialist experience, because more information is shared with specialists with longer tenure. 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, results imply 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 % higher chance to appear in more than two diversified fund portfolios of the family than other stocks.

Following the aforementioned results, I hypothesize that the more sectors are covered, the more expertise is available to be shared in the family. In consequence, the more sectors are covered, the better it is for affiliated diversified funds' performance. I can show that the number of sectors covered is significantly and positive 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 basispoints better performance p.a. than comparable peer funds from comparable 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 and the idea brought forth by Gupta-Mukherjee and Pareek (2015), more efficient attention allocation allows managers to focus on (and thus give more weight to) stocks with alpha-generating potential. Generally, this means stocks that are hard to value. According to Peng (2005), allocating more information acquisition effort to assets with uncertain payoffs is beneficial.[3] Also, when managers implement more ideas they should trade more, 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 goes for fund turnover. Taken together, these results are also supportive of why I find 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 et al. (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 focus 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 and sector specialists have on generalists and compare them to generalists from families without sector funds.

In addition, this paper makes a contribution to the literature looking at how information is shared within large business entities like mutual fund families. Augustiani et al. (2015) look at the link between interconnection of mutual funds and fund performance. Cici et al. (2016a) analyze how the speed of information diffusion within a fund family affects performance. I add to the literature by showing which fund and manager characteristics influence sub-portfolio

[3] See also Mondria (2010), Gabaix and Laibson (2005), and Gabaix et al. (2006).

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 contribute to the literature regarding how strategy or the organizational structure of mutual fund families affect the performance outcomes and investment behavior of affiliated funds. Chen et al. (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 et al. (2016b) 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 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, I analyze the performance of sector funds and their stock picks. Section 4 provides evidence on how generalists share information with specialists by analyzing portfolio overlap between sector funds and diversified funds from the same family. Section 5 analyzes how the availability of sector expertise affects fund level performance, stock selection and trading behavior of generalists. Section 6 concludes.

2. Data

2.1 Data selection

I obtain fund data from the mutual fund database compiled by CRSP and combine it with the Thomson Mutual Fund Holdings Database using MFLINKS. Holding information is supplemented by information from the CRSP stock database. The CRSP mutual fund database contains information about funds' investment objective 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.[4]

I additionally check the fund names to make sure they are assigned to the right category. Index and foreign funds are dropped in both categories. If a fund offers multiple share classes, I aggregate information like fund return, fees, etc. to the fund level by weighting the information by the TNA 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 V and VI, 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)).

[4] I select only equity oriented 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.

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.

2.2 Sample characteristics

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

<Insert Table I about here.>

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[5] and offer more domestic equity funds than non-sector fund families. 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[6], it is not surprising that the average net return is lower for funds belonging to sector fund families. There is no difference, on average, regarding total expense ratios.

Sectors covered is 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

[5] Family size comprises all assets managed.
[6] See Chen et al. (2004).

average, while a small group of families covers all available sectors. Table II shows characteristics of the 350 sector funds I identified.

<Insert Table II around here.>

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.[7] Panel B shows that most funds are offered in the sectors Health/Biotechnology, Technology, and Financial Services.

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 3.1. 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 3.2.

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. Following Jensen (1968), I interpret the intercept of these models as a measure for skill in predicting stock prices. Since sector fund portfolios comprise only a few industries of the market, it is appropriate to modify the factor return for the market. Dellva et al. (2001) highlight the importance of using the right benchmark for assessing sector fund's picking skills. I therefore construct a sector benchmark index for each of the nine sectors. First, I identify which industries where held with a weight of

[7] 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). The Data tells us that they also, e.g., hold stocks related to the medicine field in industries 35 (Computers), 41(Wholesale), and 45 (Insurance).

more than ten percent by any fund in the sector over time in the sample. I then construct a passive market capitalization weighted benchmark using all stocks from the identified industries. I finally 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 I and II. 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, e.g., 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:

$$\begin{aligned} Perf_{\mathrm{i,t}} = \alpha + \beta_1 Sectorfund_{\mathrm{i,t}} + \gamma_1 FundSize_{\mathrm{i,t-1}} + \gamma_2 FundTO_{\mathrm{i,t-1}} + \gamma_3 FundTER_{\mathrm{i,t-1}} \\ + \gamma_4 FundAge_{\mathrm{i,t-1}} + \gamma_5 FundFlow_{\mathrm{i,t-1}} + \gamma_6 FundPerf_{\mathrm{i,t-1}} + a_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \end{aligned} \quad (1)$$

My key independent variable is sectorfund. This is an indicator variable equal to one if the observation belongs to a sector fund and zero otherwise. 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.

<Insert Table III around here.>

Table III 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 basispoints p.a. higher.

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 et al. (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:

$$\begin{aligned} Perf_{\mathrm{j,f,t}} &= \alpha + \beta_1 Shared_{\mathrm{j,f,t}} + \gamma_1 Size_{\mathrm{j,t}} + \gamma_2 Pastret_{\mathrm{j,t}} + \gamma_3 Paststd_{\mathrm{j,t}} \\ &\quad + \gamma_4 Btm_{\mathrm{j,t}} + a_{\mathrm{f,t}} + a_{\mathrm{i,t}} + \varepsilon_{\mathrm{j,f,t}} \end{aligned} \tag{2}$$

Shared 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 *f* at report date *t* and zero if they were 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 ($a_{f,t}$) 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.

<Insert Table IV around here.>

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

4. Dissemination of specialist information within sector fund families

After I have shown that sector funds have stock picking skills, I go on analyzing how valuable information created by fund family specialists is disseminated within the fund family organization. In section 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 the question in which direction valuable information flows within the family. It is also related to the question 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 4.2, I analyze if sector manager ideas are held by more managers in the family than other ideas.

4.1 Individual overlap between diversified funds and sector funds

My main hypothesis regarding information sharing is that families offering sector funds rather provide access to specialist information 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 hypothesis 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 would expect manager tenure to have an impact on portfolio overlap. I assume that tenure is related to skill. This is in line with Kempf et al. (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 seek assistance. Hence, the overlap should thus 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 would 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 it's quality, importance, and visibility. In addition to be 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 also 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:

$$\begin{aligned} Overlap_{\mathrm{i,f,s,t}} = \alpha &+ \beta_1 MgrLink_{\mathrm{f,s,t}} + \beta_2 MgrTen_{\mathrm{f,t}} \\ &+ \beta_3 MgrTen_{\mathrm{s,t}} + \beta_4 PastPerf_{\mathrm{i,f,t}} + \beta_5 PastPerf_{\mathrm{i,s,t}} \\ &+ \beta_6 FundSize_{\mathrm{f,t}} + \beta_7 Fundsize_{\mathrm{s,t}} \\ &+ \beta_8 Fit_{\mathrm{f,s,t}} + a_{\mathrm{t}} + a_{\mathrm{f}} + \varepsilon_{\mathrm{i,f,s,t}} \end{aligned} \tag{3}$$

Overlap 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. Managerlink 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 measures the average time the manager or management team of the diversified fund *f*/sector funds *s* has spent managing funds in years.

PastPerf is an indicator variable 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 the sub-portfolio performed worse than the passive portfolio.

Fund size is the natural logarithm of asset under management at the report date. Fit 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 funds' score for size and book-to-market ratio at each report date. Fit is equal to one if the absolute deviation for both scores of a pair of funds is lower than one. I 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 level.

<Insert Table V approximately here.>

Table V shows strong support for my hypotheses. Managers have on average 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 basispoints 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 basispoints 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. This is an indication for managers knowing when they need assistance and that they notice sector specialists who stood out in the past year. It is in line with the findings 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.

4.2 Dissemination of sector fund stock picks within the whole fund family

My second hypothesis related to dissemination of information is that fund families behave rational 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 when reports are published 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:

$$
\begin{aligned}
Appearance_{\mathrm{i,f,t}} = \alpha + \beta_1 Sectorstock_{\mathrm{i,f,t}} + \gamma_1 MCap_{\mathrm{i,t}} + \gamma_2 Pastret_{\mathrm{i,t}} \\
+ \gamma_3 Paststd_{\mathrm{i,t}} + \gamma_4 Btm_{\mathrm{i,t}} + \gamma_5 Analysts_{\mathrm{i,t}} \\
+ \gamma_6 Peerfunds_{\mathrm{i,t}} + a_{\mathrm{t}} + a_f + \varepsilon_{\mathrm{i,f,t}}
\end{aligned}
\tag{4}
$$

For each stock *i*, I count the appearance within a fund family *f* at report date *t* as the number of diversified funds holding the stock. In the second column, I divide the number of funds holding a stock by the number of diversified funds within the family a 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 the indicator variable indicating whether it is a stock held by a sector fund of the same family at report date *t*. I add stock specific characteristics like 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 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.

<Insert Table VI around here.>

Table VI 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.

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 confirm Falkenstein's (1996) results.

I have shown in table V, 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 coefficients are slightly lower compared to panel A, results are not entirely driven by these observations.

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

In Chapter 4, I have documented that generalists make vast use of specialist ideas. In section 5, I analyze how the existence of specialist knowledge affects performance and investment behavior of affiliated funds. Section 5.1 analyzes the effect on fund level performance. Section 5.2. shows how access to specialists affects investment behavior.

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. When a sector is unlikely to perform, 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:

$$
\begin{aligned}
&Perf_{i,t} = \alpha + \beta_1 \# Sectors_{i,t} + \beta_2 FamSize_{i,t-1} + \beta_3 FamFocus_{i,t-1} \\
&+\gamma_1 FundSize_{i,t-1} + \gamma_2 FundTO_{i,t-1} + \gamma_3 FundTER_{i,t-1} + \gamma_4 FundAge_{i,t} + \gamma_5 FundFlow_{i,t-1} \\
&+\gamma_6 FundPerf_{i,t-1} + a_s + a_t + \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

I use five fund-level performance measures as dependent variables: Fund return, objective adjusted return (OAR), Fama French (1993) alpha, Carhart (1997) alpha, and characteristic benchmark adjusted returns as defined in Daniel et al. (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 substract 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, where it is rebalanced. This gives me a time series of monthly DGTW adjusted returns.

My key independent variable is the number of sectors covered. This is the number of distinct CRSP objective codes for the category sector funds within a family in a given year. E.g., 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 net assets under management (in mio. USD) and the concentration of the fund family across investment segments at the end of the past year. 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 nature. To control for unobservable year and investment segment effects on performance I include year and segment fixed effects denoted by a_t and a_s. Standard errors are clustered at the fund level.

<Insert Table VII around here.>

Table VII confirms the hypothesis that the more expertise available, the better it is for affiliated funds' performance. 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 basispoints p.a. Consistent with Berk and Green (2004) and Chen et al. (2004) I find a negative impact of fund size on performance. Results 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 effects, 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 where shown by Hendricks et al. (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 VII, 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 VII: Family size, family focus, fund size, fund age, fund turnover and fund objective. I use the performance measures from table VII, since I match on objective, raw returns correspond to objective adjusted returns.

<Insert Table VIII around here.>

Table VIII 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 basispoints per annum.

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 et al. (2013). It is defined as the turnover ratio from CRSP adjusted for the average size of the fund's holding position.

<Insert Table IX approximately here.>

Table IX 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 more costly 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.

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, you need superior skill or time. While I show specialists have the skill, I assume 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 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 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 earning forecast dispersion for a stock. A high analyst 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.[8]

- Insert Table X approximately here -

Table X 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 other measure for family specialization, family focus, has the same coefficient as the sector covered measure for every specification and is always significant. Specialisation on less investment segments seems to allow managers to pick more hard-to-value stocks. This is in line with Siggelkow (2013) 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 VIII, except for the dependent variables being the ones presented in tables IX and X.

<Insert Table XI around here.>

Table XI confirms that sector family generalists on average have an up to 21 % higher portfolio weight for hard-to-value stocks and have 25 % higher turnover relative to comparable peer funds from comparable families. The fund-level performance results taken together with

[8] See Abarnell et al. (1995), Diether et al. (2002), and Garfinkel and Sokobin (2006) for the relation between differences in opinion and hard-to-value stocks.

the results on hard-to-value stocks and turnover are in line with generalists with access to specialists being able to do a better job than their peers.

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 specialist to generalist. I can also show that generalists make vast use of specialist 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 multiplicator effect. Sector funds attract flows from investors and seemingly, more talented specialists. The latter benefit fund families' generalists through cooperation, these funds are thus more attractive to investors. Nevertheless, 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.

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Table I – Summary statistics sector vs. non-sector fund families

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 et al. (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 US 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 million USD. 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 million USD. 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 statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Sector Fund Families					Non Sector Fund Families					Difference
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	-0.0108***
OAR	-0.0006	0.0794	0.0004	-0.2355	0.2266	0.0026	0.0873	0.0001	-0.2283	0.2717	-0.0032***
Fama-French alpha	-0.0120	0.0824	-0.0155	-0.2132	0.2466	-0.0118	0.0817	-0.0148	-0.2099	0.2588	-0.0002
Carhart alpha	-0.0146	0.0741	-0.0159	-0.2161	0.2082	-0.0117	0.0781	-0.0135	-0.2156	0.2376	-0.0029***
DGTW Return	-0.0014	0.0673	-0.0006	-0.2042	0.1876	-0.0000	0.0734	-0.0006	-0.2062	0.2139	-0.0014
Total expense ratio	0.0128	0.0044	0.0123	0.0040	0.0243	0.0127	0.0049	0.0121	0.0027	0.0299	0.0001
# Sectors covered	2.4822	2.0735	2	1	9						
# Sector funds	5.1514	9.8722	2	1	42						
# Diversified funds	20.8682	15.4796	17	2	68	6.9294	6.7727	4	1	28	13.94***
Family size mio. USD	123,052.5	244,798.8	36,522.7	127,1	977,863.8	40,123.8	222,884.4	2,829.1	3.7	983,248.6	82,928.7***
Family focus	0.2189	0.1419	0.1671	0.0870	0.7662	0.4404	0.2975	0.3338	0.0997	1.0000	-0.2215***
Fund size mio. USD	1,696.1	5,047.6	359.9	2.2	23,514.6	938.36	4,274.6	138	1.3	11,669.4	757.74***
Fund turnover	0.9951	1.6081	0.7300	0.0367	4.245	0.8451	1.1929	0.6125	0.0300	4.5825	0.1500***
Fund age	13.9569	13.7580	9.9973	0.4000	70.7507	12.6613	12.2563	9.3288	0.5096	65.5014	1.2956***
Fund flow	0.2635	3.2375	-0.0456	-0.5906	5.018	0.3299	8.4893	-0.0300	-0.6559	4.8045	-0.0664

Table II – Summary statistics for sector funds

This table reports summary statistic for U.S. domestic equity sector funds between 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 million USD. 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). Stocks Held is the average number of stocks held in a sector fund portfolio at a report date. # 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.

	Sector Funds				
Variable	Mean	Stdev.	50%	1%	99%
Panel A: Fund Characteristics					
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 mio. USD	585.9	1,524.9	151.6	0.7	5,208.6
Fund turnover	1.9702	3.7694	0.9125	0.0600	18.6717
Fund age	11.8843	10.0987	9.7507	0.0849	59.3151
Fund flow	2.8010	66.7283	-0.0601	-0.6460	10.3359
# Industry sub-PF	8.1013	4.1655	8	1	20
Panel B: Sectors					
Health/Biotech			18.6%		
Financial services			11.1%		
Natural resources			9.7%		
Technology			39.7%		
Utilities			8.9%		
Consumer goods/services			3.9%		
Industrials			3.1%		
Basic materials			1.1%		
Telecommunication			4.0%		
Sector funds			350		

Table III – Stock picking skills of sector fund managers compared to diversified fund managers

This table presents results from pooled OLS regressions that analyze the stock picking skills of sector funds compared to diversified funds. I include US 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 then compound 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.

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

Table IV – Performance of stocks diversified funds share with sector funds in covered industries

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 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.

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

Table V – Determinants of pairwise overlap between affiliated diversified and sector funds

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 FF48 industry sub-portfolio. Only FF48 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 team: 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.

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

Table VI – Dissemination of sector fund stock picks within the whole fund family

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.

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 devation	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 devation	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

Table VII – Impact of number of sectors covered on performance of diversified equity funds

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: Fund return (Return), objective-adjusted Return (OAR), Fama and French (1993) 3-Factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and the holding based DGTW fund return following Daniel et al. (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 US 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.

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

Table VIII – Matched Sample Performance Comparison

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 VII. 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.

	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)

Table IX – Impact of number of sectors covered on diversified fund turnover

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. Buy and sell turnover separately measure the effect of buy and sell trading by adding the percentage change in a fund's total net assets under management as in Carhart (1997). 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 VII. 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.

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

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

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 VII. 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.

Dependent Variable:	High idiosyncratic vola	Low idiosyncratic vola	# of analysts	High analyst dispersion	Low analyst dispersion
# Sectors	0.0022**	-0.0036**	-0.0476*	0.0024***	-0.0042***
	(2.53)	(-2.34)	(-1.89)	(3.97)	(-3.75)
Family size	-0.0011	-0.0017	0.0026	0.0009	0.0007
	(-1.09)	(-0.99)	(0.09)	(1.40)	(0.60)
Family focus	0.0367***	-0.0485***	-1.6835***	0.0276***	-0.0664***
	(4.02)	(-3.07)	(-6.34)	(5.05)	(-5.54)
Fund size	-0.0038***	0.0050**	-0.0634*	0.0018**	-0.0034**
	(-3.37)	(2.54)	(-1.89)	(2.50)	(-2.26)
Fund age	-0.0003	-0.0013	0.4626***	-0.0051***	0.0147***
	(-0.15)	(-0.32)	(6.46)	(-3.77)	(5.23)
Fund turnover	0.0179***	-0.0291***	-0.0934	0.0054***	-0.0144***
	(5.96)	(-5.95)	(-1.63)	(4.41)	(-5.71)
Past flow	-0.0000	0.0001	0.0017*	-0.0001	0.0000
	(-0.14)	(0.91)	(1.66)	(-1.28)	(1.09)
Past return	-0.0335**	0.0071	-4.1582***	0.0253***	-0.1565***
	(-2.43)	(0.38)	(-14.11)	(2.72)	(-10.67)
Observations	15,617	16,940	16,950	16,826	16,942
R-squared	0.4338	0.5734	0.6248	0.2082	0.3212

Table XI – Matched Sample Holdings and Turnover Comparison

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 IX and X. The matching variables are defined as in table VII. 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 702 and 1,597 (turnover comparison) observations.

	Sector family funds	Peer funds	Difference
High idiosyncratic vola	0.0944***	0.0854***	0.0090**
	(29.28)	(21.65)	(2.35)
Low idiosyncratic vola	0.5357***	0.5672***	-0.0316***
	(74.15)	(72.20)	(-4.81)
# Analysts	12.0821***	12.3127***	-0.2305**
	(92.77)	(89.36)	(-2.07)
High analyst dispersion	0.1232***	0.1018***	0.0215***
	(48.02)	(45.33)	(7.29)
Low analyst dispersion	0.5533***	0.5861***	-0.0328***
	(122.09)	(134.15)	(-6.47)
Turnover	0.9937***	0.7976***	0.1958***
	(23.13)	(74.11)	(4.45)

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