# Essays on the Interaction of Investor Clienteles and Mutual Fund Behavior

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# Chapter 1

# Introduction

This thesis consists of three essays on the interaction of investor clienteles and mutual fund behavior. In particular, I focus on how the interrelation of investor preferences and the behavior of mutual funds determine the allocation of investor wealth to actively managed funds.

Over the last three decades the mutual fund industry has been characterized by a substantial increase in market activity. As such, only the market for U.S. mutual funds became a business with more than $15 trillion assets under management, while the number of funds took off from a couple of hundreds to almost 8,000.[1] Considering the relevance of this investment type and the increase in the number of market participants, economists explore the interaction of investor clienteles and mutual fund behavior. The academic literature addresses the matching of funds and investors from two different ankles: First, researchers analyze to what extend heterogeneity among investors determines the selection of fund investments.[2] Second, another strand of the literature investigates heterogeneity among mutual funds based on their families' decisions to compete for the different groups of investors.[3]

The first essay (Cici, Kempf, and Sorhage, 2015) adds to the literature on fund investor clienteles by addressing the question for potential benefits accruing to investors who rely on financial advisors when acquiring shares in a fund. Several academic studies show that less sophisticated investors who seek services aside from portfolio management invest through financial advisors,

[1] See Investment Company Institute (2015).

[2] Some examples for clientele effects among mutual funds are investor sophistication (see, e.g., Malloy and Zhu, 2004, Del Guercio and Reuter, 2014, Evans and Fahlenbrach, 2012), taxation (see Sialm and Starks, 2012), retirement saving (see Sialm, Starks, and Zhang, 2015), risk-taking (see Kamstra et al., 2015), or financial advice (see, e.g., Bhattacharya et al., 2012, Christoffersen, Evans, and Musto, 2013).

[3] Some examples for such behavior of fund families are the active exploitation of investor heterogeneity through product differentiation (see, e.g., Massa, 2003, Khorana and Servaes, 2012), fee structures (see, e.g., Chordia, 1996, Nanda, Narayanan, and Warther, 2000, Nanda, Wang, and Zheng, 2009), star-fund creating strategies (see, e.g., Nanda, Wang, and Zheng, 2004, Gaspar, Massa, and Matos, 2006), or varying emphasis on portfolio management (see, e.g., Del Guercio, Reuter, and Tkac, 2010, Del Guercio and Reuter, 2014).

while more sophisticated, performance-sensitive investors invest in funds directly without any intermediary.[4] However, although the benefits of direct-sold funds in the form of superior performance outcomes have been studied extensively, empirical evidence for the benefits delivered to investors of the indirect channel of funds is lacking.[5] We provide first evidence that investors under the guidance of financial advisors receive tangible benefits in the form of valuable tax advice. We focus on tax-management as the channel for advisory services because of the following reasons: First, tax advice is one of the most widely hypothesized dimensions for value generation through financial advice in the literature.[6] Second, both financial advisors and private investors emphasize the role of tax planning services as a central motive for the development and maintenance of the advisor-client relationship.[7] Hence, we explore whether investors of the indirect channel exhibit more tax savvy investment behavior. In particular, we hypothesize that financial advisors assist in reducing their clients' tax liabilities by helping them to avoid taxable fund distributions.[8]

Consistent with this Tax-Advisory Hypothesis, our main results confirm a relation between financial advice and investors' reactions to taxable fund distributions. In particular, advised investors exhibit tax-avoidance behavior that is significantly stronger than the reaction of direct channel investors who do not rely on financial advisors. Moreover, fund distributions which lead to larger tax liabilities and are harder to predict trigger stronger tax-avoidance reactions among investors in the indirect channel. Our results also suggest that financial advice encompasses multiple facets of tax-management since advised investors do not only avoid taxable distributions but simultaneously engage in tax-loss selling to reduce their tax-liabilities. We rule out several alternative explanations: We show that differences in unobservable fund characteristics such as distinct patterns in funds' distributions are not responsible for our findings. In addition, we document that the tax-avoidance differential is unaffected when we control for differences in the fraction of funds' investments through tax-exempt retirement accounts. Finally, we find that the superior tax-avoidance behavior of advised investors is limited to distributions that are taxable and is non-existent for tax-exempt distributions.

[4] See, e.g., Malloy and Zhu (2004), Investment Company Institute (2008), and Chalmers and Reuter (2015).
[5] See, e.g., Bergstresser, Chalmers, and Tufano (2009), and Del Guercio and Reuter (2014).
[6] See, e.g., Bergstresser, Chalmers, and Tufano (2009), and Bhattacharya et al. (2012).
[7] See, e.g., Investment Company Institute (2007), and Financial Advisor Magazine (2008).
[8] In accordance to the regulations of the Internal Revenue Code of 1986 (IRC) mutual funds are legally obliged to distribute dividends and capital gains to their shareholders which then are taxable at the individual investor account (see Title 26 Subchapter M of IRC). Thus, fund distributions provide investors with an incentive to delay investments into a distributing fund until after the distribution to avoid the associated tax consequences. For a detailed discussion on how fund distributions accelerate investors' tax liabilities see Johnson and Poterba (2010).

Taken together, the findings from the first essay suggest that the investment decisions of fund investors are affected by their demand for financial advice. Specifically, we show that investors from the indirect channel of mutual funds benefit from financial advisors by receiving valuable tax-management advice. Moreover, our results provide direct support for the view that funds are separated into a service-oriented and performance-oriented market segment.[9] However, this classification of funds based on their targeted group of investors provides only indirect evidence since the determinants of investors' fund selections are more diverse than the reliance on financial advice. Thus, it is still possible that other motives such as risk taking preferences are responsible for the fund-investor interaction. Hence, a more direct classification for funds' varying performance- or service-orientations should be observable by studying management decisions at the family level.

Adhering to this idea, in the second essay (Sorhage, 2015) I investigate the relation between mutual fund behavior and fund families' decisions to source fund activities unrelated to portfolio management internally or from external providers. Consistent with the literature on industrial organization, I propose that funds whose families outsource non-portfolio management services are the same funds with an emphasis on their core business portfolio management.[10]

Specifically, I classify mutual funds' focus on portfolio management based on the outsourcing status of their shareholder services. Shareholder services involve a substantial number of tasks that by nature embody an immediate link to funds' shareholders but that do not add to funds' investment abilities. Thus, shareholder services are a suitable candidate for outsourcing to performance-oriented funds, while service-oriented funds are cautious to maintain this link.[11] Moreover, according to estimates by Gremillion (2005), shareholder services are the second most expensive component of mutual fund activities which makes it attractive to performance-oriented funds to reduce resource consumption in a non-core area by relying on external specialists' comparative advantage.

To provide evidence on a relation between fund behavior and the outsourcing status of shareholder services, I employ a new dataset with information on funds' service operations

[9] According to Del Guercio, Reuter, and Tkac (2010) and Del Guercio and Reuter (2014) direct-sold funds put an emphasis on portfolio management, for instance, by employing more skilled managers from prestigious universities, while indirect-sold funds are presumed to cater to investors who value services aside from portfolio management.

[10] Some examples for an impact of outsourcing on the performance of an organization's core responsibility are Prahalad and Hamel (1990), Gilley and Rasheed (2000), Goffredson, Puryear, and Philips (2005), Lafontaine and Slade (2007), Novak and Stern (2008), Bustinza, Arias-Aranda, and Gutierrez-Gutierrez (2010), Lee and Kim (2010).

[11] For a comprehensive overview on the services rendered by funds' shareholder services as well as to what extend they are a suitable candidate for outsourcing see Gremillion (2005).

reported by mutual funds in their N-SAR reports filed with the SEC. I determine the outsourcing status of a mutual fund's shareholder service by manually checking whether the service provider in N-SAR is affiliated with the fund's family reported in the CRSP mutual fund database. I document that about 57 percent of all funds source their shareholder services externally, which emphasizes the importance of service outsourcing among mutual funds. In addition, consistent with the notion that service outsourcing represents a management decision at the family level, I find that fund families source shareholder services for all of their member funds either externally or internally.

My main results confirm a relation between the outsourcing status of funds' shareholder services and performance. In particular, service-outsourced funds deliver significantly better performance results than service-inhouse funds. I rule out several alternative explanations: I show that the performance differential is unaffected when I control for other proxies of a portfolio management focus of funds such as the distribution channel of funds and the use of portfolio subadvisors. In addition, I employ a set of empirical techniques to address endogeneity concerns and show that omitted variables are not responsible for my findings. In an additional analysis, consistent with the performance results, I document that service-outsourced funds are indeed associated with higher values for measures of successful active management. I show that service-outsourced funds create more value through superior idiosyncratic bets, unobserved actions and profitable information on specific industries. Furthermore, I find that the stronger portfolio management focus of service-outsourced funds is rewarded by investors in the form of higher growth rates. Taken together, my results suggest that funds whose families outsource non-portfolio management activities are more concerned with their core business portfolio management.

The first two essays showed that the interaction between investor clienteles and mutual fund behavior is determined by investors' varying performance- and service-needs and mutual funds' dedication to attract the specific investor groups. However, considering this interactive character the question about time-variations within the fund-investor matching arises as a result of dynamics in mutual funds' behavior.[12]

[12] Some examples for time-dependent behavior of mutual funds are their trading activity (see, e.g., Pütz and Ruenzi, 2011, Pástor, Stambaugh, and Taylor, 2015a), the use of picking and timing skills in different market periods (see Kacperczyk, Nieuwerburgh, and Veldkamp, 2014), risk-shifting (see, e.g., Brown, Harlow, and Starks, 1996, Kempf and Ruenzi, 2008, Kempf, Ruenzi, and Thiele, 2009, Huang, Sialm, and Zhang, 2011), window dressing (see, e.g., Agarwal, Gay, and Ling, 2014), or events such as manager turnover (see, e.g., Khorana, 1996, 2001) and fund mergers (see, e.g., Jayaraman, Khorana, and Nelling, 2002, Khorana, Tufano, and Wedge, 2007).

The third essay (Dahm and Sorhage, 2015) adds to the literature on time-varying fund behavior and is related to the previous two essays by examining whether funds' investment skills change to the positive or negative over time and how this is interrelated to investor groups. In particular, we investigate two competing theories from the literature on organizational ecology which postulate that funds' investment abilities improve or deteriorate with the passing time. First, the liability of newness theory suggests that funds' are subject to learning effects which allow them to improve their investment strategies and thus facilitate fund performance.[13] Second, the liability of aging theory suggests that funds experience a decline in innovative investment ideas because of a preference for proven courses of action.[14]

Consistent with the liability of aging theory, we find that the performance of a fund deteriorates over its lifetime. We show robustness for the negative age-performance relation by controlling for unobservable effects that could impact on the performance effect at the fund, family, manager and investment segment level. Furthermore, we explore the idea of the liability of aging theory that funds' diseconomies of life are attributable to less innovative investment strategies from two different ankles: First, we investigate funds' age-performance relationship in different environments that present varying potentials for mutual funds to exploit innovative investment ideas. Second, we analyze funds' actual investment behavior for a relation to innovative investments. Referring to the first set of tests, we document no impact of age on the performance of passively managed index funds whose investment activity is predefined and as such has no scope for creative investments. Relatedly, we cannot confirm a negative age-performance relation among actively managed funds with an investment focus on large, well-established companies and consistent generations of income. Moreover, we find that a decline in funds' investment success is limited to periods with reduced competitive pressure on funds.[15] With regard to the second set of tests we show that funds' investment behavior changes over their lifetime: We document that mature funds trade significantly less than their younger selves which is consistent with a diminished pursuit of new investment ideas. Moreover, older funds are associated with a less active management and fewer investments in hard-to-value stocks. However, providing support for a dynamic interaction between mutual fund behavior and fund investor clienteles, we find that mature funds are populated by less performance-sensitive and non-institutional investors relative to their earlier stages of life and that these investors poten-

[13] Some examples for a relation between an organization's age and learning are, e.g., Stinchcombe (1965), Hannan and Freeman (1984), and March (1991).

[14] Some examples for a relation between aging of organizations and innovation are, e.g., Cohen and Levinthal (1990), Singh and Lumsden (1990), and Barron, West, and Hannan (1994).

[15] Cohen (2010) provides an overview in how far competition facilitates innovation.

tially benefit from less extreme investment styles and performance outcomes. Taken together, our results show that mutual funds' investment abilities are not constant but deteriorate over time.

Overall, the results of the three essays suggest that heterogeneity in both investor clienteles and mutual fund behavior determine the fund-investor matching. For example, some investors invest into mutual funds through financial advisors because they benefit from valuable tax-management advice or mutual funds exhibit variations in their focus on portfolio management based on their families' decision to attract specific groups of investors. However, time-variant mutual fund behavior can introduce dynamics into the fund-investor matching. Accordingly, funds experience a decline in their investment abilities over their lifetime and simultaneously cater to the investment preferences of different investor groups during their earlier and advanced stages of life.

# Chapter 2

# Do Financial Advisors Provide Tangible Benefits for Investors? Evidence from Tax-Motivated Mutual Fund Flows*

## 2.1 Introduction

About one half of all mutual fund investors seek financial advice and are willing to pay for it (Investment Company Institute, 2014). Possible ways in which financial advisors can help their clients have been discussed in previous research. For example, Bergstresser, Chalmers, and Tufano (2009) suggest that investors might receive tangible and intangible benefits in the form of portfolio customization that reflects individual asset allocation needs, reduced search costs, lower susceptibility to behavioral biases, and tax management advice, among others. However, despite the list of hypothesized benefits from financial advice, there has been no empirical evidence to date documenting such benefits for U.S. investors.[16] We fill this gap in the literature by documenting that U.S. mutual fund investors do indeed receive at least one of the many previously hypothesized benefits, which comes in the form of valuable tax-management advice.

[*] This chapter is based on Cici, Kempf, and Sorhage (2015).

[16] There are very few empirical studies that document benefits related to financial advice outside of the U.S. Using data from Israel and Germany, respectively, Shapira and Venezia (2001) and Hackethal, Haliassos, and Jappelli (2012) provide evidence that investors improve their portfolio performance by following financial advice.

Specifically, we examine whether financial advisors help U.S. mutual fund investors reduce their tax liabilities by actively helping them avoid taxable fund distributions. To address this question, we compare the tax-avoidance behavior of investors who operate under the guidance of financial advisors (hereafter, indirect investors) with that of investors who do not rely on financial advisors (hereafter, direct investors).

Using a broad sample of U.S. mutual funds over the period 1999–2011, we document tax-avoidance among both groups of investors. However, this behavior is much stronger for indirect investors than for direct investors as the tax-avoidance pattern in the indirect channel is about 60 percent stronger than in the direct channel. Our results hold even after we control for the advisors' compensation, changes in fund performance, and several other factors that can affect flows. Since previous research focusing on U.S. investors shows that investors who seek advice are generally less sophisticated than those who do not (see, e.g., Malloy and Zhu, 2004, Investment Company Institute, 2008, Chalmers and Reuter, 2015),[17] we can attribute the stronger tax-avoidance pattern of indirect investors to the assistance provided by financial advisors.[18]

We consider several alternative explanations for our findings. First, we rule out the possibility that unobservable fund characteristics are responsible for our results by showing that our key finding persists even after we compare the behavior of direct and indirect investors within the same fund. Second, retirement investors, who have no incentive to avoid taxable distributions, perhaps make up a higher fraction of investors in the direct channel than in the indirect channel, which could lead to the flow patterns we observe. We rule this out by showing that the stronger tax-avoidance behavior of indirect investors persists even after we exclude share classes that are available to retirement investors. Finally, we rule out that investor trading patterns other than tax-avoidance lead to the flow patterns we observe by looking at flow patterns around tax-exempt and taxable distributions. We find flow evidence consistent with tax-avoidance only around taxable distributions but not around tax-exempt distributions. Furthermore, we find

[17] This view was first presented by Gruber (1996) in his AFA presidential address and has been corroborated by both empirical and theoretical studies. Malloy and Zhu (2004) show that investors from less affluent and less educated neighborhoods are more likely to invest through brokers. Chalmers and Reuter (2015) document younger individuals with less education and lower income to be more likely to choose financial advice for retirement decisions. Survey evidence also suggests that investors who seek financial advice are from households with lower income and financial assets (see Investment Company Institute, 2008). This empirical evidence is also supported by theoretical models of Inderst and Ottaviani (2009) and Stoughton, Wu, and Zechner (2011) which imply that advisors service mainly less sophisticated investors.

[18] In Europe unsophisticated investors who most need professional financial advice appear less interested in it (Bhattacharya et al., 2012), most likely because they seem to rely more on family and friends as their main source of financial advice and are less likely to invest in the stock market (see, e.g., Rooij, Lusardi, and Alessie, 2011, Calcagno and Monticone, 2015). The reason for the lower participation of unsophisticated investors in the stock market is likely related to the fact that in Europe, unlike in the U.S., retirement investing is mainly done by the government.

that these patterns are affected by the distribution channel only among the taxable distributions. These two findings suggest that the flow patterns around taxable distributions are more likely to be driven by tax-avoidance considerations and that the advisors' influence on investors in this particular setting is more likely related to helping investors with tax-avoidance.

Extending our investigation, we argue that if financial advisors do indeed provide tax-management services to their clients, then their advice ought to lead to stronger tax-avoidance behavior in critical situations that affect investors in the most adverse ways. One such critical situation arises in the face of distributions that can cause large tax liabilities. Another one is when investors are facing distributions associated with tax liabilities that are hard to predict and consequently make financial planning more challenging. Our results support this view. We show that the difference in tax-avoidance behavior between direct and indirect investors is more pronounced for distributions that lead to larger tax liabilities and for distributions that are harder to predict.

We next explore whether the tax-avoidance advice from financial advisors interacts with other tax-related considerations. Ivković and Weisbenner (2009) show that, consistent with tax-loss selling, investors' propensity to sell fund shares that have declined in value is more pronounced in December. We hypothesize that tax-loss selling interacts with the tax-avoidance behavior that we document and that this effect is more pronounced in the indirect channel. Our results show that the tax-avoidance difference between direct and indirect investors gets stronger in December but only for funds where investors are most likely to be subject to capital losses. This finding is consistent with indirect channel investors being advised to not only delay additional investments until after the distribution date but to also redeem shares that have declined in value prior to the distribution date to harvest losses for tax-loss selling purposes.

Our paper is related to a growing number of studies that examine whether financial advice generates measurable benefits for U.S. investors. Bergstresser, Chalmers, and Tufano (2009), Del Guercio and Reuter (2014) and Chalmers and Reuter (2015) show that financial advisors are unable to help investors pick outperforming funds. Mullainathan, Noeth, and Schoar (2012) document that financial advisors fail to moderate their clients' behavioral biases. We contribute to this literature with findings suggesting that financial advisors are providing useful tax management advice to fund investors. To the best of our knowledge, ours is the first study to provide evidence of a tangible benefit delivered by financial advisors to their clients in the U.S. As such, our evidence provides concrete support for the view espoused by Del Guercio, Reuter, and Tkac

(2010) and Del Guercio and Reuter (2014) that indirect channel investors demand and receive financial advisory services rather than purely portfolio management services.

Our study is also related to a second group of studies that examine how tax considerations shape decisions of individual fund investors (see, e.g., Barclay, Pearson, and Weisbach, 1998, Bergstresser and Poterba, 2002, Ivković and Weisbenner, 2009, Johnson and Poterba, 2010). We contribute to this literature by documenting that mutual fund investors are not homogeneous when responding to taxes. Instead, investors' reaction to taxes is related to the distribution channel through which they transact, whereby indirect channel investors display stronger tax awareness shaped in large part by financial advice.

The remainder of this paper is organized as follows. In Section 2.2, we discuss our data set and sample summary statistics. Section 2.3 presents our main findings on mutual fund investors' avoidance of taxable distribution across the direct and indirect distribution channels. In Section 2.4, we explore alternative explanations for our key finding. Section 2.5 investigates whether financial advice leads to stronger tax-avoidance behavior in situations that affect investors in the most adverse ways, and Section 2.6 examines whether the tax-avoidance effect interacts with tax-loss selling. In Section 2.7 we provide several robustness checks, and Section 2.8 concludes.

## 2.2 Data

### 2.2.1 Data sources and sample construction

We obtain mutual fund data from four databases: Thomson Reuters Lipper Flows, Thomson Reuters Mutual Fund Holdings, Center for Research in Security Prices (CRSP) Stock Files, and CRSP Survivor-Bias-Free U.S. Mutual Fund database.

Data on the primary distribution channels of U.S. equity fund shares as well as weekly data on net flows and assets under management are from Thomson Reuters Lipper Flows (Lipper). Lipper assigns each fund share class to one of its three distribution channel categories.[19] Share classes sold primarily through brokers and financial advisors are placed in the indirect channel

[19] Previous studies such as Bergstresser, Chalmers, and Tufano (2009), Del Guercio, Reuter, and Tkac (2010) and Del Guercio and Reuter (2014) rely on the distribution channel classifications from Financial Research Corporation (FRC). However, since FRC's classification is based on Lipper's, differences between the two classification schemes are very small as documented by Bergstresser, Chalmers, and Tufano (2009).

category while share classes sold directly to investors are placed in the direct channel category.[20] The remaining distribution channel comprises share classes sold primarily to institutional investors. Holdings data for U.S. equity funds are from Thomson Reuters Mutual Fund Holdings database. The database reports the name, identifier, and number of shares for each security held by each mutual fund on each reporting date. Holdings data are supplemented with individual stock prices and other information from the CRSP Monthly and Daily Stock Files.

We obtain information on share class and fund characteristics, such as returns, expense ratios, portfolio turnover, and investment objectives from the CRSP Mutual Fund database. We estimate weekly returns for each share class by compounding daily returns. For the share classes we also obtain information on distribution dates, distribution amounts, and net asset value reinvestment prices (NAV) from CRSP. Similar to Pástor and Stambaugh (2002) we assign a fund's investment objective classification based on the CRSP fund objective code.

We analyze flows at the share class level rather than at the fund level for two reasons. First, most share classes are distributed primarily only through one distribution channel, and accordingly, the Lipper classification of primary distribution channels is done at the share class level. Second, mutual funds allocate received dividends and realized capital gains on a pro-rata basis when making distributions and these distributions are paid net of expenses, causing distributions to differ across share classes.

To arrive at our final sample, we start by excluding all share classes with missing MFLINKS code. We next proceed by excluding shares sold through the institutional channel to examine the investment behavior of retail investors. This makes our study comparable to previous papers such as Bergstresser, Chalmers, and Tufano (2009) and Del Guercio and Reuter (2014).

Since our focus is on taxable and actively managed U.S. domestic equity funds, we take additional steps to exclude index, international, sector, balanced, fixed-income, and tax-exempt funds. Next, we exclude all retirement share classes (R share classes) that are designed for retirement plans. We further require that each fund share has at least 52 weeks of flow and return data. Our final sample consists of 730,007 share class-week observations. It covers 2,425 U.S. domestic equity fund shares over the period September 1999 to June 2011.

[20] Like previous studies listed above, we lack the data to distinguish between brokers and financial advisors. Thus, we will treat them as one group and for ease of exposition refer to them as financial advisors. Furthermore, given the recent growth in the activity of fee-based financial advisors who sell no-load funds but charge a fee as a percentage of the client's assets they manage, we expect there to be some funds classified as direct channel funds, part of which are sold by fee-based financial advisors. However, this effect would work against us finding a difference in the behavior of direct and indirect channels.

### 2.2.2 Sample characteristics

Table 2.1 presents summary statistics. About 75 percent of the share classes in our sample are sold through the indirect channel, which is consistent with Bergstresser, Chalmers, and Tufano (2009). In terms of assets, however, indirect-sold shares are significantly smaller than the direct-sold ones. Hence, although they are more numerous, indirect share classes control a smaller amount of total assets. This is consistent with Del Guercio and Reuter (2014). Consistent with previous studies (see, e.g., Bergstresser, Chalmers, and Tufano, 2009, Del Guercio and Reuter, 2014), indirect channel share classes have significantly higher expense ratios, which translate into a lower (net-of-fee) performance of indirect share classes. In addition, indirect share classes have higher load fees, consistent with the fact that a sizable part of advisors' compensation comes out of loads.[21]

Table 2.1: Share class characteristics by distribution channel

| | All share classes | Indirect | Direct | Difference |
|---|---|---|---|---|
| **Share class characteristics:** | | | | |
| Number of share classes | 2,425 | 1,802 | 623 | |
| Share class assets (in million USD) | 450.55 | 253.94 | 1,019.24 | -765.30 *** |
| Expense ratio (in %) | 1.64 | 1.79 | 1.21 | 0.57 *** |
| Total load (in %) | 2.66 | 3.36 | 0.63 | 2.73 *** |
| Carhart alpha (in %) | -0.98 | -1.16 | -0.45 | -0.71 *** |
| **Tax burden and taxable distributions:** | | | | |
| Number of annual observations | 18,111 | 13,260 | 4,851 | |
| Total distributions (in %) | 2.93 | 2.81 | 3.26 | -0.45 *** |
| Tax burden of distributions (in %) | 0.71 | 0.68 | 0.79 | -0.11 *** |
| Capital gains distributions (in %) | 2.61 | 2.54 | 2.80 | -0.25 ** |
| Dividend distributions (in %) | 0.32 | 0.27 | 0.46 | -0.20 *** |

Notes: This table reports share class characteristics and information on taxable distributions for our sample of U.S. equity fund shares between 1999 and 2011. Share classes are categorized by their primary channel of distribution. We classify a share class as belonging to the Indirect (Direct) distribution channel based on classification provided by Lipper. Share class assets, represents the share class' total net assets under management in million USD; Expense ratio, is the share class' fees charged for total services. Total Load, is the combined front-end and back-end load of the share class, and Carhart alpha, is the share class' annualized risk-adjusted return from the Carhart (1997) 4-factor model. Alpha estimates are obtained from 12-month window regressions of funds' net-of-fee excess returns on the excess market return, HML (value) factor, SMB (size) factor, augmented by the MOM (momentum) factor. Total distributions are measured as the distribution amount per share normalized by the share's net asset value (NAV). Tax burden of distributions are calculated by multiplying distributions' yields with the average marginal tax rate of investors as in Sialm (2009) and Sialm and Starks (2012). Capital gains distributions and Dividend distributions are measured, respectively, as the capital gains and dividend distribution amount per share normalized by the share's NAV at the distribution date. Expense ratio, Total load, Carhart alpha and the information on share class' tax burdens and distribution yields are reported in percentage points. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 2.1 also reports statistics on fund shares' annual distribution yields. There are a total of 18,111 share class-year observations with at least one taxable distribution. Such observations

[21] Our load variable is measured as the sum of front-end and back-end load fees.

are more likely in the indirect channel than in the direct channel, which is expected given the larger number of share classes in the indirect channel. Most important, share classes in the indirect channel have significantly smaller distribution yields than those in the direct channel. This difference amounts to roughly 0.45 percentage points and is almost equally driven by funds' capital gains and dividend distributions.

To get a sense for the tax implications of the documented difference in distribution yields, we multiply the difference in distribution yields (0.45 percentage points) with the average marginal tax rate of investors as in Sialm (2009) and Sialm and Starks (2012). This calculation suggests that the difference in distribution yields translates into tax savings for indirect investors relative to direct investors of 11 bp.[22]

## 2.3 Main results

This section explores our Tax-Advisory Hypothesis, which postulates that flows of indirect investors exhibit stronger tax-avoidance patterns than flows of direct investors. Our measurement of the tax-avoidance flow effect is based on a two-step procedure. First, for each share class $i$ around each taxable distribution event, we compute the flow change from the week before to the week after the distribution week $t$ as follows,

$$\Delta F_{i,t} = F_{i,t+1} - F_{i,t-1}, \tag{2.1}$$

where $F$ is the net flow of fund share class $i$ in week $t$ normalized by its total net assets under management lagged by one week. Looking at fund shares' flow changes is attractive because it directly captures investors' net reaction around distribution weeks and minimizes the influence of share class and fund level characteristics on flows. Second, we compare flow changes around distribution weeks with flow changes around non-distribution weeks. To avoid flow changes of non-distribution weeks being affected by surrounding distribution events, we eliminate all non-distribution weeks that are preceded or followed by a distribution in the two weeks before or after. The intuition behind our approach for measuring tax-avoidance behavior is that if investors are delaying their investments in a particular share class in the week prior to the distribution week to avoid that distribution, then flows in the week before should be lower

[22] This is based on the assumption that indirect investors pay the marginal tax rate of investors. However, indirect investors might have lower tax rates if their income is lower, which would potentially lead to a lower tax burden difference.

than in the week after, resulting in a higher flow change around distribution weeks compared to non-distribution weeks, all else equal.[23]

To test the Tax-Advisory Hypothesis, we employ several regression specifications in which the dependent variable, $\Delta F$, is the flow change of fund share $i$ in week $t$.[24] Our base model specification is as follows:

$$\begin{aligned} \Delta F_{i,t} = & \alpha_0 + \alpha_1 Distribution_{i,t} + \beta_0 Indirect_i + \beta_1 Distribution_{i,t} \times Indirect_i \\ & + \delta Delta\ Return_{i,t} + \gamma Advisor\ Compensation_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{2.2}$$

Our main independent variables are, *Distribution*, a binary variable that equals one if share class $i$ is subject to a taxable distribution in week $t$ and zero otherwise as well as, *Indirect*, a binary variable that equals one if share class $i$ is sold indirectly and zero otherwise. Our key test for the Tax-Advisory Hypothesis is based on the interaction of these two variables, which measures how the effect of distributions on the flow change variable differs between indirect and direct channels. Thus, we employ a difference in differences approach.

To control for flows reacting to past performance, which is an empirical regularity first documented by Ippolito (1992), Chevalier and Ellison (1997) and Sirri and Tufano (1998), we include the differential weekly return of share class $i$ between week $t$ and *t-2* (*Delta Return*). We also control for advisors' incentives to generate fees. The idea is that advisors could use taxable distributions as an excuse to encourage clients to make changes in their portfolios, which in turn generate transaction-based fees in the form of load charges. To control for this possibility, we include the total advisor compensation as an additional control, which is measured as the sum of front-end loads, back-end loads, and 12b-1 fees (*Advisor Compensation*).[25]

In further regressions we extend our baseline specification by sequentially including time (calendar month and year) fixed effects, investment objective fixed effects as well as other fund and share class level controls. Those controls include the fund share's total expense ratio (*Expense ratio*), the logarithm of the fund share's total net assets under management (*Share class assets*), and the fund's yearly turnover ratio (*Portfolio turnover*). The first two control

[23] Investors might start thinking about avoiding distributions even sooner than week t-1 and wait even after t+1 to invest in a fund. To account for this possibility we replicate all tests in the paper with the modification that the dependent variable now denotes the difference between cumulative normalized net flows in weeks *t+1* to *t+2* and the cumulative normalized net flow in weeks *t-1* to *t-2*. Results (not reported) are qualitatively the same.

[24] We acknowledge that $F_{i,t+1}$ is affected by net flows in week $t$ since net flows in $t$ determine the total net assets under management in $t$. For robustness we employ:

$$\Delta F_{i,t} = \frac{net\ flows_{i,t+1}}{assets\ under\ management_{i,t-2}} - \frac{net\ flows_{i,t-1}}{assets\ under\ management_{i,t-2}}$$

in an alternative specification and repeat our analyses. Results (not reported) are qualitatively the same.

[25] Results are not different when we do not include 12b-1 fees in this calculation.

variables are at the share class level, while the last one, *Portfolio turnover*, is at the fund level since multiple share classes are backed by the same portfolio and thus share the same turnover. To be consistent with the *Delta Return* calculation, which uses the return of week *t-2*, all four additional controls are lagged by two weeks. To account for possible correlations both within time periods and funds' share classes, we follow Petersen (2009) and cluster standard errors by fund and week.

Table 2.2: Impact of financial advice on tax-avoidance behavior

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0085 | 0.0463 | 0.0395 | 0.0055 |
| | (0.2465) | (0.4814) | (0.5453) | (0.9395) |
| Distribution | 0.3118 *** | 0.2789 *** | 0.2872 *** | 0.2876 *** |
| | (0.0000) | (0.0001) | (0.0001) | (0.0001) |
| Indirect | -0.0049 | -0.0048 | -0.0031 | -0.0059 |
| | (0.4668) | (0.9688) | (0.9798) | (0.9621) |
| Distribution × Indirect | 0.1685 ** | 0.1805 ** | 0.1845 ** | 0.1852 ** |
| | (0.0396) | (0.0272) | (0.0234) | (0.0228) |
| Delta return | 0.0189 *** | 0.0188 *** | 0.0188 *** | 0.0188 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Advisor compensation | 0.0008 | 0.0008 | 0.0007 | 0.0009 |
| | (0.3066) | (0.3158) | (0.3985) | (0.3084) |
| Expense ratio | | | | 0.0088 |
| | | | | (0.1183) |
| Share class assets | | | | 0.0020 |
| | | | | (0.3292) |
| Portfolio turnover | | | | 0.0000 |
| | | | | (0.4339) |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0024 | 0.0027 | 0.0027 | 0.0027 |

Notes: This table presents results from pooled OLS regressions that relate fund shares' flow changes with fund shares' distributions. The analysis is done at the share class and weekly level. We estimate share classes' flow changes as:

$$\Delta F_{i,t} = F_{i,t+1} - F_{i,t-1}.$$

Thereby, for each share class and week flow changes ($\Delta F$) are estimated as the differential between fund shares' weekly net flows before and after the week of observation. Net flows are reported in percentage points and normalized by fund shares' assets under management lagged by one week. The main independent variables include: Distribution, a binary variable that equals one if the share class is subject to a taxable distribution and zero otherwise as well as Indirect, a binary variable that equals one if the share class is indirectly sold and zero otherwise. Additional independent controls include Delta return, Advisor compensation, Expense ratio, Share class assets, and Portfolio turnover. Delta return, is the fund share's differential in weekly returns between the current week and the return lagged by two weeks. Advisor compensation, is the size of the compensation that financial advisors receive measured as the sum of the front-end load, back-end load, and 12b-1 fee. Expense ratio, represents the fund share's total expense ratio. Share class assets, represents the logarithm of the fund share's total net assets under management. Portfolio turnover, is the fund's yearly turnover ratio. Expense ratio, Share class assets, and Portfolio turnover are lagged by two weeks. Regressions are run with and without calendar month and year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Results reported in Table 2.2 confirm a general tax-avoidance pattern in fund flows around taxable distributions. In all models, the incremental effect of a distribution on the flow change in the direct channel is about 0.30 percentage points, that is, the flow in the week after a taxable distribution is about 0.30 percentage points larger than the flow in the week before.

More importantly, however, the estimated coefficient on the interaction term shows that the tax-avoidance effect is significantly stronger in the indirect channel than in the direct channel. It is about 0.18 percentage points and is significant in all models. This suggests that the incremental effect of a distribution on the flow change in the indirect channel is about 0.48 percentage points, thus 60 percent larger than in the direct channel. This result provides support for our Tax-Advisory Hypothesis.

Although we do not have detailed data at the account level to make precise inferences about the economic magnitude of the effect, we make an attempt at a simple back-of-the-envelope calculation. A reasonable interpretation of our coefficient estimate is that for each distribution that an advised investor is able to avoid, the direct investor avoids only 62.5 percent (1/1.6) of the associated tax liability. The distribution yields reported in Table 2.1, combined with marginal tax rates applied as in Sialm (2009) and Sialm and Starks (2012), produce tax burden estimates of 68 bp for the indirect and 79 bp for the direct share class. Thus, if the indirect investor was able to fully avoid her tax burden, the average direct investor would still carry a tax burden of 30 bp (37.5 percent of 79 bp), suggesting a tax saving of 30 bp for the indirect investor. However, this tax saving should be viewed as a rough approximation for the following reasons: First, because we rely on weekly but not daily flows, we might not be able to capture the full extent of the flow effect. Second, given the aggregate nature of the flow data, we are not able to determine the fraction of the indirect investors that are able to fully avoid their tax burdens. Finally, the tax saving is calculated based on the assumption of identical tax rates for indirect and direct investors. Again, not having investor level data, we are unable to determine the difference in tax rates faced by the direct and indirect investors in our sample.

Regarding the control variables, *Delta Return* has a significantly positive impact on the flow change variable, which is consistent with flows following returns. The coefficient on *Advisor Compensation* is insignificant indicating that the compensation of advisors has no impact of fund shares' flow changes. All our results are virtually identical in the various models, suggesting that neither the fixed effects nor the other controls have a notable impact on our main finding.

In summary, our results suggest that mutual fund investors exhibit behavior that is consistent with a tax-avoidance motivation in both channels. However, the effect of tax-avoidance on flows is much stronger among indirect channel investors. This is consistent with financial advisors informing their clients about impending distributions and advising them accordingly to delay investments until after taxable distributions take place.

## 2.4 Alternative explanations

In this section we explore alternative explanations for why indirect channel investors exhibit stronger tax-avoidance behavior.

### 2.4.1 Do unobservable fund characteristics drive the results?

To rule out the possible impact of unobserved fund characteristics, we run a matched sample analysis and focus on a subset of funds that contemporaneously offer indirect- and direct-sold share classes. This allows us to compare the tax-avoidance behavior between indirect- and direct-sold share classes within the same fund.[26]

We start by estimating investors' reaction around distribution weeks and non-distribution weeks for each share class. We calculate the average flow changes for each share class across all distribution weeks and non-distribution weeks separately and denote these averages, respectively by $\overline{\Delta F^{Dist}}$ and $\overline{\Delta F^{Non-Dist}}$. Then we compute the difference between these averages for each share class $i$ as:

$$\Delta FD_i = \overline{\Delta F_i^{Dist}} - \overline{\Delta F_i^{Non-Dist}}, \tag{2.3}$$

In economic terms, $\Delta FD$ measures the abnormal investor reaction to distributions in a particular share class. Since we are interested in comparing the abnormal reaction to fund distributions for indirect- and direct-sold share classes belonging to the same fund, we next average the abnormal flow changes, $\Delta FD$, across all share classes that belong to the indirect and direct channels of fund $n$, respectively. We denote these averages as $\overline{\Delta FD_n^{Ind}}$ and $\overline{\Delta FD_n^{Direct}}$ and calculate the difference between them as follows:

$$DID_n = \overline{\Delta FD_n^{Ind}} - \overline{\Delta FD_n^{Direct}}, \tag{2.4}$$

[26] Although most mutual fund families (e.g., Vanguard) offer automatic reinvestment programs whereby distributions are automatically reinvested on the day of the distributions, there could be families where automatic reinvestment takes place with a delay. For these families, delayed reinvestment of distributions could cause flows after the distribution week to be higher than before, creating a flow change pattern that would be consistent with tax-avoidance. However, the speed of automatic reinvestments is determined at the fund level, meaning that all the share classes that belong to the same fund would have the same reinvestment policy. Thus, comparing share classes within the same fund properly controls for unobserved reinvestment-related issues.

Table 2.3 reports average $\overline{\Delta FD_n^{Ind}}$, $\overline{\Delta FD_n^{Direct}}$, and $DID_n$ for the subset of 127 funds from our sample with share classes offered through both distribution channels.

Table 2.3: Funds with indirect- and direct-sold shares

| | $\Delta FD$ | | |
|---|---|---|---|
| Share class subsample | Indirect | Direct | DID |
| All | 0.5421 ** | 0.0836 | 0.4585 ** |
| | (0.0189) | (0.7198) | (0.0307) |
| With longest history | 0.6297 ** | 0.1760 | 0.4537 ** |
| | (0.0133) | (0.4740) | (0.0438) |

Notes: This table presents results on flow measures for funds that have contemporaneous indirect- and direct-sold fund shares. We compare the tax-avoidance behavior of indirect and direct investors within the same fund by using a difference in differences flow measure, DID. We obtain the difference in differences flow measure in a two-step procedure. First, we estimate the differential between fund shares' flow changes around distribution weeks and non-distribution weeks as:

$$\Delta FD_i = \overline{\Delta F_i^{Dist}} - \overline{\Delta F_i^{Non-Dist}},$$

where $\overline{\Delta F_i^{Dist}}$ represents a share class' average flow change ($\Delta F$) over distribution weeks and $\overline{\Delta F_i^{Non-Dist}}$ represents a share class' average flow change ($\Delta F$) over non-distribution weeks. Second, we calculate the difference in differences flow measure DID for each fund n as:

$$DID_n = \overline{\Delta FD_n^{Ind}} - \overline{\Delta FD_n^{Direct}},$$

where $\overline{\Delta FD_n^{Ind}}$ ($\overline{\Delta FD_n^{Direct}}$) represents the average flow change differential around distribution weeks and non-distribution weeks of all share classes that belong to the indirect (direct) distribution channel. We report statistics on flow change differentials and the difference in differences flow measure for two subsamples. Results in the first row include all the share classes that belong to a fund that has at least one contemporaneous direct- and indirect-sold share class. Results from the second row include only the share classes with the longest history for each fund and distribution channel. P-values are reported in parentheses. ***, **, * denote statistical significance for flow differentials larger than zero at the 1%, 5%, and 10% significance level, respectively.

In the first row of Table 2.3, the calculations are based on all share classes of a fund as described above, and in the second row we keep for each fund only the share class from each channel with the longest history. Both rows lead to the same conclusion, $DID_n$ is positive and significant at the 5 percent level. This means that the tax-avoidance behavior of investors in the indirect channel is stronger than that of investors in the direct channel from the same fund. Thus, our main result persists even after we explicitly control for unobserved fund characteristics.

### 2.4.2 Are retirement flows responsible?

Even though we removed all share classes that are exclusively designed for retirement savings plans (R shares) from our sample, the remaining shares could still be jointly available to retirement investors (through retirement plans) and to non-retirement investors. Thus, it is possible that the share classes in the two distribution channels differ with respect to the fraction of flows that come from tax-exempt retirement investments. If retirement investments are more prevalent in the direct channel, we would expect flows in the direct channel to be less sensitive to tax considerations, consistent with the main finding of our paper. To examine whether retirement flows are responsible for the differential tax-avoidance behavior between direct and indirect investors, we identify share classes that experience no retirement flows in a given year and replicate our tests on that subset.

We identify share classes with no retirement flows from *Pensions & Investments* annual surveys, where mutual fund families report the assets held in defined contribution (DC) accounts in individual fund shares that are used the most by DC plans. Fund families are asked to report the 12 most used funds by DC plans in each broad investment category (Domestic Equity, Domestic Fixed Income, International Equity, Balanced, and Money Market). We link the DC information from the *Pensions & Investments* surveys to the share classes in our sample using share tickers and classify share classes with zero retirement flows each year by identifying share classes that have no DC asset information. Focusing on domestic equity funds, we identify families that report DC asset data for fewer than 12 funds. Then we consider funds for which the fund families do not report DC assets as having zero DC assets.

Table 2.4: Impact of financial advice on tax-avoidance behavior for non-DC fund shares

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0108 | -0.0110 | -0.0168 | -0.0437 |
| | (0.1709) | (0.8453) | (0.7651) | (0.5084) |
| Distribution | 0.3306 *** | 0.2958 *** | 0.3035 *** | 0.3039 *** |
| | (0.0001) | (0.0003) | (0.0002) | (0.0002) |
| Indirect | -0.0018 | 0.0293 | 0.0307 | 0.0279 |
| | (0.8201) | (0.8383) | (0.8307) | (0.8458) |
| Distribution × Indirect | 0.1584 * | 0.1719 ** | 0.1768 ** | 0.1774 ** |
| | (0.0699) | (0.0458) | (0.0393) | (0.0385) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 570,716 | 570,716 | 570,716 | 570,716 |
| Adj. $R^2$ | 0.0024 | 0.0027 | 0.0027 | 0.0027 |

Notes: This table presents results from pooled OLS regressions that relate fund shares' flow changes with fund shares' distributions. The sample is restricted to the observations of fund shares without defined contribution (DC) investments. The main independent variables include: Distribution, a binary variable that equals one if the share class is subject to a taxable distribution and zero otherwise as well as Indirect, a binary variable that equals one if the share class is indirectly sold and zero otherwise. Other independent variables are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-4), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 4. Regressions are run with and without calendar month and year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

In Table 2.4 we repeat the analysis of Table 2.2 on the subset of all share classes that we identify as having experienced zero retirement flows. Results from these additional tests are similar to those of Table 2.2: The flow reaction to taxable distributions is about 60 percent stronger in the indirect than in the direct channel. This suggests that our main result is not driven by differences in retirement flows between share classes sold in the direct and indirect channels.

### 2.4.3 Does our flow change measure really capture tax-avoidance behavior?

To ensure that our key finding is indeed attributable to tax-induced investor reactions around fund distributions, we look for evidence of tax-avoidance behavior around taxable and tax-exempt distributions. The latter distributions have no effect on investors' tax liabilities and as such should not trigger a tax-related flow reaction. Thus, we should observe tax-avoidance behavior among taxable distributions but not among tax-exempt ones.

In Panel A of Table 2.5 we look at flow changes around taxable and tax-exempt distributions. Since tax-exempt fund distributions are very scarce among U.S. domestic equity funds (<0.1 percent), for the purposes of this analysis only, we employ a sample of U.S. municipal bond funds. An attractive feature of municipal funds is that, while their dividend (income) distributions are exempt from federal taxes (and at least partly from state taxes), their capital gain distributions are fully taxable at the federal level. This allows us to look at both taxable and tax-exempt distributions. Despite this attractive feature, the fact that municipal bond funds make distributions of monthly frequency does not allow us to compare weekly flow changes around distribution weeks and non-distribution weeks as before. Recall from Section 2.3. that in order to keep flow changes of non-distribution weeks from being affected by surrounding distribution events, we eliminate all non-distribution weeks that are preceded or followed by a distribution in the two weeks before or after. For this reason, we confine our analysis only to distribution weeks.

We repeat a modified version of the analysis of Table 2.2 with no distribution channel distinction. Specifically, we replace the intercept with two indicator variables, *Tax-exempt distribution* and *Taxable distribution*, indicating whether a distribution is, respectively, tax-exempt or taxable.

Results from Panel A support our claim that our flow change measure around taxable distributions indeed captures tax-avoidance behavior. In particular, we find flow evidence consistent with tax-avoidance only around taxable distributions but not around tax-exempt distributions.

Table 2.5: Tax-exempt versus taxable distributions

**Panel A: Tax-exempt versus taxable distributions**

| Dependent variable: difference in normalized weekly net flows around week t | | | |
|---|---|---|---|
| Model: | 1 | 2 | 3 |
| Tax-exempt distribution | 0.3259 | 0.3280 | 0.2990 |
| | (0.1252) | (0.1270) | (0.1764) |
| Taxable distribution | 0.2684 *** | 0.2431 *** | 0.2439 *** |
| | (0.0000) | (0.0001) | (0.0001) |
| Other fund and share class controls | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes |
| Year fixed effects | No | Yes | Yes |
| Number of observations | 89,582 | 89,582 | 89,582 |
| Adj. $R^2$ | 0.0020 | 0.0027 | 0.0049 |

**Panel B: Tax-exempt versus taxable distributions by distribution channel**

| Dependent variable: difference in normalized weekly net flows around week t | | | |
|---|---|---|---|
| Model: | 1 | 2 | 3 |
| Tax-exempt distribution × Direct | 0.3291 | 0.0516 | 0.1184 |
| | (0.1350) | (0.7512) | (0.5131) |
| Taxable distribution × Direct | 0.1873 | 0.2050 | 0.2507 * |
| | (0.1308) | (0.1199) | (0.0637) |
| Tax-exempt distribution × Indirect | 0.3166 | 0.3697 | 0.3101 |
| | (0.1471) | (0.1408) | (0.2345) |
| Taxable distribution × Indirect | 0.2774 *** | 0.2471 *** | 0.2423 *** |
| | (0.0000) | (0.0001) | (0.0001) |
| Other fund and share class controls | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes |
| Year fixed effects | No | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes |
| Number of observations | 89,582 | 89,582 | 89,582 |
| Adj. $R^2$ | 0.0015 | 0.0023 | 0.0042 |

Notes: This table presents results from pooled OLS regressions that analyze investors' tax-avoidance behavior to tax-exempt and taxable distributions. The sample is restricted to observations of municipal bond fund shares that are subject to a fund distribution. In Panel A, the main independent variables include: Tax-exempt distribution, a binary variable that equals one if the share class is subject to a tax-exempt distribution and zero otherwise as well as Taxable distribution, a binary variable that equals one if the share class is subject to a taxable distribution and zero otherwise. In Panel B, the additional independent variables include: Direct, a binary variable that equals one if the share class is directly sold and zero otherwise as well as Indirect, a binary variable that equals one if the share class is indirectly sold and zero otherwise. Other independent variables in all panels are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-3), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 3. In all panels, regressions are run with and without calendar month and year fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

In Panel B we conduct a more detailed exploration and investigate flow reactions around taxable and tax-exempt distributions stratified by distribution channel. We do this by interacting the variables *Tax-exempt distribution* and *Taxable distribution* with the indicator variables *Direct* and *Indirect*, which equal one if the share class is, respectively, directly or indirectly sold. Results from Panel B confirm our findings of Panel A as there is no consistent flow effect around tax-exempt distributions in both channels. However, the distribution channel seems to matter when looking at taxable distributions, as indirect-sold fund shares exhibit a significant and strong flow reaction around taxable distributions. This suggests that the difference in the flow patterns between direct and indirect investors originally documented in Table 2.2 are driven by financial advice intended to help with tax-avoidance.

## 2.5 Do advisors help more in critical situations?

In this section we test an additional hypothesis, which extends the Tax-Advisory Hypothesis. It postulates that financial advice should provide indirect investors with an even greater relative advantage in critical situations that affect investors in the most adverse ways. One such critical situation arises in the face of distributions that cause large tax liabilities. Another one is when investors are facing distributions that are hard to predict and consequently make financial planning more challenging.

### 2.5.1 Tax-avoidance and size of tax liabilities

We investigate whether the value of financial advice increases with the tax liability of underlying distributions, that is, whether the difference in tax-avoidance behavior between indirect and direct channel investors increases with the associated tax liability.

To calculate tax liabilities, we follow Sialm (2009) and Sialm and Starks (2012) and multiply distribution yields with the average marginal tax rate of taxable investors that the distribution is subject to. The tax rates include federal and state taxes and represent the weighted average of investors' tax rates across income brackets.[27]

We split fund distributions into three equally sized groups every year based on the size of their associated tax liability. We then compare investors' reactions to distributions that fall in the high, medium, and low tax liability groups across the indirect and direct channel.

Table 2.6 shows that the difference in tax-avoidance behavior between indirect and direct channel investors increases with the size of distributions' associated tax liabilities. In particular, the tax-avoidance differential among distributions with large tax liabilities amounts to 0.58 percentage points (p-value<1 percent). This number suggests that for each distribution that the average advised investor is able to avoid, the average direct investor avoids only 55.5 percent (1/1.8) of the associated tax liability and, thus, has to carry a tax burden of 44.5 percent. Given

[27] The time series on investors' average marginal tax rates are obtained from the National Bureau of Economic Research (NBER): http://users.nber.org/ taxsim/.

Table 2.6: Size of tax liability and tax-avoidance behavior

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0084 | 0.0594 | 0.0567 | 0.0365 |
| | (0.2495) | (0.3616) | (0.3810) | (0.6078) |
| High tax liability | 0.7439 *** | 0.7191 *** | 0.7219 *** | 0.7222 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Medium tax liability | 0.0546 | 0.0352 | 0.0418 | 0.0423 |
| | (0.4850) | (0.6585) | (0.5968) | (0.5932) |
| Low tax liability | -0.1064 * | -0.1216 ** | -0.1173 ** | -0.1169 ** |
| | (0.0501) | (0.0224) | (0.0284) | (0.0292) |
| Indirect | -0.0048 | -0.0131 | -0.0123 | -0.0153 |
| | (0.4777) | (0.9171) | (0.9222) | (0.9031) |
| High tax liability × Indirect | 0.5632 *** | 0.5797 *** | 0.5799 *** | 0.5800 *** |
| | (0.0003) | (0.0002) | (0.0002) | (0.0002) |
| Medium tax liability × Indirect | 0.1683 * | 0.1868 ** | 0.1889 ** | 0.1891 ** |
| | (0.0523) | (0.0370) | (0.0351) | (0.0348) |
| Low tax liability × Indirect | 0.1333 ** | 0.1484 ** | 0.1521 ** | 0.1528 ** |
| | (0.0484) | (0.0265) | (0.0232) | (0.0228) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0041 | 0.0042 | 0.0042 | 0.0042 |

Notes: This table presents results from pooled OLS regressions that relate fund shares' flow changes with distributions' tax liabilities stratified into terciles. The main independent variables include: High tax liability, Medium tax liability, Low tax liability, which are all binary variables that equal one if the share class is subject to a taxable distribution that belongs, respectively, to the highest, medium, and lowest tercile based on the distributions' implied tax liabilities and zero otherwise. Tax liabilities are calculated by multiplying distributions' size with the average marginal tax rates of investors as in Sialm (2009) and Sialm and Starks (2012). Indirect, is a binary variable that equals one if the share class is indirectly sold and zero otherwise. Other independent variables are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-4), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 4. Regressions are run with and without calendar month and year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

that the tax burden in the direct share class is now 166 basis points[28], tax-related financial advice becomes even more valuable. Financial advice now provides investors with a 74 basis points advantage while the advantage was only 30 basis points in the base case of Table 2.2.

Moving from high to medium tax liability distributions, the tax-avoidance differential, although still statistically significant, declines almost by a factor of three. Moving from medium to low tax liability distributions it drops even further.

### 2.5.2 Tax-avoidance and hard-to-predict distributions

We next examine whether the value of financial advice is greater for distributions that lead to hard-to-predict tax liabilities. Such distributions are undesirable from investors' point of

[28] This is based on a calculation that conditions on share classes with distributions in the high tax liability group.

view because they make financial planning more challenging. We argue that financial advisors are in a better position to assess distributions that are associated with hard-to-predict tax liabilities because their prior experience with selected mutual funds potentially gives them greater familiarity with the distribution patterns of these funds.[29]

To identify distributions with tax liabilities that are hard to predict, we split fund distributions into three equally sized groups every year based on the volatility of tax liabilities from distributions made by the corresponding share class during the previous three years. We argue that the tax liabilities of distributions from share classes that made distributions with very volatile tax liabilities in the past are hard to predict because in such situations it would be hard to extrapolate from past distribution patterns.[30]

Using a similar approach as in the previous section, we then compare investors' reactions to distributions with high, medium, and low volatility in their associated tax liabilities across the indirect and direct channels. Since the previous section shows that the size of the tax liability is related to the tax-avoidance behavior, we add the size of distributions' tax liabilities (*Tax liability size*) as an additional control.

As hypothesized, Table 2.7 results suggest that the difference in tax-avoidance behavior between indirect and direct channel investors increases with the historical volatility of the corresponding distribution-related tax liabilities. In particular, the tax-avoidance differential effect among distributions coming from share classes with highly volatile historical tax liabilities amounts to about 0.27 percentage points (p-value<1 percent), suggesting that the tax-avoidance behavior of indirect investors in this distribution group is much stronger than that of direct channel investors. Moving from high to medium and medium to low volatility groups, the tax-avoidance differential declines by more than a half, becoming statistically insignificant. This evidence suggests that indirect investors, with the help of financial advisors, are better able to avoid hard-to-predict tax liabilities than direct investors.

[29] The volatility of a fund's tax liabilities associated with its distributions is a function of the volatility of the distribution amounts but also of the change in the mix of the long-term capital gains, short-term capital gains, and dividends, which typically have been subject to different tax rates.

[30] Some mutual fund families announce estimates of their taxable distributions way ahead of the actual date of the year-end distributions. For example, Vanguard does so in the early part of November for all its equity funds (see https://personal.vanguard.com/us). Other fund families, such as Guggenheim, explicitly state that they do not announce distribution estimates for some of the funds to avoid tax-related flow activity (see http://guggenheiminvestments.com/products/mutual-funds/distributions). However, for families that do announce distribution estimates earlier, these are still estimates and are likely to differ from the actual distributions because of trading by mutual funds taking place after the distribution estimate announcement date but before the actual distribution date. We expect this difference to be even larger for funds that have a history of highly volatile distributions.

Table 2.7: Volatility of funds' tax liabilities and tax-avoidance behavior

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0084 | 0.0040 | 0.0047 | -0.0166 |
| | (0.2538) | (0.9521) | (0.9436) | (0.8214) |
| High volatility distribution | -0.1459 * | -0.1549 * | -0.1531 * | -0.1534 * |
| | (0.0872) | (0.0678) | (0.0707) | (0.0706) |
| Medium volatility distribution | -0.0134 | -0.0224 | -0.0196 | -0.0196 |
| | (0.8537) | (0.7605) | (0.7885) | (0.7892) |
| Low volatility distribution | -0.0662 | -0.0857 | -0.0856 | -0.0864 |
| | (0.6647) | (0.5667) | (0.5671) | (0.5638) |
| Indirect | -0.0049 | -0.0274 | -0.0273 | -0.0280 |
| | (0.4646) | (0.8346) | (0.8352) | (0.8313) |
| High volatility distribution × Indirect | 0.2592 *** | 0.2702 *** | 0.2709 *** | 0.2715 *** |
| | (0.0068) | (0.0045) | (0.0044) | (0.0044) |
| Medium volatility distribution × Indirect | 0.1083 | 0.1164 | 0.1175 | 0.1178 |
| | (0.2316) | (0.2007) | (0.1974) | (0.1963) |
| Low volatility distribution × Indirect | 0.1521 | 0.1715 | 0.1731 | 0.1750 |
| | (0.4244) | (0.3643) | (0.3593) | (0.3549) |
| Tax liability size | 0.5985 *** | 0.5971 *** | 0.5965 *** | 0.5964 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 728,760 | 728,760 | 728,760 | 728,760 |
| Adj. $R^2$ | 0.0054 | 0.0056 | 0.0056 | 0.0056 |

Notes: This table presents results from pooled OLS regressions that relate fund shares' flow changes with fund shares' volatility of distributions stratified into terciles. The main independent variables include: High volatility distribution, Medium volatility distribution, Low volatility distribution, which are all binary variables that equal one if the share class is subject to a taxable distribution that belongs, respectively, to the highest, medium, and lowest tercile based on the share classes' volatilities of distributions' tax liabilities during the previous three years and zero otherwise. Tax liability size, represents the size of distributions' tax liabilities and are calculated by multiplying distributions' size with the average marginal tax rates of investors as in Sialm (2009) and Sialm and Starks (2012). Indirect, is a binary variable that equals one if the share class is indirectly sold and zero otherwise. Other independent variables are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-4), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 4. Regressions are run with and without calendar month and year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Taken together, the findings of Section 2.5 suggest that the effect of tax-related financial advice has a targeted effect in helping investors avoid the least desirable tax events.

## 2.6 Do advisors also help with tax-loss-selling?

In this section we examine whether financial advisors help investors with tax-loss selling, another well-known tax strategy studied, for example, by Ivković and Weisbenner (2009), in addition to helping them with avoidance of taxable distributions.

We hypothesize that the tax-avoidance differential effect will get stronger in the presence of tax-loss selling considerations. This is perhaps best illustrated by the following example. Consider an investor who is subject to large unrealized capital losses in the shares she holds in a fund that is about to make a taxable distribution. The optimal strategy for her is to redeem her shares right before the distribution date because this would allow her to harvest capital losses and avoid a taxable distribution at the same time. Such redemptions prior to a distribution would add to the tax-avoidance effect of other (both existing and new) investors who simply choose to delay their fund investments until after the distribution date.

To test for this hypothesized interaction, we first identify funds whose investors are most likely to engage in tax-loss selling. Not having cost basis information for the shares held by each individual investor, we argue that funds that performed worst during the previous year while having low levels of capital gains overhang in their portfolios are most likely to be good tax-loss selling candidates in December, when tax-loss selling is most likely to happen. This is so because they are subject to both short-term and long-term portfolio paper losses, which would suggest that the shares of the average investor in these funds are subject to capital losses.

Each sample week we sort share classes into terciles based on their fund's capital gains overhang at the end of the previous quarter.[31] Within each overhang tercile, we further sort share classes into terciles based on their compounded one-year NAV return. We use NAV returns rather than (net-of-fee) fund returns because NAV returns best reflect appreciation or depreciation of the underlying shares, which in turn drives the tax-loss selling decisions of investors as shown in Ivković and Weisbenner (2009). Based on this sorting, we construct a tax-loss group, denoted by $TLG$, that consists of all share classes that belong to the low overhang low return group. We estimate a regression model based only on observations that correspond to distribution weeks as follows:[32]

$$\begin{aligned}\Delta F_{i,t} =& \alpha_0 + \alpha_1 TLG_{i,t} + \alpha_2 December_i + \alpha_3 TLG_{i,t} \times December_i \\ &+ \beta_0 Indirect_i + \beta_1 TLG_{i,t} \times Indirect_i + \beta_2 December_i \times Indirect_i \\ &+ \beta_3 TLG_{i,t} \times December_i \times Indirect_i \\ &+ \delta Delta\ Return_{i,t} + \gamma Advisor\ Compensation_{i,t} + \epsilon_{i,t},\end{aligned} \tag{2.5}$$

[31] The capital gain overhang of each mutual fund is computed by aggregating the capital gain overhangs of all positions. We use historical quarterly trades and prices at which stocks were purchased to estimate the cost basis of each position.

[32] The choice to restrict the regression observations to only distribution weeks is made primarily to keep the model traceable by reducing the number of interaction terms. However, when we repeat the analysis for all observations, that is, with the entire set of required interaction terms, our results (not reported) remain qualitatively the same.

where *TLG* represents a binary variable that equals one if share class $i$ belongs to the tax-loss group that we consider as most likely to be subject to tax-loss selling in week $t$ and zero otherwise. *December*, is a binary variable that equals one if the observation occurs in the month of December and zero otherwise. Our key test is based on the triple interaction, *TLG* $\times$ *December* $\times$ *Indirect*, which measures whether the difference in tax-avoidance between indirect and direct investors is stronger in December among funds that are candidates for tax-loss selling.

Table 2.8: Interaction of tax-deferral with tax-loss selling

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | 0.0914 | 0.3219 | 0.2118 | -0.1495 |
| | (0.2376) | (0.3183) | (0.5155) | (0.7210) |
| TLG | 0.0264 | 0.0094 | 0.0524 | 0.0551 |
| | (0.8443) | (0.9428) | (0.6853) | (0.6779) |
| December | 0.4334 *** | 0.4398 *** | 0.3035 ** | 0.3037 ** |
| | (0.0019) | (0.0003) | (0.0121) | (0.0130) |
| TLG $\times$ December | -0.3672 | -0.3144 | -0.2951 | -0.2842 |
| | (0.2252) | (0.2910) | (0.3137) | (0.3287) |
| Indirect | 0.0803 | 0.4513 | 0.5097 | 0.4303 |
| | (0.4583) | (0.2496) | (0.2037) | (0.2906) |
| TLG $\times$ Indirect | -0.2290 | -0.2456 | -0.2763 * | -0.2670 * |
| | (0.1392) | (0.1037) | (0.0658) | (0.0758) |
| December $\times$ Indirect | 0.0338 | -0.0099 | -0.0145 | -0.0270 |
| | (0.8242) | (0.9473) | (0.9241) | (0.8614) |
| TLG $\times$ December $\times$ Indirect | 0.7941 ** | 0.8476 ** | 0.8482 ** | 0.8391 ** |
| | (0.0186) | (0.0112) | (0.0116) | (0.0126) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects $\times$ Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 19,542 | 19,542 | 19,542 | 19,542 |
| Adj. $R^2$ | 0.0092 | 0.0251 | 0.0315 | 0.0319 |

Notes: This table presents results from pooled OLS regressions that relate fund shares' flow changes to determinants of tax-loss selling interacted with fund shares' distribution channel. The sample is restricted to the observations that are subject to fund distributions. The main independent variables include: TLG, a binary variable that equals one if the share class belongs to the portfolio that exhibits the lowest level of capital gains overhang and had the worst one-year performance and zero otherwise. December, a binary variable that equals one if the observation week lies in December and zero otherwise. Indirect, is a binary variable that equals one if the share class is indirectly sold and zero otherwise. Other independent variables are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-4), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 4. Regressions are run with and without year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Results from Table 2.8 show that there is a general December effect across all investors. Thus, investors seem to take a closer look at their investments and react more to distributions in December. However, the most interesting insight comes from the large positive coefficient on the triple interaction term. This suggests that the tax-avoidance differential between indirect and direct channel investors gets significantly stronger in December for funds that are most likely candidates for tax-loss selling. Thus, financial advisors seem to alert their clients to not only avoid distributions but to also engage in tax-loss selling in December if they currently hold fund shares that have depreciated in value.

## 2.7 Robustness

In this section we conduct additional robustness checks. In Section 2.7.1 we introduce alternative methods of estimating distribution's implicit tax liabilities. Section 2.7.2 examines whether our results hold for different types of distributions that are taxed at different rates, such as short-term capital gains, long-term capital gains, and dividend distributions.

### 2.7.1 Alternative ways of measuring tax liabilities

In Table 2.9 we repeat the analysis of Table 2.6 using alternative income tax rates applicable to an investor. In Panel A of Table 2.9, we use the federal tax rates that apply to the median income of U.S. households as a proxy for a representative investor. More specifically, we employ the median income of an U.S. household using U.S. Census Bureau data for each year. Then we use historical information on federal tax rates of individual income and calculate for each point in time the marginal tax rates for long-term gains distributions, short-term gains distributions, and dividends that apply to the respective median-income household.[33]

Results from Panel A of Table 2.9 are similar to those of Table 2.6. As an additional check, in Panel B we employ the highest income tax rates to which an investor could have been subjected. Our results remain unaffected. Lastly, in Panel C we repeat the analysis assuming no differences in tax rates across distributions and across time. In other words, we perform the stratification into the three tax liability groups based on the normalized dollar amount of the distributions, which explicitly assumes no differences in tax rates across distributions and time. Again, results from these additional tests are similar to those from Table 2.6.

[33] Information on federal individual income tax rates is from the Tax Foundation's website, http://taxfoundation.org/tax-basics.

Table 2.9: Size of tax liability and tax-avoidance behavior for alternative tax rates

**Panel A: Median federal tax rates**

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0084 | 0.0585 | 0.0559 | 0.0360 |
| | (0.2497) | (0.3710) | (0.3891) | (0.6135) |
| High tax liability | 0.7487 *** | 0.7231 *** | 0.7257 *** | 0.7260 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Medium tax liability | 0.0454 | 0.0258 | 0.0324 | 0.0329 |
| | (0.5608) | (0.7445) | (0.6798) | (0.6757) |
| Low tax liability | -0.0872 | -0.1022 * | -0.0979 * | -0.0975 * |
| | (0.1272) | (0.0711) | (0.0849) | (0.0865) |
| Indirect | -0.0048 | -0.0123 | -0.0115 | -0.0144 |
| | (0.4791) | (0.9220) | (0.9271) | (0.9085) |
| High tax liability × Indirect | 0.5572 *** | 0.5739 *** | 0.5743 *** | 0.5743 *** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Medium tax liability × Indirect | 0.1730 ** | 0.1912 ** | 0.1933 ** | 0.1935 ** |
| | (0.0415) | (0.0289) | (0.0273) | (0.0271) |
| Low tax liability × Indirect | 0.1149 | 0.1300 * | 0.1335 * | 0.1342 * |
| | (0.1045) | (0.0654) | (0.0592) | (0.0581) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0041 | 0.0042 | 0.0042 | 0.0042 |

**Panel B: Highest federal tax rates**

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0084 | 0.0582 | 0.0557 | 0.0358 |
| | (0.2501) | (0.3708) | (0.3890) | (0.6142) |
| High tax liability | 0.7415 *** | 0.7155 *** | 0.7181 *** | 0.7184 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Medium tax liability | 0.0527 | 0.0330 | 0.0397 | 0.0402 |
| | (0.5031) | (0.6795) | (0.6161) | (0.6123) |
| Low tax liability | -0.0861 | -0.1014 * | -0.0970 * | -0.0966 * |
| | (0.1289) | (0.0713) | (0.0856) | (0.0873) |
| Indirect | -0.0047 | -0.0122 | -0.0113 | -0.0143 |
| | (0.4824) | (0.9228) | (0.9281) | (0.9093) |
| High tax liability × Indirect | 0.5527 *** | 0.5695 *** | 0.5699 *** | 0.5700 *** |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) |
| Medium tax liability × Indirect | 0.1828 ** | 0.2010 ** | 0.2031 ** | 0.2033 ** |
| | (0.0332) | (0.0230) | (0.0217) | (0.0215) |
| Low tax liability × Indirect | 0.1091 | 0.1244 * | 0.1278 * | 0.1286 * |
| | (0.1220) | (0.0768) | (0.0698) | (0.0685) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0040 | 0.0042 | 0.0042 | 0.0042 |

(*Continued*)

Table 2.9: Size of tax liability and tax-avoidance behavior for alternative tax rates (Continued)

**Panel C: Indiscriminating tax rates**

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0085 | 0.0595 | 0.0569 | 0.0367 |
| | (0.2463) | (0.3628) | (0.3807) | (0.6070) |
| High tax liability | 0.7655 *** | 0.7413 *** | 0.7439 *** | 0.7442 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Medium tax liability | 0.0233 | 0.0040 | 0.0104 | 0.0110 |
| | (0.7619) | (0.9589) | (0.8931) | (0.8881) |
| Low tax liability | -0.0801 | -0.0946 * | -0.0904 | -0.0899 |
| | (0.1565) | (0.0901) | (0.1055) | (0.1075) |
| Indirect | -0.0049 | -0.0151 | -0.0144 | -0.0173 |
| | (0.4650) | (0.9042) | (0.9088) | (0.8899) |
| High tax liability × Indirect | 0.5775 *** | 0.5950 *** | 0.5954 *** | 0.5955 *** |
| | (0.0002) | (0.0001) | (0.0001) | (0.0001) |
| Medium tax liability × Indirect | 0.1776 ** | 0.1968 ** | 0.1987 ** | 0.1989 ** |
| | (0.0384) | (0.0266) | (0.0253) | (0.0251) |
| Low tax liability × Indirect | 0.1070 | 0.1219 * | 0.1254 * | 0.1261 * |
| | (0.1189) | (0.0740) | (0.0668) | (0.0655) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0042 | 0.0044 | 0.0044 | 0.0044 |

Notes: This table presents results from pooled OLS regressions that relates fund shares' flow changes with distributions' tax liabilities stratified into terciles. In Panel A, the main independent variables include: High tax liability, Medium tax liability, Low tax liability, which are all binary variables that equal one if the share class is subject to a taxable distribution that belongs, respectively, to the highest, medium, and lowest tercile based on the distributions' implied tax liabilities and zero otherwise. Tax liabilities are calculated by multiplying distributions' size with the federal tax rates that apply to the median income group of U.S. households. Indirect, is a binary variable that equals one if the share class is indirectly sold and zero otherwise. In Panel B, distributions belong, respectively, to the highest, medium, and lowest tercile based on distributions' implied tax liabilities that are estimated using the highest federal tax rates that these distributions could have been subject to. In Panel C, we stratify distributions into terciles based on distributions' size, that is, we assume that there is no difference in the tax rates across distribution types and over time. In all panels, other independent variables are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-4), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 4. Regressions are run with and without calendar month and year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

### 2.7.2 Capital gains versus dividends

Although Section 2.5.1 explicitly recognizes that capital gains and dividends are subject to different tax rates and thus generate different tax liabilities for the same distribution amount, it is possible that our results are driven primarily by avoidance of one type of distribution. For example, investors might be more eager to avoid capital gains distributions because these types of distributions could be caused by other investors' redemptions or the idiosyncratic trading behavior of the portfolio manager and thus are outside of their control.

We explore this possibility by slightly modifying the tests of Table 2.6. In Panel A of Table 2.10 we stratify short-term capital gains distributions into three groups based on the size of their associated tax liabilities and introduce two binary variables to account for other types of distributions. The first indicator variable, *Long-term gains distribution*, takes the value of one if share class $i$ is subject to a long-term capital gains distribution during week $t$ and zero otherwise. The second indicator variable, *Dividend distribution*, takes the value of one if there is a dividend distribution at that distribution date and zero otherwise. In Panel B we stratify long-term capital gains distributions into three groups based on the size of their associated tax liabilities and introduce two binary variables, *Short-term gains distribution* and *Dividend distribution*, to account for other types of distributions. In Panel C we stratify dividend distributions into three groups based on the size of their associated tax liabilities and use a binary variable *Gains distribution.*

Table 2.10: Size of tax liability and tax-avoidance behavior for gains and dividend distributions

**Panel A: Short-term gains distributions**

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0103 | 0.0164 | 0.0196 | 0.0032 |
| | (0.1633) | (0.8030) | (0.7653) | (0.9642) |
| High short-term gains distribution | 0.4359 | 0.4296 | 0.4295 | 0.4310 |
| | (0.1171) | (0.1223) | (0.1223) | (0.1210) |
| Medium short-term gains distribution | -0.0173 | -0.0247 | -0.0250 | -0.0248 |
| | (0.9335) | (0.9045) | (0.9035) | (0.9044) |
| Low short-term gains distribution | -0.1663 | -0.1735 | -0.1738 | -0.1744 |
| | (0.4467) | (0.4224) | (0.4217) | (0.4201) |
| Indirect | -0.0028 | -0.0211 | -0.0213 | -0.0213 |
| | (0.6894) | (0.8715) | (0.8707) | (0.8707) |
| High short-term gains distribution × Indirect | 0.8223 ** | 0.8264 ** | 0.8261 ** | 0.8263 ** |
| | (0.0258) | (0.0260) | (0.0260) | (0.0260) |
| Medium short-term gains distribution × Indirect | 0.4607 | 0.4671 | 0.4671 | 0.4672 |
| | (0.1127) | (0.1095) | (0.1095) | (0.1094) |
| Low short-term gains distribution × Indirect | 0.4089 | 0.4153 * | 0.4158 * | 0.4160 * |
| | (0.1028) | (0.0971) | (0.0968) | (0.0966) |
| Long-term gains distribution | 0.9420 *** | 0.9378 *** | 0.9376 *** | 0.9368 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Dividend distribution | 0.0125 | 0.0118 | 0.0123 | 0.0124 |
| | (0.6816) | (0.7004) | (0.6849) | (0.6842) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0048 | 0.0049 | 0.0049 | 0.0049 |

(*Continued*)

Results from Table 2.10 confirm that there is a tax-avoidance differential effect for all types of distributions. Furthermore, we again find that the tax-avoidance differential effect is stronger among the larger distributions, thus confirming our findings in Table 2.6.

Table 2.10: Size of tax liability and tax-avoidance behavior for gains and dividend distributions (Continued)

**Panel B: Long-term gains distributions**

| Dependent variable: difference in normalized weekly net flows around week t | | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Constant | -0.0099 | 0.0199 | 0.0228 | 0.0047 |
| | (0.1827) | (0.7628) | (0.7282) | (0.9480) |
| High long-term gains distribution | 1.4491 *** | 1.4400 *** | 1.4400 *** | 1.4393 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Medium long-term gains distribution | 0.5627 *** | 0.5535 *** | 0.5531 *** | 0.5526 *** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Low Long-term gains distribution | 0.1649 | 0.1550 | 0.1549 | 0.1545 |
| | (0.1067) | (0.1233) | (0.1237) | (0.1250) |
| Indirect | -0.0033 | -0.0220 | -0.0222 | -0.0227 |
| | (0.6325) | (0.8654) | (0.8643) | (0.8611) |
| High long-term gains distribution × Indirect | 0.6362 ** | 0.6477 ** | 0.6475 ** | 0.6480 ** |
| | (0.0487) | (0.0466) | (0.0466) | (0.0465) |
| Medium long-term gains distribution × Indirect | 0.5084 *** | 0.5206 *** | 0.5208 *** | 0.5210 *** |
| | (0.0078) | (0.0068) | (0.0068) | (0.0068) |
| Low long-term gains distribution × Indirect | 0.1646 | 0.1779 | 0.1779 | 0.1782 |
| | (0.1577) | (0.1266) | (0.1268) | (0.1263) |
| Short-term gains distribution | 0.3336 ** | 0.3306 ** | 0.3306 ** | 0.3306 ** |
| | (0.0292) | (0.0306) | (0.0307) | (0.0306) |
| Dividend distribution | 0.0189 | 0.0194 | 0.0199 | 0.0204 |
| | (0.5333) | (0.5219) | (0.5074) | (0.5006) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0055 | 0.0056 | 0.0056 | 0.0056 |

(*Continued*)

Table 2.10: Size of tax liability and tax-avoidance behavior for gains and dividend distributions (Continued)

**Panel C: Dividend distributions**

| Dependent variable: difference in normalized weekly net flows around week t<br>Model: | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Constant | -0.0099 | 0.0021 | 0.0047 | -0.0120 |
| | (0.1772) | (0.9750) | (0.9437) | (0.8696) |
| High dividend distribution | -0.1180 * | -0.1199 * | -0.1189 * | -0.1190 * |
| | (0.0800) | (0.0710) | (0.0743) | (0.0746) |
| Medium dividend distribution | -0.1804 | -0.1854 | -0.1843 | -0.1844 |
| | (0.1326) | (0.1229) | (0.1226) | (0.1226) |
| Low dividend distribution | -0.1335 | -0.1371 * | -0.1359 * | -0.1355 * |
| | (0.1017) | (0.0905) | (0.0930) | (0.0942) |
| Indirect | -0.0027 | -0.0002 | -0.0003 | -0.0006 |
| | (0.6958) | (0.9985) | (0.9980) | (0.9966) |
| High dividend distribution × Indirect | 0.2122 ** | 0.2127 ** | 0.2131 ** | 0.2132 ** |
| | (0.0188) | (0.0182) | (0.0180) | (0.0179) |
| Medium dividend distribution × Indirect | 0.2620 ** | 0.2687 ** | 0.2693 ** | 0.2695 ** |
| | (0.0371) | (0.0327) | (0.0333) | (0.0330) |
| Low dividend distribution × Indirect | 0.1201 | 0.1245 | 0.1243 | 0.1248 |
| | (0.2289) | (0.2093) | (0.2112) | (0.2102) |
| Gains distribution | 1.2219 *** | 1.2147 *** | 1.2143 *** | 1.2140 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Other fund and share class controls | Yes | Yes | Yes | Yes |
| Calendar month fixed effects | No | Yes | Yes | Yes |
| Calendar month fixed effects × Indirect | No | Yes | Yes | Yes |
| Year fixed effects | No | Yes | Yes | Yes |
| Year fixed effects × Indirect | No | Yes | Yes | Yes |
| Investment objective fixed effects | No | No | Yes | Yes |
| Number of observations | 730,007 | 730,007 | 730,007 | 730,007 |
| Adj. $R^2$ | 0.0044 | 0.0046 | 0.0046 | 0.0046 |

Notes: This table presents results from pooled OLS regressions that relates fund shares' flow changes with short-term gains distributions (Panel A), long-term gains distributions (Panel B), and dividend distributions (Panel C). The distributions are stratified into terciles based on the size of their associated tax liabilities. The main independent variables include: High short-term gains (long-term gains, dividend) distribution, Medium short-term gains (long-term gains, dividend) distribution, Low short-term gains (long-term gains, dividend) distribution, which are all binary variables that equal one if the share class is subject to a short-term gains (long-term gains, dividend) distribution that belongs, respectively, to the highest, medium, and lowest tercile based on the distributions' tax liabilities and zero otherwise. Indirect, is a binary variable that equals one if the share class is indirectly sold and zero otherwise. Additional control variables, added as needed, include: Long-term gains distribution, a binary variable that equals one if the share class is subject to a long-term gains distribution and zero otherwise; Short-term gains distribution, a binary variable that equals one if the share class is subject to a short-term gains distribution and zero otherwise; Dividend distribution, a binary variable that equals one if the share class is subject to a dividend distribution and zero otherwise; and Gains distribution, a binary variable that equals one if the share class is subject to a capital gain distribution and zero otherwise. In all panels, other independent variables are defined as in Table 2.2 but not reported for brevity. They include Delta return and Advisor compensation (Model 1-4), augmented by Expense ratio, Share class assets, and Portfolio turnover in Model 4. Regressions are run with and without calendar month and year fixed effects and investment objective fixed effects. P-values reported in parentheses are based on robust standard errors clustered by fund and week. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

## 2.8 Summary and conclusion

With more than 200,000 personal financial advisors, the market for financial advice in the U.S. is characterized by tremendous size and activity.[34] What happens in this market affects the investment decisions of millions of investors and shapes portfolio decisions, which collectively

[34] Bureau of Labor Statistics: http://www.bls.gov/ooh/business-and-financial/personal-financial-advisors.htm.

cover billions of dollars. Despite this level of activity in this important market and the number of individuals that are affected by it, our understanding of the economic forces that shape the interactions among its different players is limited at best.

Recent studies have begun to address the gap between the importance and our rather limited knowledge of the market for financial advice. The fact that a non-trivial fraction of mutual fund investors seek financial advice, for which they are willing to pay, suggests that these investors receive certain benefits from financial advice. However, no direct empirical evidence of these benefits for U.S. mutual fund investors has been documented.

Our paper contributes to the academic literature that seeks to understand the role of financial advisors in their clients' decision making by being the first to provide evidence of a particular tangible benefit delivered by financial advisors to U.S. mutual fund investors. The tangible benefit we document appears in the form of useful tax-management advisory services to fund investors, which help them engage in tax-avoidance strategies. Ruling out alternative explanations, we show that financial advice puts its beneficiaries, indirect channel investors, at a clear advantage over their peers who do not receive financial advice.

A more detailed exploration shows that financial advice appears to target situations when investors need this advice the most. In other words, we document financial advice to be even more valuable when investors are facing situations that significantly increase the size or the unpredictability of their tax liabilities. This, taken together with our evidence that investors' tax-avoidance behavior shaped by financial advisors is intensified by what appear to be tax-loss selling considerations, suggests that financial advice comprehensively addresses several facets of tax management.

# Chapter 3

# Outsourcing of Mutual Funds' Non-core Competencies[†]

## 3.1 Introduction

A stylized fact about mutual funds is that funds are separated into market segments based on their families' strategic decisions to attract specific groups of investors. Specifically, fund families shape their member funds' behavior to exploit heterogeneity in investors' varying performance and service preferences (Massa, 2003). Accordingly, mutual funds can be distinguished into two groups: (1) Funds that emphasize the role of portfolio management because they target performance-oriented investors and (2) funds where portfolio management plays a subordinate role since they cater to investors who value advisory services (see, e.g., Del Guercio, Reuter, and Tkac, 2010, Del Guercio and Reuter, 2014). Nevertheless, a caveat of this classification of mutual funds is that it takes place based on the group of investors that self-selects into the funds and thus could suffer from noise.

In particular, ample empirical evidence analyzes investor preferences that determine their investment decisions and confirms that the fund selection can be traced back to fund performance and advisory services unrelated to portfolio management (see, e.g., Sirri and Tufano, 1998, Cici, Kempf, and Sorhage, 2015). Still, a multitude of additional factors, e.g., risk taking (Kamstra et al., 2015), fund advertising (Jain and Wu, 2000, Gallaher, Kaniel, and Starks, 2015) or the role of retirement plan sponsors and financial advisors (Sialm, Starks, and Zhang, 2015,

[†] This chapter is based on Sorhage (2015).

Inderst and Ottaviani, 2009) shape investors' fund selections and hence introduce inaccuracies into the measurement of funds' focus on portfolio management.[35]

In this paper I propose an alternative measure to distinguish between funds with varying emphasis on portfolio management by looking directly at their families' management strategies. In particular, the literature on industrial organization suggests that firms which channel their efforts on their core business simultaneously reduce resource consumption in non-core areas through outsourcing (Prahalad and Hamel, 1990).[36] Applied to the mutual fund context, one would expect that funds with an emphasis on portfolio management are the same funds whose families delegate the execution of activities unrelated to portfolio management to external specialists and vice versa.

In this spirit, I hypothesize that funds whose families source non-portfolio management services externally (hereafter, service-outsourced funds) pursue a strong portfolio management policy and thus generate superior performance relative to funds of families that administer non-portfolio management services internally (hereafter, service-inhouse funds). I determine whether a fund is a service-outsourced fund based on the outsourcing status of its shareholder services and argue that this classification of funds' portfolio management focus allows for an accurate measurement for two reasons:

First, shareholder services encompass a vast range of individual services that are necessary for funds' daily operations but that do not add to their investment ability. For instance, shareholder services include the creation and recordkeeping of shareholder accounts, the transmission of distributions to investors or shareholder communications such as the processing of investor transactions and complaints. Hence, tangible benefits from shareholder services are small for performance-oriented funds while service-oriented funds could be reluctant to lose this link to their shareholders.[37] Second, shareholder services strongly matter for mutual funds on a monetary basis. Gremillion (2005) describes shareholder services as the largest component of funds'

[35] For a comprehensive review on the determinants of mutual fund flows see Christoffersen, Musto, and Wermers (2014).

[36] The industrial organization literature proposes a multitude of theories for 'make-or-buy' decisions that essentially aims to show when a company is best advised to outsource part of its value chain. For instance, sourcing services from external specialists can be preferable to inhouse solutions if the contractor renders the service more efficiently and thus at lower costs or clients' reservation price increases because the service is provided by a prestigious contractor. Lafontaine and Slade (2007) provide a review on firms' suitability for 'make-or-buy' decisions.

[37] Moreover, despite their extent, the tasks executed by funds' shareholder services are highly standardized (Gremillion, 2005). Therefore, performance-oriented funds could outsource their shareholder services while avoiding some of the major impediments that complicate 'make-or-buy' decisions (Del Guercio, Reuter, and Tkac, 2007), for instance, the 'hold-up' problem where components are built on exact specifications so that sourcing firms are exposed to a lack of alternatives and thus diminished bargaining power in contract negotiations (see, e.g., Grossman and Helpman, 2002).

expenses after investment management. Thus, outsourcing of shareholder services to external providers whose comparative advantage lies in rendering these services presents a considerable potential to reduce resource consumption in a non-core area for performance-oriented funds.

I begin my analysis by comparing the fund performance of service-outsourced funds with service-inhouse funds. Supporting the main hypothesis that service-outsourced funds put an emphasis on portfolio management, I find that service-outsourced funds outperform their inhouse peers. Specifically, I observe a performance difference that amounts up to 73 basis points per year.

In my second set of tests I account for the concern that the newly introduced measure for funds' varying focus on portfolio management captures similar proxies documented in the literature. In particular, I consider two alternative explanations for the outperformance of service-outsourced funds. First, referring to the investor based classification of funds, Del Guercio and Reuter (2014) analyze the distribution channel of funds and show evidence that is consistent with a market segmentation into performance-oriented direct-sold funds and service-oriented brokered funds. Thus, a potential explanation for the outperformance of service-outsourced funds could be that service outsourcing simply proxies for the direct distribution channel. Second, it is possible that service outsourcing is simply the flip side of retaining all portfolio management responsibilities, i.e., to pass on the possibility to hire sub-advisors which is hardly an indication for a fund with an emphasis on active management. In this spirit, Chen et al. (2013) show that sub-advised funds underperform funds that manage their assets internally. Thus, the outperformance of service-outsourced funds could be driven by a prevalence of portfolio sub-advisors among service-inhouse funds. I rule out both possibilities by showing that the outperformance of service-outsourced funds remains robust after controlling for funds' distribution channels and use of sub-advisors.

In a more detailed exploration, I employ a set of empirical techniques to address potential endogeneity concerns. I start with panel regressions that include family fixed effects so that identification comes from changes in the outsourcing status of fund families. To further establish causality, I provide results from a matched sample analysis that is designed to eliminate heterogeneity between service-outsourced funds and service-inhouse funds through a more narrow selection of the service-inhouse control group. Next, I employ a permutation test with randomized outsourcing status of funds' shareholder services that rejects the hypothesis of a reliable performance difference if a sufficiently large number of arbitrary iterations yield similar results to the ones originally observed. Lastly, I implement an instrumental variable approach. As an instrument I use the number of external service providers that offer shareholder services in the state of the management company. The idea is that fund families' use of service outsourcing is more prevalent if the competition among external providers is high. All approaches to establish causality yield significant results and confirm an outperformance of service-outsourced funds. In fact, the outperformance becomes even larger when controlled for endogeneity giving further support to the notion that service-outsourced funds are more concerned with portfolio management than service-inhouse funds.

In the second part of the paper, I explore potential channels through which the outsourcing status of mutual funds and the associated portfolio management focus affect performance. As outlined above, for both reasons of portfolio management concentration and cost reduction potentials performance-oriented funds outsource shareholder services. Hence, I hypothesize that service-outsourced funds outperform service-inhouse funds if service outsourcing results in lower fees and is related to superior investment skills. To examine the first channel I investigate the influence of service outsourcing on funds' service fees and total expenses that reduce their after-cost performance. As expected, I observe that service-outsourced funds have service and total expenses that are about 32 and 10 percent lower, respectively. For the second channel I explore the link between funds' outsourcing status and four measures for investment skill: active share (Cremers and Petajisto, 2009, Petajisto, 2013), return gap (Kacperczyk, Sialm, and Zheng, 2008), industry concentration (Kacperczyk, Sialm, and Zheng, 2005) and the $R^2$ measure (Amihud and Goyenko, 2013). Giving further support to the notion that funds' varying portfolio management focus can be classified through their outsourcing status, I find that service-outsourced funds exhibit higher values for all performance-predicting skill measures.

Lastly, borrowing from the literature on industrial organization that business concentration facilitates corporate success (Prahalad and Hamel, 1990), I quantify the benefits accruing to service-outsourced funds by the increase in their assets under management (Khorana and Servaes, 2012). I find that before controlling for expenses and performance, service-outsourced funds exhibit substantially higher growth rates of up to 16 percentage points per year, whereas after controlling for both mechanisms, there is no statistically significant difference in flows between the two types of funds. This is consistent with investors preferring service-outsourced funds on the basis of their expenses as well as performance and provides service-outsourced funds with a sizeable comparative advantage to their market strength.

The analysis in this paper contributes to several strands of the literature. The most closely related literature studies the relation between fund families' strategic decisions to position themselves within the fund industry and their member funds' behavior. Massa (2003) shows that fund families exploit the heterogeneity of investors by differentiating themselves through non-performance-related characteristics. Del Guercio, Reuter, and Tkac (2010) and Del Guercio and Reuter (2014) find that fund families deliberately influence their funds' behavior to cater to the needs of specific groups of investors. This paper complements these studies by showing that funds' segmentation into groups with varying performance-orientation is observable through their families' decision to outsource services unrelated to portfolio management to external specialists.

This paper is also related to studies that investigate outsourcing activities of mutual funds. Specifically, funds that delegate their portfolio management to sub-advisors underperform internally managed funds (see, e.g., Chen et al., 2013, Debaere and Evans, 2014). The setting in this analysis is different from the one analyzed in the literature because it examines the implications from outsourcing of activities that are unrelated to portfolio management. To the best of my knowledge, this is the first paper to provide evidence for a relation between fund behavior and operations that are unrelated to portfolio management.

The remainder of this paper is organized as follows. In Section 3.2, I discuss the employed data set and sample summary statistics. Section 3.3 presents the findings on the relation between shareholder service outsourcing and performance. In Section 3.4, I present the results for a number of empirical techniques that are designed to rule out endogeneity concerns. Channels for the performance difference between service-outsourced funds and service-inhouse funds are presented in Section 3.5. Section 3.6 quantifies the comparative advantage that accrues to service-outsourced funds because of their focus on portfolio management. Section 3.7 concludes.

## 3.2 Data

### 3.2.1 Sources and sample construction

I obtain data on U.S. equity mutual funds between 1996 and 2010 from three sources: CRSP Survivor-Bias-Free U.S. Mutual Fund database, Thomson Mutual Fund Holdings database and funds' filings of SEC Form N-SAR.

From the CRSP Mutual Fund databases I obtain information on fund returns, total net assets under management (TNA), expense ratios, fund family identifier and other fund characteristics. Similar to the approach by Pástor and Stambaugh (2002) I assign a fund's investment objective based on the CRSP fund objective code. Since the focus is on actively managed U.S. domestic equity funds I take further steps to eliminate global, international, balanced, fixed-income and index funds. If necessary, I aggregate data of share classes to the fund level by weighting the information with the TNA of the share classes.

The Thomson Mutual Fund Holdings database provides information about funds' portfolio holdings on each reporting date. In addition, the holdings data is supplemented with information from the CRSP Monthly and Daily Stock Files whereby databases are merged using MFLINKS from Wermers (2000).

In accordance to the Investment Company Act of 1940 management companies need to file semi-annual N-SAR reports with the SEC that contain information on a variety of fund characteristics and their operations.[38] I merge the N-SAR database to CRSP similar to Christoffersen, Evans, and Musto (2013). Among the N-SAR information mutual funds report the name of their shareholder servicing agent during the period (Question 12A on N-SAR, i.e., Q12A).[39] I determine the outsourcing status of a mutual fund's shareholder service by manually checking whether the service provider in N-SAR is affiliated with the fund's management company reported in CRSP.[40] In some instances, mutual funds have more than one service provider. In that case, I classify a fund's shareholder service as outsourced if all service providers are unaffiliated to the management company. In addition, I obtain the funds' total dollar value spent on the shareholder servicing agent(s) (Q72I), the number of months that the expense information applies to (Q72A), and the average monthly net assets during the period (Q75B) from N-SAR. I calculate funds' monthly service fees by dividing the (monthly) dollar value spent on the servicing agent(s) (Q72I / Q72A) by the average monthly net assets during the period. Then I annualize the monthly estimate to obtain funds' annual shareholder servicing fees.

The final sample includes 697 fund families, 2,740 actively managed U.S. domestic equity funds and 19,871 fund-year observations.

[38] Starting in 1996 it became mandatory for mutual funds to file N-SAR reports with the SEC. Thus, to mitigate any selection bias, the sample period begins with the year 1996.

[39] Shareholder service providers are often labeled as 'Transfer Agent' or 'Shareholder Servicing Agent'. For ease of exposition I refer to them as service provider.

[40] Specifically, the classification of a fund's service outsourcing status is based on a two-step procedure: First, CRSP assigns fund family identifier based on the investment management company that manages the fund. Thus, before determining the service status, I manually cross-check whether the management company reported in CRSP is identical to the advisor reported in N-SAR (Q8A). If the provided information diverge I adjust the CRSP family identifier in accordance to the advisor in N-SAR. In a second step, I compare the name of the service provider in N-SAR with the management company in CRSP and screen for affiliations between both entities using information from the funds' 485APOS and 485BPOS SEC filings as well as LexisNexis.

### 3.2.2 Sample characteristics

Table 3.1 presents summary statistics on family and fund characteristics for the sample. Since the outsourcing decision is presumed to be a strategic decision at the family level I report the family statistics for the total sample and for both fund families that entirely consist of service-outsourced funds and fund families with no or partially outsourced shareholder services. All other information are at the fund level.

Table 3.1: Sample characteristics by service outsourcing status

| | Total | Outsourced | Inhouse | Difference |
|---|---|---|---|---|
| **Family characteristics:** | | | | |
| Fraction of service outsourced (%) | | 100.00 | 1.85 | |
| Number of families | 697 | 579 | 177 | |
| Family size (in million USD) | 4,014.43 | 1,302.67 | 12,098.94 | -10,796.27 *** |
| Number of funds in family | 3.91 | 2.59 | 7.84 | -5.24 *** |
| Family focus (%) | 75.04 | 80.35 | 59.21 | 21.14 *** |
| **Fund characteristics:** | | | | |
| Number of funds | 2,740 | 1,562 | 1,522 | |
| Fund size (in million USD) | 1,015.30 | 493.98 | 1,537.49 | -1,043.52 *** |
| Fund age (years) | 8.13 | 7.09 | 9.34 | -2.26 *** |
| Service fee (%) | 0.21 | 0.16 | 0.25 | -0.09 *** |
| Expense ratio (%) | 1.31 | 1.33 | 1.29 | 0.05 *** |
| Turnover ratio (%) | 104.64 | 98.39 | 110.90 | -12.51 *** |

Notes: This table reports descriptive statistics for the total sample (Total) and both funds that delegate their shareholder services to unaffiliated service providers (Outsourced) and funds that administer shareholder services internally (Inhouse). Fund family characteristics are reported for fund families that entirely consist of service-outsourced funds and those with no or partially service-outsourced funds. All other characteristics are reported at the fund level. Number of families, represents the number of families within each group. Family size, is the total net assets under management of the fund family in million USD. Number of funds in family, represents the number of funds within a fund family. Family focus, represents the concentration of a fund family across investment segments defined as in Siggelkow (2003). Number of funds, is the number of total funds and both the number of service-outsourced and service-inhouse funds. Fund size, represents the fund's total net assets under management in million USD. Fund age, is the fund's age in years. Service fee, represents the costs spent on shareholder servicing relative to total net assets under management. Expense ratio, is the fund's fees charged for total services. Turnover ratio, is the fund's yearly turnover. Family focus, Service fee, Expense ratio and Turnover ratio, are reported in percentage points. The last column of the table reports the difference in fund family and fund statistics between the outsourced and inhouse group. ***, **, * denote statistical significance for the difference in means between both groups at the 1%, 5%, and 10% significance level, respectively.

On aggregate service-outsourced funds constitute about 57 percent of the sample. In addition, consistent with the view of outsourcing as a strategic decision of management companies, outsourcing is highly concentrated within fund families, i.e., among families that do not entirely consist of service-outsourced funds only 1.85 percent of the funds receive shareholder services from unaffiliated service providers. Looking at fund family size, I observe that families with outsourced shareholder services are much smaller. In addition, the typical fund family in our sample consists of roughly 4 actively managed U.S. domestic equity funds. However, consistent with the difference in size, fund families with unaffiliated service providers consist of a smaller number of funds. Likewise service-outsourced funds are smaller ($0.5 billion vs. $1.5 billion) and younger (7.1 years vs. 9.3 years) than service-inhouse funds. Looking at shareholder servicing costs, service-inhouse funds exhibit expenses that amount to 25 basis points per year and are about 9 basis points higher than for service-outsourced funds.

## 3.3 Main result

In this section I explore the main hypothesis that service-outsourced funds perform better than service-inhouse funds because they pursue a stronger portfolio management-oriented policy. I test this relation in Section 3.3.1. Section 3.3.2 provides additional robustness checks for measures documented in the literature that proxy for funds' focus on portfolio management.

### 3.3.1 Service outsourcing and fund performance

In this section I study the relation between funds' service outsourcing status and fund performance. To analyze the impact of service outsourcing on mutual fund performance, I run a panel regression model:

$$\begin{aligned} Performance_{i,t} = &\alpha_0 + \beta Service\ outsourced_{i,t} + \gamma_1 Ln\ TNA\ family_{i,t-1} \\ &+ \gamma_2 Family\ focus_{i,t-1} + \gamma_3 Ln\ TNA_{i,t-1} + \gamma_4 Ln\ age_{i,t} \\ &+ \gamma_5 Expense\ ratio_{i,t} + \gamma_6 Turnover\ ratio_{i,t} \\ &+ \alpha_s + \alpha_t + \epsilon_{i,t}, \end{aligned} \tag{3.1}$$

where the dependent variable, *Performance*, is the performance of fund $i$ in year $t$ measured as a fund's net-of-fee return, Khorana (1996) objective-adjusted return, Jensen (1968) alpha, and Carhart (1997) 4-factor alpha. Alpha estimations are based on 12-month window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable, *Service outsourced*, is a binary variable that equals one if the service provider of fund $i$ is unaffiliated to its management company in year $t$ and zero otherwise. To control for potential family and fund influences I include the logarithm of the fund family's total net assets under management (*Ln TNA family*), the investment concentration of a fund family across investment segments defined as in Siggelkow (2003) (*Family focus*), the logarithm of the fund's total net assets under management (*Ln TNA*), the logarithm of the fund's age in years (*Ln age*), the expense ratio of a fund (*Expense ratio*), and the fund's yearly turnover ratio (*Turnover ratio*). In addition, I add investment segment and year fixed effects, denoted by $\alpha_s$ and $\alpha_t$ respectively, to control for any unobservable segment and time effects. Furthermore, because service outsourcing is a strategic fund family decision, I cluster standard errors at the family level to account for possible correlations within family groups.

Table 3.2: Service outsourcing and fund performance

| Dependent variable: | Return | OAR | Jensen | Carhart |
|---|---|---|---|---|
| Service outsourced | 0.0070 *** | 0.0073 *** | 0.0062 ** | 0.0039 * |
| | (0.0060) | (0.0075) | (0.0114) | (0.0900) |
| Ln TNA family | 0.0044 *** | 0.0047 *** | 0.0034 *** | 0.0023 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0001) |
| Family focus | 0.0153 *** | 0.0150 ** | 0.0137 ** | 0.0088 * |
| | (0.0052) | (0.0132) | (0.0112) | (0.0617) |
| Ln TNA | -0.0079 *** | -0.0076 *** | -0.0050 *** | -0.0024 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0002) |
| Ln age | 0.0109 *** | 0.0090 *** | 0.0051 *** | -0.0017 |
| | (0.0000) | (0.0000) | (0.0008) | (0.1895) |
| Expense ratio | -1.1998 *** | -0.7903 *** | -1.0074 *** | -0.9708 *** |
| | (0.0000) | (0.0056) | (0.0001) | (0.0002) |
| Turnover ratio | -0.0021 ** | -0.0009 | -0.0015 ** | -0.0015 |
| | (0.0171) | (0.3880) | (0.0165) | (0.1478) |
| Segment fixed effects | Yes | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 19,871 | 19,871 | 19,871 | 19,871 |
| Adj. $R^2$ | 0.7250 | 0.0051 | 0.1508 | 0.1049 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of service outsourcing on mutual fund performance using four different performance measures: Fund return (Return), Khorana (1996) objective-adjusted return (OAR), Jensen (1968) alpha (Jensen), and Carhart (1997) 4-factor alpha (Carhart). Alpha estimations are based on 12-month window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. Additional independent controls include Ln TNA family, Family focus, Ln TNA, Ln age, Expense ratio, and Turnover ratio. Ln TNA family, is the logarithm of the fund family's total net assets under management. Family focus, represents the concentration of a fund family across investment segments defined as in Siggelkow (2003). Ln TNA, represents the logarithm of the fund's total net assets under management. Ln TNA family, Family focus, Ln TNA are all lagged by one year. Ln age, is the logarithm of the fund's age in years. Expense ratio, represents the fund's total expense ratio. Turnover ratio is the fund's yearly turnover ratio. Regressions are run with segment and year fixed effects. P-values reported in parentheses are based on robust standard errors clustered at the fund family level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Results reported in Table 3.2 confirm the main hypothesis that service-outsourced funds exhibit superior performance relative to their inhouse peers independent of the employed performance benchmark. In particular, the performance difference is most pronounced for fund returns and Khorana (1996) objective-adjusted returns with, respectively, 70 basis points and 73 basis points per year. Using alpha performance metrics the difference declines to 62 basis points for the Jensen (1968) alpha and 39 basis points for the Carhart (1997) 4-factor alpha, however, all coefficients are significant at the conventional levels of statistical significance.

Regarding the control variables, the results are consistent with the existing literature. Confirming the findings of Chen et al. (2004) and Siggelkow (2003) I find a positive impact of fund family size and family focus on fund performance. On the contrary, fund size and turnover ratio impact negatively on performance as described in Berk and Green (2004) and Carhart (1997), respectively.

### 3.3.2 Service outsourcing and alternative measures for funds' portfolio management focus

In this section I explore the possibility that funds' service-outsourcing status accidentally captures the effect of an alternative measure for an emphasis on portfolio management documented in the literature.

First, a growing number of studies examine the distribution channel of mutual funds and show that funds that are marketed directly to fund investors outperform funds that are sold through financial advisors (see, e.g., Bergstresser, Chalmers, and Tufano, 2009, Chalmers and Reuter, 2015). Del Guercio and Reuter (2014) suggest that this performance difference is attributable to the market segmentation of fund families that cater to sophisticated do-it-yourself investors who purely value portfolio management, i.e., the direct channel of mutual funds, and those families that attract investors who demand advisory services, i.e., the brokered distribution channel of mutual funds. Thus, service-outsourcing could capture this kind of market segmentation. For example, fund families that decide to compete for performance-oriented direct channel investors could use service outsourcing as a means to achieve their goals, while families of the brokered channel that cater to investors' service needs are also the ones that decide against service outsourcing. Second, mutual funds can opt to complement their portfolio management expertise by hiring portfolio sub-advisors. However, Chen et al. (2013) show that sub-advised funds underperform internally managed funds. Moreover, since service-inhouse funds are presumed to put less emphasis on portfolio management they are prone to employ portfolio sub-advisors. Thus, service outsourcing potentially captures the performance difference of this sub-advisor effect.

To rule out the possibility that the observed performance effect of service-outsourced funds is attributable to both concerns, I repeat the analysis from Table 3.2 and explicitly control for funds' distribution channel and use of sub-advisors. In particular, I obtain data on the primary distribution channel of U.S. domestic equity fund shares from Thomson Reuters Lipper (Lipper). Lipper assigns each fund share class either to the direct, indirect, or institutional distribution channel. Since the Lipper classification is at the share class level I define a fund's distribution channel based on the share's channel that encompasses at least 50 percent of the fund's assets similar to Del Guercio, Reuter, and Tkac (2010) and Del Guercio and Reuter (2014). In addition, to ensure comparability to related studies, I eliminate all fund-year observations that belong to the institutional channel from this analysis.

Regarding funds' employment of portfolio sub-advisors I identify the existence and the name of mutual funds' sub-advisors using information from item Q8A and Q8B in the N-SAR reports filed with the SEC.[41] Since some mutual funds have multiple sub-advisors I follow the example by Chen et al. (2013) and consider a fund as sub-advised if the fund hires at least one sub-advisor.

Table 3.3: Service outsourcing and alternative measures for a portfolio management focus

| Dependent variable: | Return | OAR | Jensen | Carhart |
|---|---|---|---|---|
| Service outsourced | 0.0102 *** | 0.0093 *** | 0.0080 *** | 0.0045 * |
| | (0.0015) | (0.0067) | (0.0083) | (0.0929) |
| Direct channel | 0.0028 | 0.0056 * | 0.0020 | -0.0002 |
| | (0.3642) | (0.0828) | (0.4981) | (0.9473) |
| Advisor outsourced | -0.0050 | -0.0062 ** | -0.0055 ** | -0.0025 |
| | (0.1128) | (0.0426) | (0.0491) | (0.3199) |
| Ln TNA family | 0.0044 *** | 0.0044 *** | 0.0034 *** | 0.0025 *** |
| | (0.0000) | (0.0000) | (0.0002) | (0.0018) |
| Family focus | 0.0097 | 0.0095 | 0.0070 | 0.0048 |
| | (0.1929) | (0.2155) | (0.3352) | (0.4583) |
| Ln TNA | -0.0087 *** | -0.0080 *** | -0.0057 *** | -0.0029 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0008) |
| Ln age | 0.0112 *** | 0.0088 *** | 0.0047 ** | -0.0019 |
| | (0.0000) | (0.0001) | (0.0162) | (0.2643) |
| Expense ratio | -1.1485 *** | -0.6765 | -1.2646 *** | -1.3374 *** |
| | (0.0068) | (0.1012) | (0.0023) | (0.0008) |
| Turnover ratio | -0.0025 ** | -0.0020 ** | -0.0020 *** | -0.0016 |
| | (0.0106) | (0.0223) | (0.0009) | (0.1571) |
| Segment fixed effects | Yes | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 12,879 | 12,879 | 12,879 | 12,879 |
| Adj. $R^2$ | 0.7193 | 0.0070 | 0.1454 | 0.0964 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of service outsourcing on mutual fund performance using four different performance measures: Fund return (Return), Khorana (1996) objective-adjusted return (OAR), Jensen (1968) alpha (Jensen), and Carhart (1997) 4-factor alpha (Carhart). Alpha estimations are based on 12-month window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The sample is restricted to the observations that belong to funds that are marketed either directly to investors or brokered through financial advisors. I classify a fund as belonging to the direct (indirect) distribution channel based on the classification provided by Thomson Reuters Lipper. The main independent variable is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. Additional independent controls include: Direct channel and Advisor outsourced. Direct channel, a binary variable that equals one if the fund is marketed directly to fund investors and zero otherwise. Advisor outsourced, a binary variable that equals one if the fund has at least one sub-advisor and zero otherwise similar to Chen et al. (2013). Other independent variables and fixed effects are defined as in Table 3.2. P-values reported in parentheses are based on robust standard errors clustered at the fund family level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

[41] For earlier studies that follow the same approach see, e.g., Kuhnen (2009) and Debaere and Evans (2014).

Results from Table 3.3 confirm the performance effects associated with the alternative measures for a varying portfolio management focus of funds. Consistent with the results of Bergstresser, Chalmers, and Tufano (2009) and Del Guercio and Reuter (2014) I find a positive performance difference between funds that are direct-sold relative to those funds that are distributed via financial advisors. Furthermore, funds' use of sub-advisors impacts negatively on fund performance confirming the finding of Chen et al. (2013) and Debaere and Evans (2014). However, controlling for funds' distribution channel and use of sub-advisors does not dampen the outperformance of service-outsourced funds. In fact, the results gain in statistical and economic significance. The difference in net-of-fee returns between service-outsourced and service-inhouse funds amounts to 102 basis points per year. For risk-adjusted performance measures the difference is about 93 basis points for Khorana (1996) objective-adjusted returns, 80 basis points for the Jensen (1968) alpha, and 45 basis points for the Carhart (1997) 4-factor alpha.

Overall, the results of Section 3.3 support the main hypothesis that service-outsourced funds outperform service-inhouse funds. Thus, evidence is consistent with the notion that funds of families that delegate the execution of non-core tasks to external providers also put a stronger focus on their actual field of expertise and perform better.

## 3.4 Endogeneity concerns

In this section I implement a number of empirical techniques to address potential endogeneity concerns for the outperformance of service-outsourced funds relative to service-inhouse funds. Specifically, in Section 3.4.1, I start with a panel regression model that includes family fixed effects to eliminate unobservable family influences. Section 3.4.2 provides evidence from a matched sample analysis that eliminates heterogeneity by selecting a more comparable control group of service-inhouse funds. Results in Section 3.4.3 are based on a permutation test and Section 3.4.4 presents results of an instrumental variable approach.

### 3.4.1 Panel regression with family fixed effects

I begin my analysis by running panel regressions to investigate the impact of service outsourcing on fund performance and include fixed effects at the fund family level. In particular, since service outsourcing is a strategic decision at the fund family level it could be that unobservable differences between fund families that delegate shareholder services to external service providers and those that administer these services internally drive the performance difference between service-outsourced funds and service-inhouse funds. Hence, in a perfect experiment I would compare the performance of a fund which belongs to a fund family that sources shareholder services externally in a specific year to the performance of the fund in the same family in the same year but when shareholder services are administered internally. An empirical strategy that effectively allows to investigate the performance difference between service-outsourced funds and service-inhouse funds within the same fund family is to include family fixed effects.[42]

Table 3.4: Service outsourcing and fund performance with family fixed effects

| Dependent variable: | Return | OAR | Jensen | Carhart |
|---|---|---|---|---|
| Service outsourced | 0.0214 ** | 0.0165 * | 0.0132 * | 0.0090 * |
| | (0.0182) | (0.0510) | (0.0803) | (0.0650) |
| Ln TNA family | -0.0162 *** | -0.0175 *** | -0.0115 *** | -0.0064 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0002) |
| Family focus | 0.0060 | 0.0073 | -0.0026 | -0.0045 |
| | (0.6151) | (0.6085) | (0.8274) | (0.6738) |
| Ln TNA | -0.0104 *** | -0.0100 *** | -0.0072 *** | -0.0036 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Ln age | 0.0166 *** | 0.0140 *** | 0.0088 *** | 0.0006 |
| | (0.0000) | (0.0000) | (0.0000) | (0.6863) |
| Expense ratio | -0.4107 | -0.2844 | -0.8183 ** | -0.5071 |
| | (0.2640) | (0.4985) | (0.0312) | (0.1318) |
| Turnover ratio | -0.0015 * | -0.0006 | -0.0006 | 0.0002 |
| | (0.0685) | (0.6544) | (0.4695) | (0.8119) |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 19,871 | 19,871 | 19,871 | 19,871 |
| Adj. $R^2$ | 0.7345 | 0.0287 | 0.1731 | 0.1289 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of service outsourcing on mutual fund performance using four different performance measures: Fund return (Return), Khorana (1996) objective-adjusted return (OAR), Jensen (1968) alpha (Jensen), and Carhart (1997) 4-factor alpha (Carhart). Alpha estimations are based on 12-month window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. In addition, regressions are run with family fixed effects to control for any unobservable heterogeneity across families. Other independent variables and fixed effects are defined as in Table 3.2. P-values reported in parentheses are based on robust standard errors clustered at the fund family level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Results from Table 3.4 clearly support the main finding of the earlier tests. Independent of the performance benchmark service-outsourced funds outperform service-inhouse funds. In fact, the performance difference becomes even larger up to 214 basis points per year for funds' net-of-fee returns. Levels of statistical significance decrease to the 5 percent and 10 percent level

[42] Note that, in this and subsequent analyses, I employ the (full) sample as in Table 3.2. However, as an additional check I repeat the analysis including all additional controls from the alternative explanations of Section 3.3.2, i.a., the sample is restricted to the observations that belong to funds that are marketed either directly to investors or brokered through financial advisors. The results (not reported) are qualitatively the same.

which is to be expected since in these specifications identification on the coefficient of *Service outsourced* comes from changes in the sourcing status of some fund families. In this regard less than 10 percent of the 697 fund families experience a change in the sourcing status of their shareholder services over the sample period.

### 3.4.2 Matched sample analysis

An alternative means to deal with unobserved heterogeneity that impacts on the performance difference between service-outsourced and service-inhouse funds is to ensure that the set of control funds represents a close as possible match to the service-outsourced funds. Hence, I apply a matched sample analysis that constructs a set of control groups that represent a more comparable subsample. Specifically, each service-outsourced fund is matched with an equally weighted portfolio of service-inhouse funds that share the same characteristics. In the base model I match a service-outsourced fund to all service-inhouse funds that belong to the same investment segment and *Ln TNA family* decile in a certain year. I select *Ln TNA family* as the dominant matching criterion to account for the fact that service outsourcing is a strategic decision at the family level as well as that service-outsourced and service-inhouse funds belong to families that on average strongly differ with respect to size as described in Section 3.2.2.

Table 3.5: Matched sample analysis

| | | Dependent variable: | | |
|---|---|---|---|---|
| Matching characteristics | Observation | Return | Jensen | Carhart |
| Year, Segment, and Ln TNA family | 9,951 | 0.0114 *** | 0.0101 *** | 0.0073 *** |
| | | (0.0000) | (0.0000) | (0.0000) |
| Year, Segment, Ln TNA family, and Family focus | 5,173 | 0.0097 *** | 0.0085 *** | 0.0069 *** |
| | | (0.0000) | (0.0000) | (0.0001) |
| Year, Segment, Ln TNA family, and Ln TNA | 6,665 | 0.0101 *** | 0.0089 *** | 0.0074 *** |
| | | (0.0000) | (0.0000) | (0.0000) |
| Year, Segment, Ln TNA family, and Ln age | 5,827 | 0.0057 *** | 0.0050 *** | 0.0031 * |
| | | (0.0002) | (0.0048) | (0.0717) |
| Year, Segment, Ln TNA family, and Expense ratio | 5,772 | 0.0090 *** | 0.0086 *** | 0.0044 *** |
| | | (0.0000) | (0.0000) | (0.0000) |
| Year, Segment, Ln TNA family, and Turnover ratio | 5,462 | 0.0089 *** | 0.0093 *** | 0.0082 *** |
| | | (0.0000) | (0.0000) | (0.0000) |

Notes: This table presents results from a matched sample analysis where each service-outsourced fund is matched with an equally weighted portfolio of service-inhouse funds using the following matching criteria: Year, Segment, Ln TNA family, Family focus, Ln TNA, Ln age, Expense ratio and Fund turnover. In the first row, service-outsourced funds are matched to all service-inhouse funds that belong to the same segment and the same Ln TNA family decile in a certain year. In rows two through six the decile ranking based on Family focus, Ln TNA, Ln age, Expense ratio and Turnover ratio are used as additional matching criterion. Then performance differences between service-outsourced funds and the corresponding inhouse matching portfolio are tested for the performance measures Fund return (Return), Jensen (1968) alpha (Jensen), and Carhart (1997) 4-factor alpha (Carhart). ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

I account for other family and fund influences by extending the baseline match with other controls from Section 3.3.1 that have also been documented to impact on fund performance (see, e.g., Carhart, 1997, Siggelkow, 2003, Berk and Green, 2004, Chen et al., 2004, Ferreira et al., 2013). Thus, in additional tests I link service-outsourced funds to all service-inhouse funds that, respectively, belong to the same *Family focus*, *Ln TNA*, *Ln age*, *Expense ratio* or *Turnover ratio* decile. Finally, I measure performance differences between service-outsourced funds and the corresponding service-inhouse matching portfolio for the performance measures: net-of-fee fund return, Jensen (1968) alpha, and Carhart (1997) 4-factor alpha.

The results from Table 3.5 clearly confirm the results from Table 3.2. Independent of the employed performance measure service-outsourced funds outperform their comparable service-inhouse funds by up to 114 basis points per year on average. In addition, the coefficients are in 17 out of 18 specifications significant at the 1 percent level.

### 3.4.3 Permutation test

Another approach to rule out the possibility that the performance effect of service-outsourcing is attributable to an omitted factor is to apply a permutation test. Specifically, the permutation test requires to assign the outsourcing status to funds' shareholder services randomly and then to measure the multivariate performance difference between service-outsourced funds and service-inhouse funds. This process is repeated 10,000 times which yields the exact distribution of performance differences under the null hypothesis that the service outsourcing status does not matter. Accordingly, p-values are equal to the fraction of permutations that show an effect that are as strong as the performance difference observed in Table 3.2.

Table 3.6: Permutation test for the impact of funds' shareholder service outsourcing status on performance

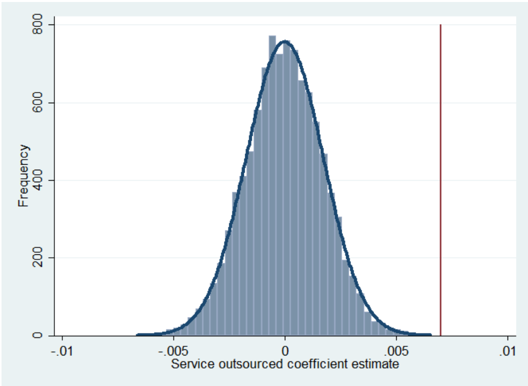
**Panel A: Regression results**

| Dependent variable: | Return | OAR | Jensen | Carhart |
|---|---|---|---|---|
| Service outsourced | 0.0070 *** | 0.0073 *** | 0.0062 *** | 0.0039 *** |
| | (0.0000) | (0.0001) | (0.0002) | (0.0099) |
| Fund and family controls | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 19,871 | 19,871 | 19,871 | 19,871 |
| Permutations | 10,000 | 10,000 | 10,000 | 10,000 |

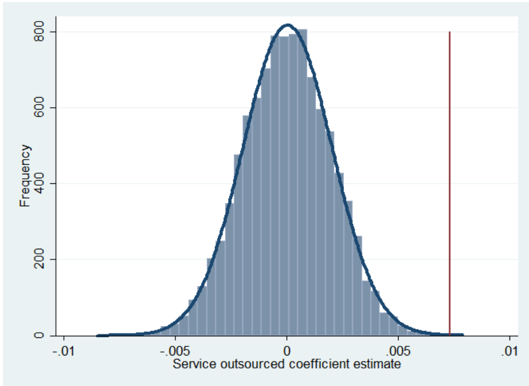
(*Continued*)

Table 3.6: Permutation test for the impact of funds' shareholder service outsourcing status on performance (Continued)

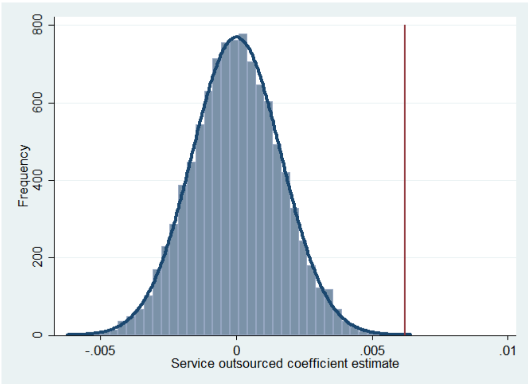
**Panel B: Distribution of performance differentials**



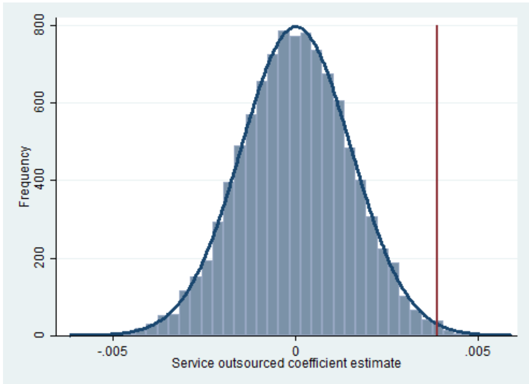

(a) Return




(b) OAR




(c) Jensen




(d) Carhart

Notes: This table presents results from a permutation test that investigates the impact of service outsourcing on mutual fund performance using four different performance measures: Fund return (Return), Khorana (1996) objective-adjusted return (OAR), Jensen (1968) alpha (Jensen), and Carhart (1997) 4-factor alpha (Carhart). Alpha estimations are based on 12-month window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. In particular, the outsourcing status of shareholder services is randomly assigned to funds and the performance difference measured between service-outsourced funds and service-inhouse funds. This process is repeated 10,000 times. In Panel A, I report the regression results of the permutation tests and Panel B shows the distribution of the performance differentials. The main independent variable in both panels is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. Other independent variables and fixed effects are defined as in Table 3.2 and not reported for brevity. P-values reported in parentheses represent the fraction of permutations that show an effect that is at least as strong as the performance difference observed in Table 3.2. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

As expected, results from Panel A of Table 3.6 strongly support earlier findings that service-inhouse funds underperform service-outsourced funds. Specifically, the coefficient on *Service outsourced* is significant at the 1 percent level in all specifications. For illustration purposes Panel B of Table 3.6 shows the empirical distribution of performance differences across all permutations. From that, one can see that the performance effect is indeed normally distributed under the null that service outsourcing has no effect but that only very few iterations yield performance differences between service-inhouse funds and service-outsourced funds that are comparable to the ones from Table 3.2.

### 3.4.4 Instrumental variable regression

As a final identification strategy to establish causality I implement an instrumental variable approach. As an instrument for funds' outsourcing status I employ the number of service companies that render shareholder services in the state where the fund's management company is located. To be considered as a good instrument the number of service providing companies in the state of the fund's management company needs to be correlated with funds' service outsourcing status but correlated with fund performance solely because of the outsourcing decision. I propose that the number of service providing companies serves as such a good instrument since I expect fund families to be more likely to delegate the execution of shareholder services to an external provider if the competition among external service providers is high, i.e., the number of available external providers in the proximity of the fund's management company is high.

I identify the state where funds' management companies are located using information from item Q8D in the N-SAR reports filed with the SEC. Since the dependent variable *Service outsourced* is a binary variable that equals one if the service provider of fund $i$ is unaffiliated to its management company in year $t$ and zero otherwise, I employ a two-stage residual inclusion (2SRI) model as in Chen et al. (2013). The first-stage specification is:

$$\begin{aligned} \textit{Service outsourced}_{i,t} = &\alpha_0 + \beta \textit{Number service providers in state}_{i,t} \\ &+ \gamma_1 \textit{Ln TNA family}_{i,t-1} + \gamma_2 \textit{Family focus}_{i,t-1} \\ &+ \gamma_3 \textit{Ln TNA}_{i,t-1} + \gamma_4 \textit{Ln age}_{i,t} \\ &+ \gamma_5 \textit{Expense ratio}_{i,t} + \gamma_6 \textit{Turnover ratio}_{i,t} \\ &+ \alpha_s + \alpha_t + \epsilon_{i,t}, \end{aligned} \tag{3.2}$$

whereby the main independent variable, *Number service providers in state*, represents the logarithm of 1 plus the number of service companies that render shareholder services in the state where the management company of fund $i$ is located in year $t$. The remaining control variables are defined as in Table 3.2. In addition, the first-stage regression includes investment segment and year fixed effects and standard errors that are clustered at the fund family level.

The results of Table 3.7 confirm the notion of a significantly positive impact of the competition among service providers on fund families' decisions to source shareholder services externally. Specifically, the coefficient on *Number service providers in state* suggests that a one-standard

Table 3.7: First stage of 2SRI – The impact of the number of service providing companies located in the state of the fund's management company on outsourcing

| Dependent variable: | Service outsourced |
|---|---|
| Number service providers in state | 0.5804 *** |
| | (0.0070) |
| | [14.3112] |
| Ln TNA family | -0.6578 *** |
| | (0.0000) |
| | [-16.2192] |
| Family focus | 1.4289 ** |
| | (0.0106) |
| | [35.2311] |
| Ln TNA | 0.0925 * |
| | (0.0772) |
| | [2.281] |
| Ln age | -0.3563 *** |
| | (0.0004) |
| | [-8.7849] |
| Expense ratio | -67.1623 *** |
| | (0.0050) |
| | [-16.5602] |
| Turnover ratio | -0.1014 * |
| | (0.0854) |
| | [-2.500] |
| Segment fixed effects | Yes |
| Year fixed effects | Yes |
| Number of observations | 18,302 |
| Pseudo $R^2$ | 0.3050 |

Notes: This table presents results from the logit first-stage regression of the 2SRI estimation of the effect of service outsourcing on performance. The first-stage regression measures the effect of the competitive environment among service providing companies on whether the mutual fund sources shareholder services externally. The dependent variable is the binary variable Service outsourced that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. The main independent variable is Number service providers in state, which represents the number of service companies that provide external shareholder services in the state that the fund's management company is located. Other independent variables and fixed effects are defined as in Table 3.2. P-values reported in parentheses are based on robust standard errors clustered at the fund family level. Average marginal effects in percentages are shown in square brackets. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

deviation increase in the log number of services companies who do business in the state of the fund's management company (0.5886) increases the likelihood that the funds delegate their shareholder services to an external provider by about 8.42 (14.3112 $\times$ 0.5886) percentage points.

In the second-stage I regress funds' performance on the binary variable *Service outsourced* and include the residual from the first-stage regression (*First stage residual*) as additional independent variable.

The results of the second-stage regressions show a strong and significantly positive impact of *Service outsourced* on fund performance. In particular, controlling for endogeneity, service-outsourced funds outperform their internally administered peers by 179 for funds' net-of-fee

Table 3.8: Second stage of 2SRI – The impact of service outsourcing on fund performance

| Dependent variable: | Return | OAR | Jensen | Carhart |
|---|---|---|---|---|
| Service outsourced | 0.0179 * | 0.0253 ** | 0.0186 * | 0.0191 ** |
| | (0.0934) | (0.0291) | (0.0687) | (0.0368) |
| First stage residual | -0.0116 | -0.0188 | -0.0134 | -0.0158 * |
| | (0.2896) | (0.1176) | (0.2026) | (0.0939) |
| Ln TNA family | 0.0056 *** | 0.0065 *** | 0.0046 *** | 0.0040 *** |
| | (0.0000) | (0.0000) | (0.0002) | (0.0006) |
| Family focus | 0.0146 *** | 0.0131 ** | 0.0120 ** | 0.0065 |
| | (0.0059) | (0.0193) | (0.0141) | (0.1404) |
| Ln TNA | -0.0082 *** | -0.0081 *** | -0.0051 *** | -0.0026 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0002) |
| Ln age | 0.0118 *** | 0.0104 *** | 0.0057 *** | -0.0009 |
| | (0.0000) | (0.0000) | (0.0002) | (0.4779) |
| Expense ratio | -0.9533 *** | -0.4832 | -0.7786 *** | -0.8468 *** |
| | (0.0018) | (0.1362) | (0.0081) | (0.0013) |
| Turnover ratio | -0.0020 *** | -0.0008 | -0.0013 * | -0.0012 * |
| | (0.0048) | (0.4403) | (0.0692) | (0.1000) |
| Segment fixed effects | Yes | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 18,302 | 18,302 | 18,302 | 18,302 |
| Adj. $R^2$ | 0.7283 | 0.0051 | 0.1471 | 0.1025 |

Notes: This table presents results from the second-stage regression of the 2SRI estimation of the effect of service outsourcing on performance. The main independent variable is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. Additional independent controls include: First stage residual, the residual from the first stage logit regression of the 2SRI estimation from Table 3.7. Other independent variables and fixed effects are defined as in Table 3.2. P-values reported in parentheses are based on robust standard errors clustered at the fund family level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

returns, 253 basis points for Khorana (1996) objective-adjusted returns, 186 basis points for the Jensen (1968) alpha, and 191 basis points for the Carhart (1997) 4-factor alpha.

Taken together, results of Table 3.8 provide further support to the idea that funds whose families eliminate responsibilities in a non-core area also put a focus on portfolio management. In fact, the outperformance is not only robust to the instrumental variable test but becomes even larger when controlled for endogeneity.

## 3.5 Potential channels for the performance effect of service outsourcing

Building on the robust finding that service-outsourced funds outperform service-inhouse funds, I study potential channels through which the pronounced portfolio management focus of funds that belong to families with delegated shareholder services affects performance. Specifically, one can think of two possible mechanisms that impact on funds' performance.

First, service-outsourcing could impact on fund performance directly since it affects fund expenses. In particular, the reliance of service-outsourced funds on external service providers' comparative advantage in rendering these services could allow them to source shareholder services at lower costs which in turn lessens the strain on net-of-fee returns. Thus, the first group of measures that investigates potential channels of a relation between service outsourcing and performance consists of funds' service fees and expense ratios. Mutual funds' service fees are calculated as described in Section 3.2.1 using information from N-SAR while information on funds' expense ratios are obtained from CRSP.

Second, since fund families' strategic decision to eliminate responsibilities in non-core fund activities is associated with a focus on portfolio management of its member funds, I expect to observe a positive relation between the service sourcing status and measures on superior investment skills. Specifically, the employed skill measures consists of funds' active share (Cremers and Petajisto, 2009, Petajisto, 2013), return gap (Kacperczyk, Sialm, and Zheng, 2008), industry concentration (Kacperczyk, Sialm, and Zheng, 2005) and the $R^2$ measure (Amihud and Goyenko, 2013). Thereby, active share is estimated as the deviation of funds' stock portfolio weights from the stocks' weights in the benchmark portfolio of the funds. Hence, active share detects investment skill based on funds' under- or overweighting of the benchmark portfolios' stocks (Cremers and Petajisto, 2009).[43] Return gap is calculated as the difference between the gross-of-fee return and the hypothetical return of the recently reported holdings of the fund and captures superior investment decisions unreported to the public (Kacperczyk, Sialm, and Zheng, 2008). Kacperczyk, Sialm, and Zheng (2005) show that funds with more concentrated portfolios in terms of industry diversification perform better which suggests that these funds have managers with superior investment abilities. Finally, the 1-$R^2$ selectivity measure from Amihud and Goyenko (2013), obtained from fund return regressions on the risk factors suggested by the Carhart (1997) 4-factor model, predicts better future fund performance since these funds seem to take more profitable idiosyncratic bets.

Results from Table 3.9 show evidence clearly in favor of both channels how service outsourcing is related to the superior performance of service-outsourced funds. In particular, consistent with the first mechanism, service-outsourced funds exhibit service fees that are 8 basis points lower than service fees of service-inhouse funds. To put this number into perspective it is important to note that service-inhouse funds have service fees of about 25 basis points per year.

[43] I obtain the data on the active share information of mutual funds from the website of Antti Petajisto: http://www.petajisto.net/index.html.

Table 3.9: Mechanisms for the performance impact of service outsourcing

| Dependent variable: | Service fee | Expense Ratio | Active share | Return Gap | Industry concentration | 1-$R^2$ |
|---|---|---|---|---|---|---|
| Service outsourced | -0.0008 *** | -0.0012 *** | 0.0378 *** | 0.0002 * | 0.0083 *** | 0.0093 ** |
| | (0.0000) | (0.0010) | (0.0000) | (0.0808) | (0.0023) | (0.0122) |
| Ln TNA family | 0.0001 | -0.0003 *** | -0.0005 | 0.0002 *** | 0.0000 | -0.0007 |
| | (0.1917) | (0.0008) | (0.8199) | (0.0002) | (0.9721) | (0.4608) |
| Family focus | 0.0000 | 0.0012 * | 0.0974 *** | -0.0003 | 0.0213 *** | 0.0270 *** |
| | (0.9004) | (0.0875) | (0.0000) | (0.2155) | (0.0015) | (0.0022) |
| Ln TNA | -0.0001 ** | -0.0005 *** | -0.0070 *** | -0.0001 ** | 0.0004 | -0.0032 *** |
| | (0.0408) | (0.0000) | (0.0027) | (0.0190) | (0.5872) | (0.0013) |
| Ln age | 0.0002 *** | -0.0001 | 0.0160 *** | -0.0001 | 0.0035 ** | 0.0088 *** |
| | (0.0023) | (0.6756) | (0.0008) | (0.4325) | (0.0461) | (0.0002) |
| Expense ratio | | | 8.2636 *** | -0.0052 | 1.7183 *** | 1.7870 *** |
| | | | (0.0000) | (0.7478) | (0.0000) | (0.0016) |
| Turnover ratio | 0.0000 | 0.0001 | -0.0051 | 0.0000 | 0.0029 *** | 0.0003 |
| | (0.5616) | (0.1982) | (0.4756) | (0.6975) | (0.0023) | (0.7360) |
| Segment fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 19,562 | 19,562 | 12,797 | 15,606 | 16,758 | 19,871 |
| Adj. $R^2$ | 0.0650 | 0.2232 | 0.3789 | 0.0264 | 0.7040 | 0.3742 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of service outsourcing on fund expenses and measures of active management. The group of measures on fund expenses includes Service fee and Expense ratio. Service fee, represents the costs spent on shareholder servicing relative to total net assets under management. Expense ratio, represents the fund's total expense ratio. The group of measures on active management includes Active share, Return Gap, Industry concentration, and 1-$R^2$. Active share, measures the difference between the stock's portfolio weights in the fund and the portfolio weights of the stocks in the fund's benchmark portfolio. Return gap, is the difference between the actual gross-of-fee fund return and the hypothetical return of the recently reported fund holdings as in Kacperczyk, Sialm, and Zheng (2008). Industry concentration, is the concentration of funds' stock positions across industries as in Kacperczyk, Sialm, and Zheng (2005). 1-$R^2$, is the selectivity measure of Amihud and Goyenko (2013) that is obtained from 12-month window regressions of funds' net-of-fee excess returns on the excess market return and the SMB, HML, and MOM (momentum) factors as in the Carhart (1997) 4-factor model. The main independent variable is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. Other independent variables, added as needed, and fixed effects are defined as in Table 3.2. P-values reported in parentheses are based on robust standard errors clustered at the fund family level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

In other words, service fees of service-outsourced funds are 32 percent lower, consistent with outsourcing as an effective means to exploit potentials for cost reductions in non-core activities of mutual funds. Relatedly, the coefficient on *Service outsourced* suggests that service-outsourced funds have total expense ratios that are lower by about 12 basis points per year. This corresponds to a difference of approximately 10 percentage points in a typical fund's expense ratio.

Moreover, Table 3.9 provides support for the second hypothesized mechanism. Specifically, the main independent variable *Service outsourced* is significantly positive related to all four measures for active management. In addition, these effects are not only statistically significant but matter also from an economical point of view. For instance, service-outsourced funds exhibit values for industry concentrations and 1-$R^2$ that are, on average, 83 basis points and 93 basis points higher. This corresponds to a difference of about 11.81 percentage points and 10.33 percentage points, respectively, relative to a typical service-inhouse fund.

In summary, the results of this set of tests are in favor of the hypothesis that service-outsourced funds can be associated with superior investment skills. This provides further support to the idea that the service outsourcing status of funds indicates an emphasis on portfolio management.

## 3.6 Service outsourcing and fund flows

Earlier results show that service outsourcing can take effect on funds' performance results in the form of a direct influence through cost reductions as well as in the form of a pursuit of superior investment strategies. Both effects are in line with the literature on industrial organization which suggests that companies should eliminate responsibilities in non-core tasks and focus on their core activities to be successful in the market (Prahalad and Hamel, 1990). Thus, in this section I quantify the benefits accruing to service-outsourced funds because of their emphasis on their core business and how this is attributable to the two channels outlined above. Moreover, I measure the degree of fund success by the ability to maximize assets under management (Khorana and Servaes, 2012, Investment Company Institute, 2015).

Specifically, I relate the service outsourcing status of mutual funds to their net-inflows using the method suggested by Sirri and Tufano (1998) and estimate *Fund flow* for each fund $i$ and year $t$ as:

$$\textit{Fund flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{3.3}$$

whereby *TNA* represents the total net assets under management and *R* the total net-of-fee return of fund $i$ in year $t$. Thus, *Fund flow*, denotes the percentage growth rate of fund $i$ in year $t$ adjusted for the fund's internal growth. The main independent variable is as before, *Service outsourced*, a binary variable that equals one if the service provider of fund $i$ is unaffiliated to its management company in year $t$ and zero otherwise. In addition, I include several characteristics that have been documented to affect funds' net-inflows. Specifically, I control for family and fund characteristics by including *Ln TNA family*, *Family focus*, *Ln TNA*, *Ln age*, and *Turnover ratio* as defined in Section 3.3 as well as fund flows lagged by one year since Gruber (1996) and Sirri and Tufano (1998) show a positive influence of past flows on subsequent flows. I augment the baseline specification with funds' expense ratios (*Expense ratio*) to control for the expense related heterogeneity between service-outsourced funds and service-inhouse funds that stems from their decision to source shareholder services externally or not. Lastly, I extend the regression models with controls for funds' past performance to account for service-outsourced funds ability to generate better performance outcomes. Specifically, a number of studies show a non-linear influence of past performance on net-inflows (see, e.g., Ippolito, 1992, Chevalier and Ellison, 1997, Sirri and Tufano, 1998). Hence, I control for past performance using a quadratic performance rank of the fund (Barber, Odean, and Zheng, 2005). Alternatively, I use a piecewise linear regression approach as in Sirri and Tufano (1998), whereby I estimate three slope coefficients based on the performance rank of the fund: one coefficient for the *Bottom quintile*, one for the three *Middle quintiles*, and one for the *Top quintile* that are defined as:

$$\begin{aligned} \textit{Bottom quintile}_{i,t-1} &= Min(0.2; PerfRank_{i,t-1}) \\ \textit{Middle quintiles}_{i,t-1} &= Min(0.6; PerfRank_{i,t-1} - \textit{Bottom quintile}_{i,t-1}) \\ \textit{Top quintile}_{i,t-1} &= PerfRank_{i,t-1} - (\textit{Bottom quintile}_{i,t-1} + \textit{Middle quintiles}_{i,t-1}). \end{aligned} \tag{3.4}$$

whereby the performance rank, *PerfRank*, of fund $i$ in year *t-1* is based on its performance relative to all other funds within the same investment segment and year. Furthermore, I run pooled OLS regressions with time and segment fixed effects and cluster standard errors at the fund family level.

The results of Table 3.10 clearly show that service outsourced funds grow at considerably higher rates than their inhouse administered peers. The coefficient for *Service outsourced* suggests that service-outsourced funds exhibit annual growth rates that are about 16 percentage points larger than their service-inhouse peers. Still, once the heterogeneity in expenses is controlled for, the total benefit for service-outsourced funds is reduced to about 13 percentage

Table 3.10: Service outsourcing and fund flows

| Dependent variable: | Fund flow in t | | | |
|---|---|---|---|---|
| Model: | 1 | 2 | 3 | 4 |
| Service outsourced | 0.1594 ** | 0.1286 ** | 0.0992 | 0.1004 |
| | (0.0296) | (0.0483) | (0.1166) | (0.1133) |
| Expense ratio | | -24.2708 ** | -25.4126 ** | -25.5861 ** |
| | | (0.0139) | (0.0127) | (0.0126) |
| PerfRank | | | -1.6220 *** | |
| | | | (0.0045) | |
| PerfRank$^2$ | | | 2.5360 *** | |
| | | | (0.0001) | |
| Bottom quintile | | | | -0.1361 |
| | | | | (0.7933) |
| Middle quintiles | | | | 0.3313 *** |
| | | | | (0.0001) |
| Top quintile | | | | 6.2392 *** |
| | | | | (0.0001) |
| Ln TNA family | 0.1961 *** | 0.1880 *** | 0.1867 *** | 0.1867 *** |
| | (0.0005) | (0.0007) | (0.0007) | (0.0008) |
| Family focus | 0.4223 *** | 0.4545 *** | 0.3661 *** | 0.3663 *** |
| | (0.0002) | (0.0001) | (0.0008) | (0.0008) |
| Ln TNA | -0.3241 *** | -0.3374 *** | -0.3496 *** | -0.3511 *** |
| | (0.0002) | (0.0002) | (0.0001) | (0.0001) |
| Ln age | -0.0521 | -0.0560 | -0.0385 | -0.0337 |
| | (0.3635) | (0.3209) | (0.4996) | (0.5601) |
| Turnover ratio | 0.0419 * | 0.0457 ** | 0.0428 * | 0.0417 |
| | (0.0908) | (0.0479) | (0.0933) | (0.1107) |
| Fund flow | 0.0012 ** | 0.0013 ** | 0.0008 * | 0.0008 ** |
| | (0.0219) | (0.0152) | (0.0522) | (0.0297) |
| Sigma fund flow | -0.0014 | -0.0021 | -0.0014 | -0.0013 |
| | (0.3241) | (0.1409) | (0.2893) | (0.3130) |
| Sigma fund return | -0.6630 | -0.4040 | -0.1987 | -0.3667 |
| | (0.1594) | (0.4128) | (0.6921) | (0.4739) |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 18,063 | 18,063 | 18,063 | 18,063 |
| Adj. $R^2$ | 0.0196 | 0.0202 | 0.0289 | 0.0305 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of service outsourcing on fund flows. Fund flows are estimated as the fund's percentage growth rate adjusted for the internal growth of the fund as in Sirri and Tufano (1998). The main independent variable is Service outsourced, a binary variable that equals one if all service providers of the fund are unaffiliated to the fund's management company and zero otherwise. Additional independent controls include Ln TNA family, Family focus, Ln TNA, Ln age, Turnover ratio, Fund flow, Sigma fund flow, and Sigma fund return. Ln TNA family, is the logarithm of the fund family's total net assets under management. Family focus, represents the concentration of a fund family across investment segments defined as in Siggelkow (2003). Ln TNA, represents the logarithm of the fund's total net assets under management. Ln TNA family, Family focus, Ln TNA are all lagged by one year. Ln age, is the logarithm of the fund's age in years. Turnover ratio is the fund's yearly turnover ratio. Fund flow, is the net-inflow of the fund lagged by one year. Sigma fund flow, represents the standard deviation of the fund's monthly flows during the previous year. Sigma fund return, is the standard deviation of the fund's monthly net-of-fee returns during the previous year. Furthermore, I include Expense ratio, the fund's total expense ratio (Model 2-4). To account for the non-linear influence of fund performance on net-inflows I include PerfRank and PerfRank$^2$ representing the performance rank and squared performance rank of the fund in the previous year (Model 3). Alternatively, Model 4 reports results using a piecewise linear regression approach as in Sirri and Tufano (1998). Regressions are run with segment and year fixed effects. P-values reported in parentheses are based on standard errors clustered by fund family. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

points per year. Moving to the model specifications that account for a performance difference between service-outsourced funds and service-inhouse funds the loading on *Service outsourced* becomes statistically insignificant. This result is robust, independent of the employed performance control (the quadratic performance rank in column 3 or the piecewise linear regression approach in column 4). The relation between the remaining control variables and mutual funds' net-inflows are in line with the findings of previous studies (see, e.g., Gruber, 1996, Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Bergstresser and Poterba, 2002, Del Guercio and Tkac, 2002).

Taken together, the results from Table 3.10 show that funds with delegated shareholder services are also equipped with a substantial comparative advantage that materializes in the form of considerable higher growth rates. Moreover, the results indicate that the benefits to service-outsourced funds are largely driven by their superior performance generating ability, consistent with evidence from the literature that investors reward fund performance.

## 3.7 Conclusion

Mutual fund families strategically shape their member funds' behavior to match targeted positions in the fund industry. Accordingly, the supply side of professional asset management is not homogeneous but segmented through families' decisions to attract investors that vary by their performance and service preferences. In this paper, I argue that funds of families which delegate the execution of non-portfolio management services to external specialists are more concerned with portfolio management. This view is supported by theories from the literature on industrial organization that firms with a focus on their core competencies reduce resource consumption in non-core areas.

In particular, I document that service-outsourced funds outperform service-inhouse funds after controlling for other factors that could impact on performance. Extending this finding I observe that the sourcing status of funds' shareholder service is negatively related to fund expenses and positively related to measures associated with superior investment abilities. In particular, from the latter observation I conclude that funds with varying emphasis on portfolio management can be classified by the outsourcing status in their non-core responsibilities.

# Chapter 4

# Milk or Wine: Mutual Funds' (Dis)economies of Life‡

## 4.1 Introduction

In the U.S. millions of households delegate the management of considerable wealth to actively managed funds whose quality is represented by their competence to beat a benchmark through the generation of influential ideas (Kacperczyk, Sialm, and Zheng, 2008, Cremers and Petajisto, 2009). Nonetheless, asset management companies stress the importance that fund shareholders should exercise patience and give investment strategies the time to evolve instead of hoping for large profits in the short-run. This view of sturdiness is also nicely underpinned by funds' frequent self-portrayal as trees that - just like them - portfolios do not grow over night but can reach substantial heights.[44] In the mutual fund literature tremendous efforts have been made to detect superior fund investment skills cross-sectionally, however, the dynamics of this ability over a fund's lifetime is still an unattended issue. In other words, once the investor has selected a specific fund investment, does the fund live up to its promise over time?

We address this gap in the literature and investigate whether funds' time-series capabilities to generate abnormal returns alter to the positive like wine or negative like milk. Specifically, we study the impact of a fund's age on its performance to measure the influence of the passing of time. Hence, the aim of this paper is to explore whether funds are exposed to economies or diseconomies of life.

‡ This chapter is based on Dahm and Sorhage (2015).

[44] See Wall Street Journal (2013): Why So Many Trees in Fund Names?

Paralleling this view the literature on organizational ecology postulates that an organization's ability to be successful in the market is shaped by its demographic features. Specifically, the literature offers two competing hypotheses. The liability of newness theory (see, e.g., Stinchcombe, 1965, Hannan and Freeman, 1984, Cohen and Levinthal, 1989, March, 1991) suggests that mature organizations were subject to learning effects. Consequently, mature funds have constantly improved their investment strategies and make superior investment decisions compared to their earlier stage of life. In contrast, the liability of aging theory (see, e.g., Cohen and Levinthal, 1989, 1990, Barron, West, and Hannan, 1994, Balasubramanian and Lee, 2008) suggests that aging leads to dogmatic pursuits of proven courses of action and thus diminished innovations. Hence, mature funds find it more appealing to stick with best-practice approaches and to ignore untested strategies which results in fewer profit opportunities over time.

Along these lines we analyze in the first part of the paper whether fund performance improves or deteriorates with fund age. We use a sample of 3,489 actively managed U.S. domestic equity funds between 1991 and 2014 and find strong support for the liability of aging theory that a fund's age impacts negatively on its performance. Specifically, a doubling in a typical fund's age is associated with a performance decrease between 58 basis points and 75 basis points per year depending on the performance measure.

A natural concern with our empirical approach is that omitted factors could counteract the age effect on performance. In particular, our observation is based on the premise that fund size is held constant. Many scholars, however, argue that fund size is associated with decreasing returns to scale (see, e.g., Perold and Salomon, 1991, Berk and Green, 2004, Chen et al., 2004, Yan, 2008, Pástor, Stambaugh, and Taylor, 2015b), while an inconclusive body of work of organizational economists relate an organizations' size to innovativeness (see, e.g., Schumpeter, 1942, Aldrich and Auster, 1986, Cohen and Klepper, 1996). To rule out this explanation we control for fund size and a range of other fund and family characteristics as well as fund fixed, family fixed, manager fixed and investment segment fixed effects to account for unobservable fund, family, manager and investment segment heterogeneity.

Having established a robust negative relationship between fund age and performance, we provide supportive evidence that the observed performance effect is indeed attributable to less innovative investment strategies as suggested by the liability of aging theory. Therefore, we conduct two additional tests. First, we examine the impact of fund age on performance among index funds that fully replicate their benchmarks. For those funds, investment strategies are predefined and innovation should not really matter. In the same spirit, we also analyze the age-performance relation among more or less innovative investment segments of actively managed funds. Supporting our argument, we find no performance impact of age on the performance of index funds and on the performance of actively managed funds whose investment focus is on stocks of large and well-established companies with consistent generations of income. Our second test is based on evidence from the organizational economist literature that suggests a generally positive relationship between competition and a drive for innovation among organizations (see, e.g., Cohen, 2010). In particular, we investigate how fund age impacts on performance in environments of higher and lower competition. Thereby, we study a simple idea: If competition is high, mature funds cannot afford to be less innovative relative to their younger competitors. Correspondingly, we find that aging is associated with decreases in fund performance if the competitive strength of their environment is low.

In the second part of our paper we make a more detailed exploration of the mechanism that generates the performance difference between a mature fund and its younger self. In general, we find strong support that the observed underperformance of older funds is attributable to them being less active and pursuing less innovative investment ideas. We start by showing that funds' trading activity decreases with age and that this substantial effect of up to 20 percent per year is robust to a battery of alternative measures for fund turnover. We further extend our analysis and examine an age effect on measures for active management that present a more direct link to future fund performance. In particular, we find that fund age is negatively related to active share (Cremers and Petajisto, 2009, Petajisto, 2013), return gap (Kacperczyk, Sialm, and Zheng, 2008) and the $R^2$ measure (Amihud and Goyenko, 2013). In addition, we take another, more thorough step by investigating differences in funds' innovation at the stock holdings level. Consistent with our previous findings, we show that the held amount of hard-to-value stocks is lower in the portfolio of older funds. Taken together, our results provide strong evidence for the liability of aging theory. Mature funds do not reinvent themselves over time and thus are subject to diseconomies of life.

In the final part of our paper we investigate which types of investors have demand for fund shares of mature funds. Confirming the notion that funds seem to cater to different types of investors during their earlier and advanced stage of life, we find that shareholders of older funds are considerably less performance sensitive and less likely to be an institutional investor. Nevertheless, in further tests we show that these investors could benefit from mature funds' less extreme investment styles and more stable performance outcomes.

Our paper is linked to three strands of the economics literature. First, our paper is related to the literature on the identification of active management skills that has been of long-standing interest in mutual fund research (see, e.g., Jensen, 1968, Carhart, 1997, Daniel et al., 1997, Fama and French, 2010). A number of papers study the existence of investment skills by looking at fund actions reflected in the composition of their holdings. For example, Kacperczyk, Sialm, and Zheng (2008) find that funds' hidden investment decisions, captured by the difference between their actual return and the hypothetical return of the disclosed portfolio, predict performance. Relatedly, Cremers and Petajisto (2009) show that more active funds, represented by the deviation of their stock holdings position from their benchmark's composition, exhibit better performance. Still, despite these considerable efforts to explore the value of active management, it has mostly been a quest at a cross-sectional level. We contribute to this strand of the literature in documenting that funds' investment skills are not constant at the fund level but that dynamics over time determine their ability to generate superior performance. This has important implications for fund investors which should take the time dimension of investment skills into account when making their fund selection. In this spirit, our paper is also related to a group of papers that analyze time variations in investment skills. For instance, Kacperczyk, Nieuwerburgh, and Veldkamp (2014) show that fund managers' use of their timing and picking abilities is dependent on the business cycle. Pástor, Stambaugh, and Taylor (2015a) take an intra-fund perspective and revisit the idea that a fund's turnover is in fact a display of skill. However, none of these studies relate fund performance to fund age which in itself presents an influence of time on funds.[45]

Second, our paper is related to the literature on how aging affects organizational behavior which is an unresolved issue in organizational ecology (Hannan, 1998, Sørensen and Stuart, 2000). In their survey article Singh and Lumsden (1990) show a large body of inconclusive empirical research on the support of the liability of newness and liability of aging theory. We contribute to this literature by showing that the mutual fund industry as an archetype for a knowledge-intensive industry that crucially depends on the competence to be innovative is characterized by decreasing returns to life.

Finally, a third strand of the literature investigates the relation between characteristics of actively managed funds and their shareholders. For instance, Evans and Fahlenbrach (2012)

[45] Our paper also joins a recent study by Pástor, Stambaugh, and Taylor (2015b) that takes an in-depth look at fund size as a mutual fund demographic that could proxy for active management skills. Specifically, Pástor, Stambaugh, and Taylor (2015b) pick up the large and ongoing debate of a negative effect of fund size on performance that is arguably attributed to funds' diseconomies of scale and show that the measurement of skill is counteracted by the scale of the industry.

show that institutional ownership in a fund improves performance. Relatedly, Del Guercio and Reuter (2014) find that the retail fund market is segmented into funds that cater to performance-oriented do-it-yourself investors and to investors that put more emphasis on advisory services. Our paper adds to this literature by showing that heterogeneity in funds' shareholder structures is not limited to the comparison between fund types but that there are also considerable dynamic changes within a fund's group of investors.

The paper proceeds as follows. In Section 4.2, we briefly review the liability of newness and the liability of aging theory and develop our main hypotheses that emerge from these theories. In Section 4.3, we discuss our employed data set and report the summary statistics. Section 4.4 presents the main result of our study. In Section 4.5, we provide additional tests for the validity of the age-performance relation. In Section 4.6, we study the relation between fund age and innovative investment behavior. We investigate the demand for mature funds and their potential benefits in Section 4.7. Section 4.8 concludes.

## 4.2 Theoretical foundation of the age-performance relation

### 4.2.1 Liability of newness theory

The concept of learning over time intuitively applies to individuals in general and in particular in the mutual fund context (Kempf, Manconi, and Spalt, 2014). However, learning does not only relate to personal improvements but also represents a determinant to the rise and fall of organizations. Specifically, the liability of newness theory indicates that mature organizations accumulated more experience in the execution of organizational processes than their younger competitors and thus are more successful (Stinchcombe, 1965). For instance, March (1991) argues that the reliability with which new strategies of firms' are implemented increases with experience. Hannan and Freeman (1984) suggest that internal learning increases with age and improves organizations' reliability and accountability. This in turn facilitates organizations' ability to adapt to environmental changes. Relatedly, Tushman and Anderson (1986) and Cohen and Levinthal (1990) argue that established firms' accumulation of organizational knowledge enhances their ability to recognize and adapt new ideas.

Overall, the liability of newness theory predicts that mature funds make better investment decisions than their younger peers because they accumulated a rich set of experience on a history of investment strategies. Specifically, older funds possess detailed track records on past failures and successes which allows them to constantly improve their investment strategies and to derive supportive investment guidelines. This leads us to the conclusion:

*H1: Funds are subject to economies of life, i.e., fund age has a positive impact on fund performance.*

### 4.2.2 Liability of aging theory

Paralleling this view the liability of aging theory can be considered as the counterpart of the liability of newness theory. Specifically, the liability of aging theory suggests that aging manifests in the reduced propensity of mature organizations to undergo transformations and thus to be successful (Singh and Lumsden, 1990). In more detail, strict documentations of experience-based practices result in rigidities such as self-imposed constraints, bureaucratization or the dogmatic pursuit of best-practice approaches which prevent mature organizations to exploit their capabilities and diminish innovation (Barron, West, and Hannan, 1994). Relatedly, Cohen and Levinthal (1990) argue that the ability of organizations to recognize new ideas and to assimilate them depends on its innovative capabilities. Thus, if organizational rigidities increase with firms' age, their innovative capabilities will deteriorate over time.

Overall, the liability of aging theory suggests that older funds are less likely to change their investment routines and consequently underperform their younger peers. In particular, the documentation of experience-dependent success and derived investment guidelines make it more appealing to stick with proven returns of an existing course of action instead of choosing unproven investment routes. However, exactly this line of action is especially unfavorable in the context of mutual funds. Mutual funds' success is primarily driven by their ability to detect market inefficiencies and by their competence to deviate from their benchmarks' composition (see, e.g., Kacperczyk, Sialm, and Zheng, 2005, Cremers and Petajisto, 2009). At the same time these market inefficiencies have timestamps which make the ignorance to untested approaches costly. Furthermore, due to market inefficiencies' temporary existence mature funds' used investment strategies become less valuable over time:

*H2: Funds are subject to diseconomies of life, i.e., fund age has a negative impact on fund performance.*

## 4.3 Data

### 4.3.1 Sample selection

Our paper uses two databases. First, the CRSP Survivor-Bias-Free U.S. Mutual Fund database that contains information on a range of fund characteristics such as funds' monthly returns, total net assets under management (TNA), age, expenses, turnover, and other characteristics. We assign each fund to a specific fund family and a specific investment segment based on the fund family identifier and investment objective code provided in CRSP. Since we focus on actively managed U.S. domestic equity funds we use funds' investment objective codes and keywords in their names to exclude index funds as well as global, international, balanced, fixed-income and other non-equity funds. Furthermore, frequently mutual funds offer multiple share classes that differ with respect to their fee structures but have the same underlying assets. Thus, we aggregate information on a fund's returns, expenses and other characteristics to the fund level by weighting the information with the TNA of the fund shares in the prior month. In addition, we take the maximum age, defined as the difference between the observation period and the inception date, across a fund's shares as its age.

Second, from the Thomson Mutual Fund Holdings database we obtain portfolio holdings information on securities held by each fund on each reporting date. We supplement the holdings data with information from the CRSP Monthly and Daily Stock Files and merge both databases using MFLINKS from Wermers (2000).

Our final sample consists of 3,489 actively managed U.S. domestic equity funds between 1991 and 2014.[46]

### 4.3.2 Summary statistics

In Table 4.1 we present summary statistics (mean, median, standard deviation and cutoffs at the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile) on the most important variables in our analysis. In Panel A, we report funds' performance measures as our main dependent variables. Panel B of Table 4.1 presents our main independent variable fund age in number of years and the remaining variables that are employed as controls in the paper.

[46] We start the sample period in 1991, the first year in which CRSP reports information on funds' total net assets under management at the monthly not quarterly level.

Table 4.1: Summary statistics

| Variable | Mean | Stdev. | Percentiles 25% | 50% | 75% | N |
|---|---|---|---|---|---|---|
| **Panel A: Performance measures** | | | | | | |
| Jensen alpha (%) | 0.005 | 3.724 | -1.244 | -0.066 | 1.144 | 411,713 |
| Fama French alpha (%) | -0.076 | 2.348 | -1.119 | -0.094 | 0.928 | 411,713 |
| Carhart alpha (%) | -0.083 | 2.376 | -1.105 | -0.097 | 0.914 | 411,713 |
| Pástor Stambaugh alpha (%) | -0.075 | 2.490 | -1.133 | -0.093 | 0.949 | 399,438 |
| **Panel B: Independent variables** | | | | | | |
| Fund age (years) | 13.11 | 12.99 | 4.93 | 9.34 | 16.09 | 417,830 |
| Family size (in million USD) | 34,612 | 95,277 | 584 | 4,353 | 20,311 | 371,440 |
| Family focus (%) | 50.70 | 24.91 | 31.67 | 42.10 | 63.80 | 371,440 |
| Fund net-of-fee return (%) | 0.71 | 5.62 | -2.10 | 1.17 | 3.90 | 417,817 |
| Fund size (in million USD) | 1,144 | 4,668 | 48 | 186 | 722 | 417,830 |
| Fund flow (%) | 0.43 | 5.54 | -1.46 | -0.26 | 1.34 | 417,179 |
| Expense ratio (%) | 1.31 | 0.96 | 0.99 | 1.24 | 1.52 | 417,728 |
| Turnover ratio (%) | 94.64 | 163.01 | 34.00 | 65.00 | 112.00 | 415,460 |

Notes: This table reports summary statistics on the major variables for our sample of actively managed U.S. domestic equity funds between 1991 and 2014. In Panel A, we report funds' performance measures as our main dependent variables. Panel B presents our main independent variable fund age and the remaining variables that are employed as controls in the paper. Jensen (1968) alpha, Fama and French (1993) alpha, Carhart (1997) alpha, and Pástor and Stambaugh (2003) alpha are obtained from 36-month rolling-window regressions of funds' net-of-fee excess returns on the excess market return for the Jensen alpha, additionally the SMB, HML factors for the Fama French alpha, augmented by the MOM (momentum) factor for the Carhart alpha, and the LIQ (liquidity) factor for the Pástor Stambaugh alpha. Fund age, is the fund's age in years. Family size, is the total net assets under management of the fund family in million USD. Family focus, represents the concentration of a fund family across investment segments defined as in Siggelkow (2003). Fund net-of-fee return, is the fund's monthly return after expenses. Fund size, represents the fund's total net assets under management in million USD. Fund flow, is the fund's monthly growth rate adjusted for internal growth as in Sirri and Tufano (1998). Expense ratio, is the fund's fees charged for total services. Turnover ratio, is the fund's yearly turnover. The performance metrics, Family focus, Fund net-of-fee return, Expense ratio and Turnover ratio, are reported in percentage points.

Given the nature of our study that we are interest in the age impact on the superiority of investment strategies, we focus on risk-adjusted metrics for fund performance measurement.[47] We use four performance measures: Jensen (1968) alpha, Fama and French (1993) 3-factor alpha, Carhart (1997) 4-factor alpha, and the Pástor and Stambaugh (2003) 5-factor alpha. Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. Matching observations from the literature, the average fund in our sample of about 400,000 fund-month observations underperforms its passive benchmark. Referring to our main independent variable, the average fund in our sample is about 13 years old, that shows the typically skewed nature of the age distribution as its range between the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile amounts to approximately 5 and 16 years. The typical fund in our sample

[47] In this spirit, we follow a number of recent studies such as Evans and Fahlenbrach (2012), Del Guercio and Reuter (2014), Kacperczyk, Nieuwerburgh, and Veldkamp (2014), and Kumar, Niessen-Ruenzi, and Spalt (2015).

has about \$1.1 billion assets under management. Mean net-of-fee return is 71 basis points per month and the average fund's growth is 43 basis points per month. Considering fund expenses and trading activity, the average expense ratio amounts to 1.31 percent per year and the mean turnover ratio is about 95 percent per year. Hence, our sample exhibits fund characteristics that are consistent with the prior literature (see, e.g., Kacperczyk and Seru, 2012, Evans and Fahlenbrach, 2012, Chen et al., 2013, Pástor, Stambaugh, and Taylor, 2015b).

## 4.4 Impact of fund age on performance

In this section we investigate the relation between fund age and performance. In Section 4.4.1, we explore the two competing hypotheses liability of newness and liability of aging that suggest that fund performance, respectively, improves or deteriorates with fund age. In Section 4.4.2, we provide additional support for the main finding by making a number of robustness tests.

### 4.4.1 Main result: Liability of newness versus liability of aging

We begin our analysis by illustrating the impact of fund age on performance graphically. To obtain a first indication of the age-performance relation over a fund's lifetime, we run a piecewise-linear regression model:

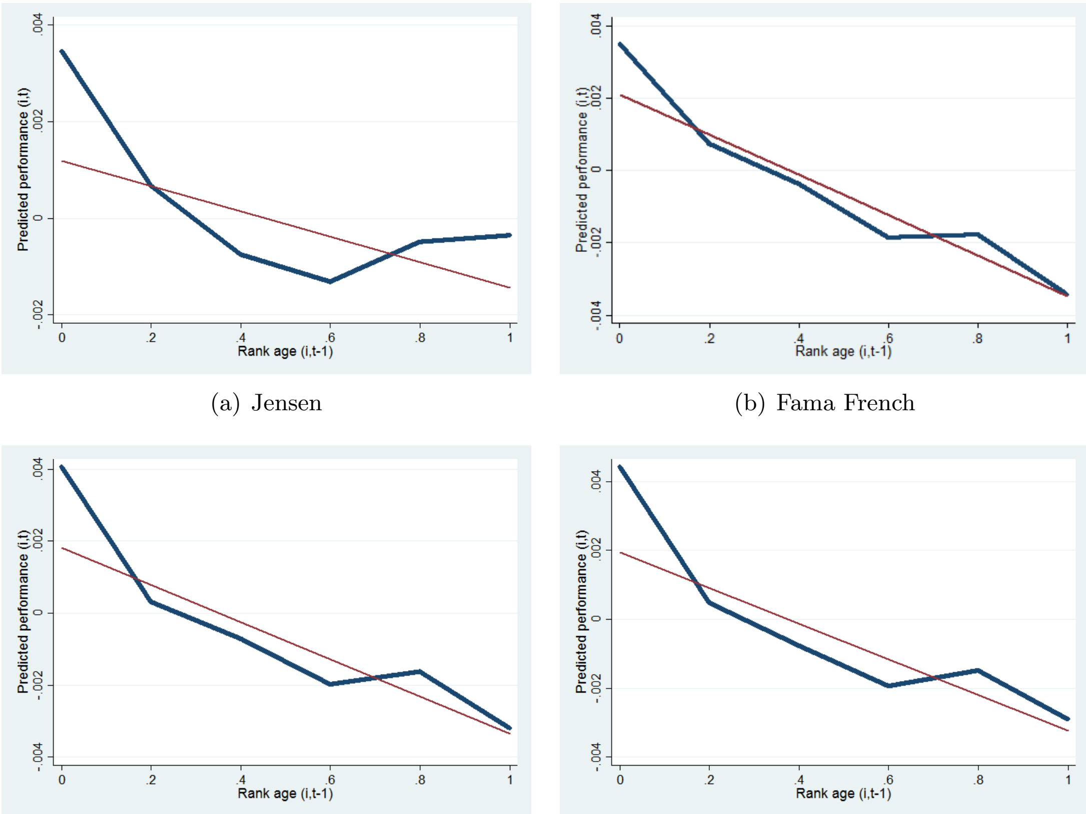
$$Performance_{i,t} = \alpha + \sum_{j=1}^{5} \beta_j AgeQuintile_{j,i,t-1} + \alpha_i + \epsilon_{i,t}, \tag{4.1}$$

where the dependent variable, *Performance*, is the performance of fund $i$ in month $t$ measured as: Jensen (1968) alpha, Fama and French (1993) 3-factor alpha, Carhart (1997) 4-factor alpha, and Pástor and Stambaugh (2003) 5-factor alpha. Alphas are obtained through 36-month rolling window regressions of funds' net-of-fee returns on the common factors of the respective risk-factor model. The independent variables, *AgeQuintile*, are the five piecewise-linear ranges $j$ based on funds' fractional age ranks in month *t-1*.[48] Thus, the coefficients on these piecewise decompositions represent the slope of the performance-age relation over their range of sensitivity. In addition, we include fund fixed effects, denoted by $\alpha_i$, to account for unobservable fund effects that could impact on our results. More specifically, fund fixed effects absorb the cross-sectional variation in performance so that identification comes only from within-fund time

[48] In particular, the piecewise-linear regression coefficients are calculated according to the definitions: $AgeQuntile_1$ = Min(0.2; $AgeRank_{t-1}$) whereby $AgeRank_{t-1}$ is a fund's fractional age rank defined as the fund's percentile age relative to other funds in the same investment segment and month. Accordingly, the second quintile is estimated as $AgeQuntile_2$ = Min(0.2; $AgeRank_{t-1}$ - $AgeQuntile_1$), and so forth, up to the fourth quintile. The top quintile is defined as $AgeQuntile_5 = AgeRank_{t-1}$ - ($AgeQuntile_1$ + $AgeQuntile_2$ + $AgeQuntile_3$ + $AgeQuntile_4$).

variation (Pástor, Stambaugh, and Taylor, 2015a). Thus, using fund fixed effects in our regressions effectively allow us to estimate the age impact on fund performance within the same fund.[49]

Figure 4.1: Age-performance relation




(a) Jensen

(b) Fama French

(c) Carhart

(d) Pástor Stambaugh

Notes: This figure shows the relationship between fund age ranks and mutual fund performance. We obtain funds' performance-age sensitivities from piecewise-linear regressions of the performance measures Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh) on funds' relative age ranks and fund fixed effects. Funds' fractional age ranks represent a fund's percentile age relative to other funds with the same investment segment and month. Then, these fractional ranks are used to estimate five age quintiles similar to Sirri and Tufano (1998). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. Robust standard errors are clustered at the fund level.

Figure 4.1 shows that the performance of a fund declines with its age irrespective of the employed performance benchmark. Our estimates depict an almost linear negative performance effect of fund age with four out of five *AgeQuintiles* also being statistically significant negative. Again, since our regression design includes fund fixed effects, we measure the performance

[49] For a formal proof that panel regressions with fund fixed effects provide slope estimates that reflect time-series variation at the within-fund level and are equal to a weighted average of the slope estimates from pure time-series regressions see Pástor, Stambaugh, and Taylor (2015a).

difference of a mature fund relative to its younger self. Thus, results from Figure 4.1 provide first evidence in favor of the liability of aging theory.

We support this performance impact of fund age by running the following panel regression model:

$$Performance_{i,t} = \alpha + \beta Ln\ age_{i,t-1} + \gamma X_{i,t-1} + \alpha_i + \alpha_s + \alpha_t + \epsilon_{i,t}, \tag{4.2}$$

The main independent variable, *Ln age*, is the age of fund $i$ in month *t-1* measured as the natural logarithm of one plus the time difference between the prior month and the month when fund $i$ first appears in the CRSP mutual fund database. We employ *Ln age* as our main independent variable because of the usual econometric concerns regarding the empirical distribution of age as well as to account for the fact that an equal year has a larger percentage impact, i.e. economic relevance, on younger funds.

We include a broad range of other fund characteristics that have been documented to impact on fund performance to avoid that our assessment of age induced differences in funds' performance is contaminated. Specifically, $X$ is a set of control variables (in month *t-1*) that includes the net-of-fee return of fund $i$ in the prior month (*Fund return*), the logarithm of the fund's total net assets under management (*Ln TNA*), the fund's growth rate defined as in Sirri and Tufano (1998) (*Fund flow*), and the fund's turnover ratio (*Turnover ratio*). We also control for a fund's expense ratio (*Expense ratio*) to capture differences in funds' expenses that impact on performance. Hence, regression estimates correspond to gross-of-fee performance effects that better account for investment skill.[50] As before, we include fund fixed effects to maintain our perspective on an intra-fund level effect of fund age on performance and to control for unobservable fund heterogeneity. Furthermore, we include investment segment and time (month $\times$ year) fixed effects, denoted by $\alpha_s$ and $\alpha_t$ respectively, to account for unobservable segment and time effects that could impact on our results. Thus, our regression design estimates the performance impact of fund age within the same fund, while controlling for changes in the state of the mutual fund industry.[51] We cluster standard errors at the fund level.

[50] For robustness we repeat our analysis with gross-of-fee performance metrics as our dependent variables instead of controlling explicitly for funds' expense ratios. Specifically, we obtain gross-of-fee alphas based on 36-month rolling-window regressions of funds' gross-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. Funds' gross-of-fee returns are estimated by dividing their yearly expense ratios by twelve and adding it to their net-of-fee returns. Results (not reported) are qualitatively the same.

[51] Including time fixed effects in our regressions also accounts for the effects observed by Pástor, Stambaugh, and Taylor (2015b) that changes in the mutual fund industry's scale could impact on fund age as a determinant of fund performance.

Table 4.2: Impact of fund age on performance

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| Ln age | -0.0009 ** | -0.0008 *** | -0.0007 *** | -0.0008 *** |
| | (0.0168) | (0.0000) | (0.0001) | (0.0000) |
| Fund return | -0.0044 | 0.0169 *** | 0.0049 ** | 0.0087 *** |
| | (0.3283) | (0.0000) | (0.0422) | (0.0003) |
| Ln TNA | -0.0022 *** | -0.0011 *** | -0.0015 *** | -0.0015 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 *** | 0.0000 | 0.0000 | 0.0000 |
| | (0.0023) | (0.1388) | (0.2321) | (0.2443) |
| Expense ratio | -0.0966 | -0.0189 | -0.0202 | -0.0202 |
| | (0.1980) | (0.3825) | (0.4888) | (0.5147) |
| Turnover ratio | 0.0002 * | 0.0002 *** | 0.0002 *** | 0.0002 ** |
| | (0.0988) | (0.0088) | (0.0057) | (0.0149) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 399,438 | 399,438 | 399,438 | 399,438 |
| Adj. $R^2$ | 0.0798 | 0.0760 | 0.0790 | 0.0778 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on mutual fund performance using four different performance measures: Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable is Ln age, the logarithm of the fund's age in years. Additional independent controls include Fund return, Ln TNA, Fund flow, Expense ratio, and Turnover ratio. Fund return, is the net-of-fee return of the fund. Ln TNA, represents the logarithm of the fund's total net assets under management. Fund flow, represents the fund's growth rate defined as in Sirri and Tufano (1998). Expense ratio, represents the fund's total expense ratio. Turnover ratio is the fund's yearly turnover ratio. All independent variables are lagged by one month. Regressions are run with fund, segment, and time (month × year) fixed effects. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Results reported in Table 4.2 confirm our findings of Figure 4.1 and show that the performance of a fund deteriorates with its age. Specifically, the slope estimates for fund age show a negative impact on fund performance between 7 basis points for the Carhart (1997) 4-factor alpha and 9 basis points for the Jensen (1968) alpha. Thus, a doubling in a typical fund's age leads to a performance deterioration of up to 75 basis points per year.[52] In other words, to put the economic magnitude more into perspective our age estimates imply that a 12 year old fund underperforms its 3 year old self by up to 150 basis points per year. All effects are statistically significant with three out of four measures being significant at the 1 percent level. Hence, our

[52] In more detail, consider our linear regression model where the dependent variable, *Performance*, is in level terms and the independent variable of interest, *Ln age*, is in log terms. Holding all independent variables constant except fund age, a change in performance is equal to $\Delta Performance_i = \beta ln(Age_{i,t-1}(1+\Delta\%)) - \beta ln(Age_{i,t-1}) = \beta ln(1+\Delta\%)$. Thus, a doubling in a typical fund's age corresponds to a decline in the annualized fund performance of 0.0009*ln(2)*12=75 basis point for the Jensen (1968) alpha.

empirical approach confirms performance effects that are consistent with the existence of the liability of aging theory in the mutual fund industry.[53]

To address the possibility that this underperformance is attributable to a diseconomies of scale effect we include fund size in our performance regression.[54] Consistent with the results of Berk and Green (2004) and Chen et al. (2004) fund size impacts negatively on fund performance across all performance measures. We also include as controls a fund's past return, growth rate, expense ratio and turnover ratio. Notably, we can confirm the findings of Pástor, Stambaugh, and Taylor (2015a) that fund turnover impacts significantly positive on fund performance which is consistent with their finding that fund turnover is a proxy for investment skill.[55] Furthermore, funds' past performance impacts positively on performance consistent with Hendricks, Patel, and Zeckhauser (1993), Bollen and Busse (2005), and Busse and Irvine (2006), who argue that fund performance is persistent on short-term horizons.

### 4.4.2 Robustness

#### 4.4.2.1 Incubation bias

One potential explanation for the negative age-performance relation could be that fund-month observations that are special with respect to fund age and size could drive our result. Specifically, Evans (2010) documents that fund families start a series of mutual funds but that only a limited number, presumably those with a better performance record, continue to be managed while the others are shut down. As a consequence these incubated funds outperform non-incubated funds. Thus, as a first methodological robustness check, we repeat our analysis and control for fund-month observations that are likely to belong to incubated funds. The additional control *Incubation* is a binary variable that equals one if the fund-month observation belongs to a fund whose age is less than three years or whose TNA are below $15 million, and zero otherwise.

[53] We additionally run our regression for each fund separately and perform standard t-tests over all coefficients of our main independent variable, *Ln age*. Irrespective of the employed performance measure the results remain statistically significant at the 1 percent level and the negative age-performance relation ranges from an underperformance of 34 basis points to 52 basis points per month.

[54] As an additional check, we repeat our analysis including squared values for fund size and all other control variables to allow for nonlinearities. Results (not reported) are qualitatively the same, if anything, they gain in statistical significance.

[55] The evidence on the impact of funds' trading activity on performance is rather mixed in the literature. While Carhart (1997) finds a negative impact of turnover on fund performance, Elton et al. (1993) and Chen et al. (2004) find no significant effect. On the contrary, Wermers (2000), Chen, Jegadeesh, and Wermers (2000), Kacperczyk, Sialm, and Zheng (2008), and Pástor, Stambaugh, and Taylor (2015a) observe a positive impact. However, following Pástor, Stambaugh, and Taylor (2015a) earlier studies look at cross-sectional differences between funds while our study investigates intra-fund changes. In line with this argumentation, we observe a positive performance impact of a fund's turnover ratio that becomes insignificant when we do not control for the heterogeneity across funds, i.e., include fund fixed effects.

We define the indicator variable *Incubation* based on a three year cut-off since Evans (2010) suggests that the first three years of a fund largely account for the incubation bias. In addition, we complement this adjustment by accounting for funds that are very small in size, similar to Chen et al. (2004) and Pástor, Stambaugh, and Taylor (2015b).

Table 4.3: Impact of fund age on performance with incubation control

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| Ln age | -0.0011 ** | -0.0007 *** | -0.0006 *** | -0.0007 *** |
| | (0.0232) | (0.0011) | (0.0056) | (0.0014) |
| Fund return | -0.0044 | 0.0169 *** | 0.0049 ** | 0.0087 *** |
| | (0.3289) | (0.0000) | (0.0422) | (0.0003) |
| Ln TNA | -0.0022 *** | -0.0011 *** | -0.0015 *** | -0.0015 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 *** | 0.0000 | 0.0000 | 0.0000 |
| | (0.0022) | (0.1406) | (0.2336) | (0.2464) |
| Expense ratio | -0.0963 | -0.0191 | -0.0203 | -0.0203 |
| | (0.1991) | (0.3789) | (0.4870) | (0.5122) |
| Turnover ratio | 0.0002 * | 0.0002 *** | 0.0002 *** | 0.0002 ** |
| | (0.0969) | (0.0090) | (0.0057) | (0.0151) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 399,438 | 399,438 | 399,438 | 399,438 |
| Adj. $R^2$ | 0.0798 | 0.0760 | 0.0790 | 0.0778 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on mutual fund performance using four different performance measures: Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable is Ln age, the logarithm of the fund's age in years. Additional independent controls include: Incubation fund fixed effect, a binary variable that equals one if the fund-month observation belongs to a fund whose age is less than three years or whose TNA are below \$15 million, and zero otherwise. Other independent variables and fixed effects are defined as in Table 4.2. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

The results from Table 4.3 clearly confirm the findings of Table 4.2 that mature funds are subject to diseconomies of life. The estimates remain statistically significant at comparable levels and the magnitude of the effect tends to become slightly smaller.

#### 4.4.2.2 Influences of the fund family

A growing strand of the literature documents that fund families' strategic decisions impact on their member funds' performance. For instance, Nanda, Wang, and Zheng (2004) and Gaspar, Massa, and Matos (2006) investigate favoritism and cross-subsidization of funds in fund families. Other papers analyze the consequences arising from structural differences in fund families' organization (see, e.g., Kacperczyk and Seru, 2012, Chen et al., 2013, Cici, Dahm, and Kempf, 2014, Sorhage, 2015). Thus, as a second methodological robustness check, we include time-varying family controls (in month *t-1*): the logarithm of the fund family's total net assets under management (*Ln TNA family*) and the concentration of a fund family across investment segments defined as in Siggelkow (2003) (*Family focus*). In addition, we add family fixed effects in the performance regressions to rule out that the age effect is affected by fund family influences.[56] Family fixed effects effectively allow us to control for any unobservable per se heterogeneity across families. Thus, in this specification we estimate the performance difference of a mature fund relative to its younger self, controlled for changes in the fund's family organization and the state of the world.

Table 4.4: Impact of fund age on performance with family controls

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| Ln age | -0.0011 * | -0.0006 ** | -0.0006 ** | -0.0007 *** |
| | (0.0779) | (0.0138) | (0.0191) | (0.0061) |
| Ln TNA family | -0.0005 ** | -0.0003 ** | -0.0002 * | -0.0003 ** |
| | (0.0163) | (0.0140) | (0.0575) | (0.0186) |
| Family focus | 0.0009 | 0.0004 | 0.0004 | 0.0006 |
| | (0.2621) | (0.4772) | (0.4945) | (0.2956) |
| Fund return | -0.0194 *** | 0.0160 *** | 0.0049 ** | 0.0077 *** |
| | (0.0000) | (0.0000) | (0.0452) | (0.0021) |
| Ln TNA | -0.0027 *** | -0.0013 *** | -0.0018 *** | -0.0017 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 *** | 0.0000 *** | 0.0000 * | 0.0000 * |
| | (0.0000) | (0.0018) | (0.0536) | (0.0827) |
| Expense ratio | -0.0693 | -0.0150 | -0.0166 | -0.0179 |
| | (0.2305) | (0.4718) | (0.5891) | (0.5766) |
| Turnover ratio | 0.0001 | 0.0001 | 0.0001 * | 0.0001 * |
| | (0.5429) | (0.1269) | (0.0557) | (0.0974) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 353,217 | 353,217 | 353,217 | 353,217 |
| Adj. $R^2$ | 0.0812 | 0.0825 | 0.0870 | 0.0864 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on mutual fund performance using four different performance measures: Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable is Ln age, the logarithm of the fund's age in years. Additional independent controls include: Ln TNA family and Family focus. Ln TNA family, is the logarithm of the fund family's total net assets under management. Family focus, represents the concentration of a fund family across investment segments defined as in Siggelkow (2003). Ln TNA family and Family focus are both lagged by one month. In addition, regressions are run with family fixed effects to control for any unobservable heterogeneity across families. Other independent variables and fixed effects are defined as in Table 4.3. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

[56] Including family controls effectively sets the sample period begin to the year 1996 since funds' family identifiers are not available for earlier periods in CRSP.

Table 4.4 supports our findings of the earlier tests. Independent of the employed performance benchmark fund age impacts significantly negative on fund performance. Levels of economic and statistical significance are almost unaffected to our findings from Table 4.3.

#### 4.4.2.3 Influences of the fund manager

When thinking about the success of funds' investment decisions an intuitive determinant that comes to mind is the fund manager and her abilities. Thus, a final concern is that the observed age-performance effect is attributable to the fund manager who is managing the fund at its earlier or advanced stage of life. For instance, one might argue that time dependent manager characteristics such as manager age that proxies for the effort put into the investment process drives the observed negative age-performance relation. This concern becomes more serious when a fund is not subject to a manager change since time dependent manager characteristics and fund age develop in lock-step leaving us unable to separate both effects.

If this conjecture is true, manager changes – especially those to younger managers – that represent structural breaks in funds' performance generating processes (Khorana, 1996, 2001), must reflect on the age-performance relation. We obtain information on fund managers from CRSP and assign them to the fund-month observations based on the derived manager identities.[57] This allows us to observe all changes in the manager who is running the fund. In addition, similar to Chevalier and Ellison (1999) we construct an approximate manager age as the time difference between the period of observation and the first time the manager appears in the CRSP sample plus 21 years to capture the time the manager graduated from college. Then, in Panel A of Table 4.5 we explore the impact of fund age on performance during regular periods and periods of managerial change by including two indicator variables, *Change young* and *Change old*, which equal one if the fund-month observation lies within a 12 month period around the change of the fund's manager to, respectively, a younger or older manager.[58]

As expected, results from Panel A of Table 4.5 show clear support for our finding that the performance of funds declines over their lifetime. In fact, the negative age-performance relation gains in economic significance and ranges from 7 basis points to 16 basis points per month

[57] In case of team-managed funds we assign the fund-month observations to the manager who arrived first at the fund as suggested by Pástor, Stambaugh, and Taylor (2015b). Unfortunately, CRSP does not provide the identities of fund managers in all team-managed funds. Thus, we identify manager names that cannot be associated with an identity of individuals similar to Bär, Kempf, and Ruenzi (2011) and drop their observations from our analysis. As a further robustness check we re-run our analysis for single-managed funds only. Results (not reported) are qualitatively the same.

[58] For robustness we also measure the age-performance relation during periods of managerial change that span 10 months, 8 months, 4 months, and 2 months. Results (not reported) are qualitatively the same.

Table 4.5: Impact of fund age on performance with manager controls

**Panel A: Fund manager changes**

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| Ln age | -0.0016 * | -0.0009 *** | -0.0007 ** | -0.0009 *** |
| | (0.0689) | (0.0066) | (0.0309) | (0.0081) |
| Ln age × Change young | 0.0003 | 0.0001 | 0.0001 | 0.0002 |
| | (0.4139) | (0.6562) | (0.6100) | (0.3128) |
| Ln age × Change old | 0.0002 | 0.0002 | 0.0003 | 0.0003 |
| | (0.6956) | (0.4932) | (0.3053) | (0.2630) |
| Change young | -0.0007 | -0.0002 | -0.0004 | -0.0007 |
| | (0.4999) | (0.7833) | (0.4720) | (0.1940) |
| Change old | -0.0009 | -0.0008 | -0.0009 | -0.0010 |
| | (0.5472) | (0.3017) | (0.1761) | (0.1600) |
| Ln TNA family | -0.0005 * | -0.0002 | -0.0001 | -0.0002 |
| | (0.0686) | (0.1448) | (0.3954) | (0.2065) |
| Family focus | 0.0009 | 0.0007 | 0.0003 | 0.0006 |
| | (0.4166) | (0.3564) | (0.6342) | (0.3936) |
| Fund return | -0.0219 *** | 0.0137 *** | 0.0042 | 0.0067 ** |
| | (0.0000) | (0.0000) | (0.1370) | (0.0206) |
| Ln TNA | -0.0030 *** | -0.0014 *** | -0.0020 *** | -0.0020 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.5943) | (0.5118) | (0.7868) | (0.8140) |
| Expense ratio | -0.0460 | -0.0157 | -0.0164 | -0.0178 |
| | (0.2609) | (0.4533) | (0.5936) | (0.5791) |
| Turnover ratio | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.7433) | (0.2973) | (0.1936) | (0.3202) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 251,233 | 251,233 | 251,233 | 251,233 |
| Adj. $R^2$ | 0.0839 | 0.0839 | 0.0884 | 0.0877 |

(*Continued*)

for a doubling in a typical fund's lifetime depending on the employed performance benchmark. More importantly, however, the estimated coefficients for the interaction terms of *Ln age* with *Change young* and *Change old* are insignificant. This indicates that time dependent manager characteristics do not drive our results since funds' age related performance deterioration is not different during times of managerial change and periods when the fund is persistently managed by the same manager.[59]

In Panel B we address the conjecture that also differences in managers' skills could drive our main result. In fact, it could even be the case that more skilled managers are selected to younger funds. In this setting, we follow the argumentation of Custódio and Metzger (2014)

[59] Furthermore, to account for managerial changes with strong age gaps we repeat our analysis and additionally separate both variables *Change young* and *Change old* based on whether the differential between the managers' age is above or below median. Again, results (not reported) are qualitatively the same.

Table 4.5: Impact of fund age on performance with manager controls (Continued)

**Panel B: Fund manager selection**

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| Ln age | -0.0019 *** | -0.0012 *** | -0.0008 *** | -0.0008 *** |
| | (0.0013) | (0.0000) | (0.0026) | (0.0055) |
| Ln TNA family | 0.0005 | 0.0003 * | 0.0002 | 0.0002 |
| | (0.1851) | (0.0898) | (0.2084) | (0.4329) |
| Family focus | -0.0022 | -0.0009 | -0.0014 | -0.0010 |
| | (0.1030) | (0.2870) | (0.1020) | (0.2192) |
| Fund return | 0.0078 *** | 0.0122 *** | 0.0117 *** | 0.0110 *** |
| | (0.0011) | (0.0000) | (0.0000) | (0.0000) |
| Ln TNA | -0.0044 *** | -0.0021 *** | -0.0027 *** | -0.0028 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.6567) | (0.1868) | (0.7144) | (0.7615) |
| Expense ratio | -0.0461 | -0.0152 | -0.0186 | -0.0205 |
| | (0.2696) | (0.4489) | (0.5749) | (0.5511) |
| Turnover ratio | 0.0002 | 0.0001 | 0.0002 | 0.0002 |
| | (0.3020) | (0.3918) | (0.1639) | (0.2625) |
| Fund×Manager fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 251,233 | 251,233 | 251,233 | 251,233 |
| Adj. $R^2$ | 0.0439 | 0.0381 | 0.0393 | 0.0386 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on mutual fund performance using four different performance measures: Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable in both Panel A and Panel B is Ln age, the logarithm of the fund's age in years. Additional independent controls in Panel A include: Change young, a binary variable that equals one if the fund-month observation is within a 12 month period around the change of the fund's manager to a younger manager; and Change old, a binary variable that equals one if the fund-month observation is within a 12 month period around the change of the fund's manager to an older manager. Other independent variables and fixed effects in both panels are defined as in Table 4.4. Still, regressions in Panel B are run with fund fixed effects × manager fixed effects to control for any unobservable heterogeneity across funds and managers but without time fixed effects. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

that our closest test is to compare the same fund manager, managing the same fund during the fund's younger and older stage of life. Thus, we repeat the analysis from Table 4.4 with fund fixed effects × manager fixed effects.[60] Fund × manager fixed effects do not only take care of unobservable heterogeneity across funds and managers but allow us to adjust for manager-specific time periods within funds. Hence, identification comes from within-fund variation after subtracting time-varying manger effects. Results from Panel B of Table 4.5 confirm our finding from Panel A and earlier tables as fund age impacts significantly negative on fund performance.

[60] The large number of fixed effects in our regression model gives rise to collinearity problems. Thus, to mitigate this bias we exclude time fixed effects from our testing model. However, when we insist on the inclusion of time fixed effects our results (not reported) are qualitatively the same.

Overall, the results from Section 4.4 strongly confirm the notion that younger funds outperform mature funds and that this effect holds for a large number of robustness checks at the fund, family, and manager level. Hence, evidence is consistent with the liability of aging theory that older funds are subject to diseconomies of life.

## 4.5 Do we capture innovation induced performance effects?

Building on the observation that funds are subject to decreasing returns to life, we take a first step in exploring whether the negative age-performance relation is attributable to differences in innovative investment behavior as suggested by the liability of aging theory. In Section 4.5.1, we explore a quasi-natural experiment and we investigate the impact of fund age on the performance of passively managed index funds whose investment behavior is unlikely to be related to innovative investment strategies. Furthermore, we augment this test and analyze the age-performance relation among more or less innovative investment segments of actively managed funds. In Section 4.5.2, we study how fund age relates to performance in environments of different competitive strength.

### 4.5.1 Age-performance relation among index and actively managed funds

The presence of actively and passively managed funds in the mutual fund industry provides us with a prime example to test whether active funds' diseconomies of life are attributable to a decline in innovative investment behavior. In contrast to actively managed funds that pursue investment strategies which purposely deviate from their benchmarks to generate abnormal returns, passively managed index funds aim to track an index as closely as possible. Thus, index funds' investment strategies are predefined and their performance is not likely to be related to an innovative investment style. We follow the approach used in Cici, Dahm, and Kempf (2014) to identify passively managed index funds that fully replicate their benchmarks.[61,62]

Contrary to the analyses from Section 4.4 our results from Panel A of Table 4.6 show evidence that is clearly in favor of our hypothesis that fund age has no significant impact on the performance of index funds whose daily business is almost by definition unrelated to innovative investment behavior.

[61] We focus on S&P500 index funds since they represent the lion's share of passively managed index funds in the U.S. (Investment Company Institute, 2014). In addition, we include small-cap and mid-cap index funds that track the S&P400, S&P600, NASDAQ 100, and the Russell 2000 index.

[62] Since results from the reduced sample of Table 4.5 where manager information are available do not change our main results we employ the empirical approach from Table 4.4 in this and all subsequent analyses. Results for the empirical approach from Table 4.5 (not reported) are qualitatively the same.

Table 4.6: Impact of fund age on performance among index funds and actively managed funds

**Panel A: Index fund sample**

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| Ln age | 0.0016 | 0.0003 | 0.0004 | 0.0003 |
| | (0.2817) | (0.5810) | (0.5034) | (0.6455) |
| Ln TNA family | 0.0006 | 0.0003 | 0.0003 | 0.0004 |
| | (0.1811) | (0.3062) | (0.2949) | (0.2426) |
| Family focus | 0.0036 | 0.0025 | 0.0018 | 0.0019 |
| | (0.1872) | (0.1790) | (0.2616) | (0.2221) |
| Fund return | -0.0494 * | -0.0223 | -0.0169 | -0.0006 |
| | (0.0824) | (0.2274) | (0.3631) | (0.9818) |
| Ln TNA | -0.0020 *** | -0.0002 | -0.0003 * | -0.0003 * |
| | (0.0000) | (0.3086) | (0.0891) | (0.0749) |
| Fund flow | 0.0012 | -0.0007 | -0.0008 | -0.0010 * |
| | (0.2085) | (0.1415) | (0.1205) | (0.0865) |
| Expense ratio | -0.2955 | -0.1552 | -0.1089 | -0.1045 |
| | (0.1597) | (0.1705) | (0.3258) | (0.3366) |
| Turnover ratio | 0.0003 | 0.0002 | 0.0001 | 0.0002 |
| | (0.5339) | (0.3627) | (0.3643) | (0.3623) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 14,372 | 14,372 | 14,372 | 14,372 |
| Adj. $R^2$ | 0.0759 | 0.0713 | 0.0584 | 0.0593 |

(*Continued*)

In Panel B we transfer the above rationale to our sample of actively managed funds and separate them into two groups based on their investment segments' potential for innovative investment strategies. Specifically, we would expect that funds that invest for example in Blue Chip stocks, i.e., stocks of large and well-established companies with consistent generations of income provide weaker opportunities for innovative investment strategies than an investment focus on smaller and more specialized stocks. Thus, we define funds with the CRSP investment objectives "Income", "Growth & Income" and "Mid Cap" ("Micro Cap", "Small Cap", "Sector" and "Growth") as less (more) innovative and repeat the performance analysis from Section 4.4 for both subsamples of actively managed funds. Results from Panel B of Table 4.6 confirm our hypothesis that the negative age-performance relation cannot be confirmed among funds whose investment focus is on stocks with higher market capitalization and stable cash flows. However, a doubling in a typical fund's age whose investment segment permits more innovative investments is associated with a performance deterioration of up to 141 basis points per year.

Table 4.6: Impact of fund age on performance among index funds and actively managed funds (Continued)

**Panel B: Actively managed funds**

| Subsample: | Less innovative investment segment | | | | More innovative investment segment | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh | Jensen | Fama French | Carhart | Pástor Stambaugh |
| Ln age | 0.0004 | -0.0002 | -0.0001 | -0.0002 | -0.0017 * | -0.0007 ** | -0.0009 ** | -0.0010 *** |
| | (0.6101) | (0.6041) | (0.7538) | (0.5897) | (0.0625) | (0.0339) | (0.0153) | (0.0067) |
| Ln TNA family | -0.0004 * | -0.0003 * | -0.0002 | -0.0003 | -0.0004 | -0.0002 | -0.0002 | -0.0002 |
| | (0.0975) | (0.0574) | (0.1844) | (0.1621) | (0.1042) | (0.1580) | (0.2380) | (0.1019) |
| Family focus | 0.0017 | 0.0007 | 0.0003 | 0.0005 | 0.0006 | 0.0003 | 0.0002 | 0.0004 |
| | (0.1736) | (0.3979) | (0.6862) | (0.5141) | (0.5648) | (0.7162) | (0.7280) | (0.5789) |
| Fund return | -0.0064 | 0.0330 *** | 0.0202 *** | 0.0220 *** | -0.0219 *** | 0.0106 *** | 0.0006 | 0.0036 |
| | (0.2826) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.8345) | (0.2214) |
| Ln TNA | -0.0022 *** | -0.0011 *** | -0.0015 *** | -0.0016 *** | -0.0030 *** | -0.0014 *** | -0.0019 *** | -0.0019 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 *** | 0.0000 *** | 0.0000 ** | 0.0000 * |
| | (0.4702) | (0.4192) | (0.7649) | (0.7455) | (0.0000) | (0.0008) | (0.0372) | (0.0612) |
| Expense ratio | 0.1464 | 0.0825 | 0.0648 | 0.0613 | -0.0763 | -0.0186 | -0.0196 | -0.0205 |
| | (0.4994) | (0.3709) | (0.4286) | (0.4437) | (0.2186) | (0.4104) | (0.5498) | (0.5472) |
| Turnover ratio | 0.0005 | 0.0002 | 0.0002 | 0.0001 | 0.0000 | 0.0001 | 0.0002 * | 0.0001 |
| | (0.1962) | (0.1921) | (0.1565) | (0.2814) | (0.9242) | (0.2323) | (0.0800) | (0.1152) |
| Fund fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Incubation fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 110,967 | 110,967 | 110,967 | 110,967 | 242,250 | 242,250 | 242,250 | 242,250 |
| Adj. $R^2$ | 0.0888 | 0.1059 | 0.1095 | 0.1065 | 0.0999 | 0.0847 | 0.0882 | 0.0875 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on fund performance using four different performance measures: Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. In Panel A we restrict our sample to observations of passively managed index funds. In Panel B regressions are run separately for funds that, respectively, belong to less and more innovative investment segments. Based on the style classification from CRSP we define the investment segments "Income", "Growth & Income" and "Mid Cap" ("Micro Cap", "Small Cap", "Sector" and "Growth") as less (more) innovative investment segments. The main independent variable in both Panel A and Panel B is Ln age, the logarithm of the fund's age in years. Other independent variables and fixed effects are defined as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Overall, the observations from Table 4.6 supports our claim that mature funds' diseconomies of life are indeed related to their ability to generate influential new investment ideas, respectively, by their inability to reinvent themselves over time.

### 4.5.2 Age-performance relation and competition

Evidence from the organizational economist literature suggests a generally positive relationship between competition, respectively, market concentration and a drive for innovation among organizations. Cohen (2010) provides a comprehensive review on the link between innovative activity and performance as well as its associated determinants such as competition. These views in turn resemble observations in the fund literature that the mutual fund industry is shaped by its competitive forces. Specifically, Khorana and Servaes (2012) suggest that fund families gain market share through product differentiation. Relatedly, Wahal and Wang (2011) find that higher product competition through the market entry of funds with similar stockholdings affects funds' performance and survival in the market. This suggests that times of higher competition require a fund to put more emphasis on investing differently than its competitors. According to this narrative, we would expect that the negative age-performance relation can be observed in times of low competition but should be less pronounced in more competitive environments. We address this notion by repeating the performance analysis for subsamples that proxy for environments of different competitive strengths.

In Panel A of Table 4.7, we investigate the age-performance relation for different intensities of industry competition and split our sample into low and high competitive based on the market concentration (Herfindahl index) among mutual funds in the industry. Specifically, times with above median Herfindahl index values are classified as less competitive than times with below median values. In Panel B we extend this logic to the fund family level. We study the underperformance of mature funds for varying intra-family competition and thus environments that facilitate innovation at a more micro level. In particular, we classify observations as low (high) competitive if the fund belongs to a fund family with below (above) median number of funds in its investment segment.[63]

[63] We additionally distinguish between other proxies that capture different intensities of intra-family competition. For instance, we classify observations as low (high) competitive if the fund belongs to a fund family with below (above) median number of funds in the family or, analogous to the definition for industry competition, above (below) median asset concentration (Herfindahl index) across investment segments measured as in Siggelkow (2003). The results (not reported) are qualitatively the same.

Table 4.7: Impact of fund age on performance stratified by competitive environment

| Dependent variable: | Jensen | Fama French | Carhart | Pástor Stambaugh |
|---|---|---|---|---|
| **Panel A: Industry concentration** | | | | |
| Industry competition - Low | -0.0014 ** | -0.0011 *** | -0.0012 *** | -0.0012 *** |
| | (0.0143) | (0.0085) | (0.0094) | (0.0071) |
| Industry competition - High | -0.0010 | 0.0003 | 0.0006 | 0.0005 |
| | (0.4885) | (0.4137) | (0.1502) | (0.3056) |
| **Panel B: # Funds in the investment segment of the family** | | | | |
| Family competition - Low | -0.0022 ** | -0.0015 *** | -0.0011 *** | -0.0012 *** |
| | (0.0402) | (0.0002) | (0.0060) | (0.0025) |
| Family competition - High | -0.0006 | 0.0002 | 0.0000 | 0.0000 |
| | (0.5330) | (0.6796) | (0.9039) | (0.9961) |
| Other fund and family controls | Yes | Yes | Yes | Yes |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |

Notes: This table presents results from pooled OLS regressions that analyze the impact fund age on mutual fund performance using four different performance measures: Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh). Alpha estimations are based on 36-month rolling-window regressions of funds' net-of-fee excess returns on the market excess return and, as required, the long-short portfolio returns of the benchmark mimicking portfolios. The main independent variable in each Panel is Ln age, the logarithm of the fund's age in years. In Panel A, we split fund-month observations into two subsamples of low and high industry competition based on the median cutoff of the industry concentration within a month. Industry concentration is defined as the Herfindahl index value among funds. In Panel B, we split fund-month observations into two subsamples of low and high intra-family competition based on the median cutoff of the number of funds in the same investment segment within a fund family. Other independent variables are defined as in Table 4.4 and not reported for brevity. Regressions are run with fixed effects as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

The results from Table 4.7 confirm that the negative age-performance effect is related to the competitive environment of the funds. Times of higher industry concentration and funds of families with less populated investment segments, all proxies for environments of lower competitive strength, show that fund performance deteriorates with age. Depending on the employed performance benchmark a doubling in a typical fund's lifetime is associated with a performance decline of up to 114 basis points per year. In contrast, when competition is higher we find no significant effect of fund age on performance.

Overall, the results from Table 4.7 show that funds' negative returns to life are limited to observations that are associated with lower competition and thus lower needs for funds to reinvent themselves.

## 4.6 Fund age and innovative investment behavior

In this section we explore age induced differences in investment behavior as the main mechanism for the observed diseconomies of life as suggested by the liability of aging theory. We investigate funds' innovative investment behavior from two different ankles. In Section 4.6.1, we provide evidence on how fund age impacts on trading behavior. In Section 4.6.2, we explore whether the difference in innovative investment behavior is observable in funds' stock holding characteristics.

### 4.6.1 Impact of fund age on trading behavior

Funds that exhibit truly innovative investment behavior through a constant pursuit of new profit opportunities need to put their ideas into practice and simultaneously abandon obsolete investment strategies (Pástor, Stambaugh, and Taylor, 2015a). Hence, we hypothesize that funds that aim to reinvent themselves time and again trade more heavily compared to funds that are less innovative and stick to the status quo of their portfolio.

To test this hypothesis, we study an impact of fund age on various measures of turnover. As in Cici, Dahm, and Kempf (2014) we use funds' turnover ratios, buy and sell turnover as well as funds' position-adjusted turnover as measures for trading behavior. A fund's turnover ratio is defined as the minimum of security purchases and sales divided by the fund's average total net assets under management during the period. Buy and sell turnover, defined as in Carhart (1997), intend to separately measure buy and sell induced trading behavior. As in Edelen, Evans, and Kadlec (2013) the position-adjusted turnover of a fund is equal to the turnover ratio adjusted for the average size of the fund's holdings position. The idea is that the adjustment for a fund's relative position size takes the price impact of a fund's trading into account.

We complement the first group of measures with another set that is similar in spirit but does not employ funds' reported turnover ratios. Specifically, Dorn and Huberman (2009) suggest to measure funds' trading behavior based on their holdings. Accordingly, we estimate a fund's holdingsbased turnover as the absolute value of the fund's purchases and sales divided by twice the average portfolio value. In addition, we derive a fund's speculation induced turnover. Thereby, sales (buys) are classified as speculative trades only if the entire stock position is closed (newly added) (Barber and Odean, 2002). Hence, speculative trades are more driven by beliefs about future performance.

Table 4.8 provides strong evidence that fund age is negatively related to trading behavior. In particular, a doubling in a typical fund's lifetime is associated with a decrease in fund turnover

Table 4.8: Impact of fund age on turnover

| Dependent variable: | Fund Turnover | Buy Turnover | Sell Turnover | Position-adjusted Turnover | Turnover (holdingsbased) | Speculative Turnover (holdingsbased) |
|---|---|---|---|---|---|---|
| Ln age | -0.1809 *** | -0.2011 *** | -0.1761 *** | -0.0684 *** | -0.1614 *** | -0.0950 *** |
| | (0.0076) | (0.0030) | (0.0096) | (0.0069) | (0.0004) | (0.0008) |
| Ln TNA family | -0.0243 | -0.0233 | -0.0246 | -0.0187 ** | -0.0034 | -0.0006 |
| | (0.1621) | (0.1791) | (0.1565) | (0.0200) | (0.8299) | (0.9563) |
| Family focus | 0.5179 *** | 0.5212 *** | 0.5178 *** | 0.1128 | 0.0514 | -0.0216 |
| | (0.0027) | (0.0025) | (0.0027) | (0.1244) | (0.6124) | (0.7614) |
| Fund return | 0.1637 | 0.2818 ** | 0.1143 | 0.2048 *** | 0.2654 *** | 0.1559 ** |
| | (0.1556) | (0.0148) | (0.3230) | (0.0009) | (0.0068) | (0.0235) |
| Ln TNA | -0.0430 ** | -0.0497 ** | -0.0440 ** | 0.1129 *** | -0.0754 *** | -0.0453 *** |
| | (0.0427) | (0.0190) | (0.0382) | (0.0000) | (0.0004) | (0.0006) |
| Fund flow | 0.0000 ** | 0.0000 *** | 0.0000 ** | 0.0001 | 0.0003 | 0.0001 |
| | (0.0339) | (0.0000) | (0.0338) | (0.2478) | (0.2893) | (0.4997) |
| Expense ratio | -1.7749 | -1.6477 | -1.7949 | 0.3485 | 6.5933 | 5.0159 |
| | (0.3638) | (0.3941) | (0.3627) | (0.2731) | (0.1518) | (0.1936) |
| Fund fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 371,310 | 371,310 | 371,310 | 296,878 | 285,166 | 285,166 |
| Adj. $R^2$ | 0.5913 | 0.5936 | 0.5927 | 0.5770 | 0.3420 | 0.5114 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on mutual fund trading behavior. The dependent variables are categorized in three different groups of trading measures. The first group of measures consists of Fund turnover, Buy turnover, and Sell turnover. 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 period. Buy and sell turnover separately measure the effects of buy and sell trading by adding the percentage change in a fund's total net assets under management as in Carhart (1997). Another measure is Position-adjusted turnover, defined as in Edelen, Evans, and Kadlec (2013), that is equal to the turnover ratio adjusted for the average size of the fund's holdings position. The third group of measures consists of three additional turnover variables that are estimated based on funds' portfolio holdings as in Dorn and Huberman (2009). Turnover (holdingsbased), is the absolute value of the fund's purchases and sales divided by twice the average portfolio value. Speculative turnover (holdingsbased) represents a fund's speculation induced turnover. Whereby sales (buys) are classified as speculative trades only if the entire stock position in a fund is closed (newly added). The main independent variable is Ln age, the logarithm of the fund's age in years. Other independent variables and fixed effects are defined as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

of up to 20 percent per year. This effect of less active investment behavior among older funds holds irrespective of the employed turnover measure. Particularly interesting is the strong and significantly negative loading on *Speculative turnover (holdingsbased)* that younger funds alter entire stock positions more frequently than their future selves. Thus, our findings are consistent with the liability of aging theory and present a first indicator that mature funds are less innovative than their younger peers.

To extend our finding from Table 4.8 we investigate the impact of fund age on a number of recent measures for active management that present more direct links to superior fund performance.

As proxies for this kind of activity we employ funds' active share (Cremers and Petajisto, 2009, Petajisto, 2013), return gap (Kacperczyk, Sialm, and Zheng, 2008) and the $R^2$ measure (Amihud and Goyenko, 2013). Specifically, Cremers and Petajisto (2009) suggest that superior investment skill is associated with an under- or overweight of particular stocks in the fund's portfolio relative to those stocks' weights in the benchmark portfolio. Hence, funds' active share, that are based on a comparison of the stocks' portfolio weights in the fund and the portfolio weights of the stocks in the fund's benchmark portfolio, predict future fund performance.[64] Kacperczyk, Sialm, and Zheng (2008) contribute to the literature on active management skill by showing that unreported actions add to a fund's performance. They measure this hidden performance benefit as the difference between the actual gross-of-fee fund return and the hypothetical return of the recently reported fund holdings. Accordingly, return gap positively predicts future fund performance. Lastly, Amihud and Goyenko (2013) propose that the $R^2$ from a regression of fund returns on a multifactor model indicates investment skill. In particular, funds with low values of $R^2$ generate superior future fund performance. We obtain the $R^2$ measures from 36-month rolling window regressions of funds' net-of-fee excess returns on the excess market return and the SMB, HML, and MOM (momentum) factors as in the Carhart (1997) 4-factor model. Then, as suggested by Amihud and Goyenko (2013) we define 1-$R^2$ as funds' measure of selectivity.

Overall, in light of the liability of aging theory, we hypothesize that fund age is negatively related to all three measures of performance generating activity.

Results reported in Table 4.9 support our hypothesis and show a negative impact of fund age on active share, return gap and the $R^2$ measure which are associated with positive future fund performance. This finding provides further support to the liability of aging theory that

[64] We obtain the data on the active share information of mutual funds from the website of Antti Petajisto: http://www.petajisto.net/index.html.

Table 4.9: Impact of fund age on active management

| Dependent variable: | Active share | Return Gap | 1-$R^2$ |
|---|---|---|---|
| Ln age | -0.0082 ** | -0.0010 *** | -0.0124 *** |
| | (0.0211) | (0.0000) | (0.0041) |
| Ln TNA family | -0.0010 | 0.0001 ** | -0.0006 |
| | (0.5651) | (0.0377) | (0.6655) |
| Family focus | 0.0578 *** | 0.0009 *** | 0.0190 ** |
| | (0.0000) | (0.0047) | (0.0170) |
| Fund return | 0.0252 *** | 0.0042 ** | 0.0440 *** |
| | (0.0000) | (0.0382) | (0.0000) |
| Ln TNA | -0.0069 *** | -0.0004 *** | -0.0070 *** |
| | (0.0002) | (0.0000) | (0.0000) |
| Fund flow | 0.0001 *** | 0.0000 | 0.0000 *** |
| | (0.0083) | (0.1921) | (0.0003) |
| Expense ratio | 0.1432 | -0.0202 | 0.3820 |
| | (0.8038) | (0.4686) | (0.1586) |
| Turnover ratio | -0.0020 | -0.0001 | 0.0046 *** |
| | (0.2542) | (0.1269) | (0.0071) |
| Fund fixed effects | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes |
| Number of observations | 168,391 | 281,279 | 278,667 |
| Adj. $R^2$ | 0.8543 | 0.0773 | 0.8389 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on measures of active management. We use three measures for fund's activity: Active share, measures the difference between the stock's portfolio weights in the fund and the portfolio weights of the stocks in the fund's benchmark portfolio. Return gap, is the difference between the actual gross-of-fee fund return and the hypothetical return of the recently reported fund holdings as in Kacperczyk, Sialm, and Zheng (2008). 1-$R^2$, is the selectivity measure of Amihud and Goyenko (2013) that is obtained from 36-month rolling window regressions of funds' net-of-fee excess returns on the excess market return and the SMB, HML, and MOM (momentum) factors as in the Carhart (1997) 4-factor model. The main independent variable is Ln age, the logarithm of the fund's age in years. Other independent variables and fixed effects are defined as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

funds engage in less performance generating, innovative trading behavior when they grow older. Hence, evidence from Table 4.8 and Table 4.9 confirm our claim that the mechanism behind the observed diseconomies of life is attributable to a decline in innovative investments.

### 4.6.2 Fund age and hard-to-value stocks

In this section we make a more detailed exploration in identifying the mechanism that drives funds' diseconomies of life. Specifically, we investigate how mature funds moderate their engagement in innovative investment activity by looking at funds' stock holding positions. Generating abnormal returns requires of a fund to put effort in the identification of new profit opportunities. Stocks that bear the potential for higher profit opportunities are stocks that are relatively harder to value. Thus, we expect that older funds hold less stocks in their portfolio whose valuation takes effort and are hard-to-value.

We measure hard-to-value stocks with various measures documented in the literature. First, Kumar (2009) suggests that stocks with more valuation uncertainty are characterized by higher idiosyncratic volatility, lower turnover and lower firm age. Thus, our first measure, *Idiosyncratic stock*, represents a fund's weight in stocks that belong to the top three deciles of stocks' idiosyncratic volatility in a month. We obtain stocks' idiosyncratic volatility as the variance of the residual from excess return regressions on the Carhart (1997) 4-factor model. As a complementary we also consider *Non-idiosyncratic stock*, a fund's weight in stocks that belong to the bottom three deciles, which are presumed to be associated with low valuation uncertainty and thus are easy-to-value. Furthermore, *Stock turnover*, is the portfolio weighted average of the stocks' turnover of all stocks in a fund's portfolio. Thereby stock turnover is defined as the ratio of the number of shares traded in a month to the total number of shares outstanding. *Firm age*, is the mean firm age of a fund's holdings in a month. Firm age is estimated as the number of years since the stock appears for the first time in the CRSP database. Second, we employ measures from the literature on differences of opinion among investors (see, e.g., Abarbanell, Lanen, and Verrecchia, 1995, Diether, Malloy, and Scherbina, 2002, Garfinkel and Sokobin, 2006). In particular, stocks that are subject to less analyst coverage or show a higher dispersion of analyst forecast are expected to be harder to value. Thus, *Analyst coverage* and *Analyst dispersion*, respectively, represent the average analyst coverage and analyst forecast dispersion of the fund's stock holdings. Lastly, we employ measures of portfolio illiquidity that are related to the differences of opinion measures but are based on the market's perception and not just on a group of specialists. In particular, the literature documents a relation between the illiquidity of securities and information asymmetries in prices (see, e.g., Glosten and Milgrom, 1985, Glosten and Harris, 1988). Hence, we use *Relative spread* and the *Amihud* measure as proxies for the illiquidity of stocks. Relative spread is the difference between the logarithm of the best offer and the logarithm of the best bid price (see, e.g., Holden, Jacobsen, and Subrahmanyam, 2014). The Amihud (2002) measure is derived as the ratio of a stock's absolute return to its dollar volume. Both stock illiquidity measures are aggregated to the fund-portfolio level as the portfolio weighted mean (see Massa and Phalippou, 2005).

Results from Table 4.10 confirm our hypothesis that older funds hold significantly less stocks that are hard to value. In particular, as fund age increases the fraction of stocks with higher idiosyncratic volatility, higher analyst dispersion and higher illiquidity, all proxies for higher valuation uncertainty, decreases. At the same time, their holdings in non-idiosyncratic volatility

Table 4.10: Impact of fund age on funds' holdings in hard-to-value stocks

| Dependent variable: | Idiosyncratic Stock | Non-Idiosyncratic Stock | Stock Turnover | Firm age | Analyst Coverage | Analyst Dispersion | Relative Spread | Amihud |
|---|---|---|---|---|---|---|---|---|
| Ln age | -0.0028 ** | 0.0102 ** | 0.0004 *** | 0.0438 *** | 0.0130 * | -0.0012 ** | -0.0004 *** | -0.0165 ** |
| | (0.0457) | (0.0383) | (0.0000) | (0.0000) | (0.0644) | (0.0349) | (0.0005) | (0.0266) |
| Ln TNA family | 0.0006 | -0.0023 | 0.0000 *** | 0.0019 | 0.0082 ** | -0.0004 | -0.0001 ** | -0.0118 *** |
| | (0.3900) | (0.3265) | (0.0001) | (0.7126) | (0.0164) | (0.2242) | (0.0315) | (0.0065) |
| Family focus | 0.0062 * | -0.0182 | -0.0004 *** | -0.0225 | -0.0356 ** | -0.0017 | 0.0002 | -0.0003 |
| | (0.0803) | (0.1141) | (0.0000) | (0.3110) | (0.0378) | (0.1956) | (0.3998) | (0.9878) |
| Fund return | 0.0160 *** | 0.0113 | -0.0015 *** | -0.1046 *** | 0.0188 | -0.0100 *** | -0.0044 *** | -0.2444 *** |
| | (0.0002) | (0.2351) | (0.0000) | (0.0000) | (0.2286) | (0.0000) | (0.0000) | (0.0000) |
| Ln TNA | 0.0007 | -0.0036 ** | 0.0000 *** | -0.0012 | 0.0191 *** | 0.0002 | -0.0004 *** | -0.0274 *** |
| | (0.1521) | (0.0330) | (0.0070) | (0.7488) | (0.0000) | (0.5621) | (0.0000) | (0.0000) |
| Fund flow | 0.0000 | 0.0000 | 0.0000 *** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 ** |
| | (0.1339) | (0.1107) | (0.0000) | (0.1967) | (0.2507) | (0.2257) | (0.2836) | (0.0457) |
| Expense ratio | 0.0995 | -0.1199 | -0.0006 | -0.2634 | -0.0741 | 0.0447 | -0.0168 *** | 0.3383 |
| | (0.2659) | (0.1657) | (0.3391) | (0.3642) | (0.5882) | (0.4484) | (0.0026) | (0.1366) |
| Turnover ratio | 0.0009 * | -0.0033 | 0.0000 * | -0.0013 | 0.0006 | 0.0000 | 0.0000 * | -0.0028 * |
| | (0.0597) | (0.1487) | (0.0577) | (0.6948) | (0.6847) | (0.7307) | (0.0958) | (0.0685) |
| Fund fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 296,945 | 296,945 | 296,945 | 296,945 | 296,866 | 296,589 | 296,927 | 296,927 |
| Adj. $R^2$ | 0.6657 | 0.8311 | 0.4839 | 0.8780 | 0.9006 | 0.2416 | 0.6452 | 0.7138 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on funds' holdings in hard-to-value stocks. The dependent variables are categorized in three different groups. The first group of measures includes Idiosyncratic stock, Non-idiosyncratic stock, Stock turnover, and Firm age that measures the valuation uncertainty of stocks as in Kumar (2009). Idiosyncratic stock, is the fund's weight in stocks that belong to the top three deciles of stocks' idiosyncratic volatility in a month. Complementary, Non-idiosyncratic stock, is the fund's weight in stocks that belong to the bottom three deciles of stocks' idiosyncratic volatility in a month. Stock turnover, is the portfolio weighted average of the stocks' turnover of all stocks in a fund's portfolio. Firm age, is the mean firm age of all stocks in a fund's portfolio. For the second group of measures we use: Analyst coverage and Analyst dispersion, defined as the average analyst coverage and analyst forecast dispersion, respectively, of the fund's stock holdings. Both measures proxy for differences of opinion among investors (Abarbanell, Lanen, and Verrecchia, 1995, Diether, Malloy, and Scherbina, 2002, Garfinkel and Sokobin, 2006). The third group measures fund's portfolio illiquidity. Relative spread, is the difference between the logarithm of the best offer and the logarithm of the best bid price as in Holden, Jacobsen, and Subrahmanyam (2014). Amihud, is based on the illiquidity measure of Amihud (2002). The main independent variable is Ln age, the logarithm of the fund's age in years. Other independent variables and fixed effects are defined as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

stocks, higher turnover stocks, older firms, and higher analyst coverage, all proxies for easier-to-value stocks, increases.

Overall, the conclusion that mature funds hold less stocks associated with higher valuation uncertainty and thus higher profit opportunities is robust to the various measures. This is consistent with the liability of aging theory that when funds grow older they pursue less innovative investment strategies.

## 4.7 Demand for mature funds and their potential benefits

In this section we explore what types of investors seek to invest in older funds and touch on potential benefits that these shareholders receive. In Section 4.7.1, we investigate whether there are differences in the investor types who populate funds between their earlier or advanced stages of life. In Section 4.7.2, we analyze what investors could stand to gain from investing in mature funds. In particular, since older funds seem to pursue less innovative investment strategies, we hypothesize that they exhibit less extreme investment styles and consequently deliver more stable performance outcomes.

### 4.7.1 Diversity in investor characteristics

In this section we study whether the type of shareholders change during a fund's lifetime. Unfortunately, data limitations on the availability of fund investor characteristics prevent us to establish a direct link between investor types and funds' age. However, we try to circumvent these limitations by using tests that relate to distinguishing characteristics among investor groups documented in the literature. Specifically, Evans and Fahlenbrach (2012) show that the response to a fund's past performance is significantly different among funds that cater exclusively to retail investors and those that are also populated by institutional investors. Hence, we hypothesize that investors' responsiveness to funds' past performance as well as the prevalence of institutional investors are indicators of significantly different shareholder structures in a fund.

We begin our analysis of whether mature funds attract different types of investors by studying the relation of fund age and the performance-flow sensitivity. In particular, we measure net-inflows as suggested by Sirri and Tufano (1998) for each fund $i$ in each month $t$ as:

$$\textit{Fund flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{4.3}$$

whereby *TNA* represents the total net assets under management and $R$ the total net-of-fee return. Thus, a fund's monthly net-inflow, *Fund flow*, denotes the percentage growth rate of the fund adjusted for its internal growth. We then relate the growth of a fund to our main independent variable, *Ln age*, and the fund's past performance. To account for the well documented non-linear influence of past performance on net-inflows (see, e.g., Ippolito, 1992, Chevalier and Ellison, 1997, Sirri and Tufano, 1998), we employ a piecewise-linear regression model and estimate separate slope coefficients for the performance groups *Bottom quintile*, *Middle quintiles*, and *Top quintile* that represent piecewise decompositions of funds' fractional performance ranks and are defined as:

$$\begin{aligned} \textit{Bottom quintile}_{i,t-1} &= Min(0.2; PerfRank_{i,t-1}) \\ \textit{Middle quintiles}_{i,t-1} &= Min(0.6; PerfRank_{i,t-1} - \textit{Bottom quintile}_{i,t-1}) \\ \textit{Top quintile}_{i,t-1} &= PerfRank_{i,t-1} - (\textit{Bottom quintile}_{i,t-1} + \textit{Middle quintiles}_{i,t-1}). \end{aligned} \tag{4.4}$$

Thereby, funds' performance ranks, *PerfRank*, are based on the percentile risk-adjusted performance relative to all other funds within the same investment segment and month as in Sirri and Tufano (1998). As control variables we include: *Ln TNA Family, Family focus, Ln TNA, Fund flow, Expense ratio,* and *Turnover ratio* as defined in Section 4.4. We supplement these controls with the average growth rate (in month *t-1*) of the fund's segment within a month (*Objective flow*) and cluster standard errors at the fund level.

The results of Table 4.11 clearly confirm the findings from the literature of a convex performance-flow relationship. This observation holds irrespective of the employed performance ranks that are based on the Jensen (1968) alpha, Fama and French (1993) 3-factor alpha, Carhart (1997) 4-factor alpha, or Pástor and Stambaugh (2003) 5-factor alpha. In addition, we confirm the findings of Barber, Huang, and Odean (2015) that investors seem to account for market beta risk and respond most heavily to performance ranks based on Jensen (1968) alpha. More importantly, however, we find significantly negative loadings on the interaction term of *Ln age* and *Top quintile* indicating that investors who populate funds at their earlier stages of life are considerably more sensitive to superior fund performance than at their advanced stages of life. This gives support to our hypothesis that the demand for mature funds stems from different kinds of shareholders than during their earlier years. Even further, looking at the results for Carhart (1997) 4-factor and Pástor and Stambaugh (2003) 5-factor we find evidence that shareholders in young funds are more sensitive to poor risk-adjusted fund performance and seem to avoid underperformers more strongly. However, consistent with the literature we

Table 4.11: Fund age and the performance sensitivity of investors

| Dependent variable: | Fund flow in t | | | |
|---|---|---|---|---|
| Performance quintiles based on: | Jensen | Fama French | Carhart | Pástor Stambaugh |
| Top quintile | 0.0843 *** | 0.0718 *** | 0.0689 *** | 0.0690 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Middle quintiles | 0.0081 *** | 0.0031 * | 0.0032 * | 0.0033 * |
| | (0.0000) | (0.0602) | (0.0570) | (0.0564) |
| Bottom quintile | 0.0212 *** | 0.0165 ** | 0.0071 | 0.0009 |
| | (0.0088) | (0.0371) | (0.3572) | (0.9026) |
| Ln age | -0.0156 *** | -0.0163 *** | -0.0166 *** | -0.0170 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Top quintile × Ln age | -0.0162 *** | -0.0135 *** | -0.0129 *** | -0.0131 *** |
| | (0.0000) | (0.0001) | (0.0002) | (0.0001) |
| Middle quintiles × Ln age | -0.0009 | 0.0005 | 0.0003 | 0.0003 |
| | (0.1823) | (0.4656) | (0.6125) | (0.6420) |
| Bottom quintile × Ln age | 0.0010 | 0.0029 | 0.0058 * | 0.0084 *** |
| | (0.7491) | (0.3408) | (0.0532) | (0.0057) |
| Ln TNA family | 0.0013 *** | 0.0013 *** | 0.0012 *** | 0.0013 *** |
| | (0.0030) | (0.0035) | (0.0038) | (0.0035) |
| Family focus | 0.0025 | 0.0026 | 0.0027 | 0.0026 |
| | (0.2058) | (0.1903) | (0.1893) | (0.1939) |
| Ln TNA | -0.0057 *** | -0.0059 *** | -0.0058 *** | -0.0058 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Fund flow | 0.2269 *** | 0.2290 *** | 0.2293 *** | 0.2294 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Objective flow | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.7484) | (0.8164) | (0.8081) | (0.8016) |
| Expense ratio | -0.1122 | -0.1209 | -0.1200 | -0.1169 |
| | (0.3818) | (0.3471) | (0.3506) | (0.3635) |
| Turnover ratio | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.8699) | (0.8818) | (0.9020) | (0.9215) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 351,934 | 351,934 | 351,934 | 351,934 |
| Adj. $R^2$ | 0.1867 | 0.185 | 0.1846 | 0.1845 |

Notes: This table presents results from piecewise-linear regressions that analyze the relation between fund age and the performance-flow sensitivity. Fund flows are estimated as the fund's percentage growth rate adjusted for the internal growth of the fund as in Sirri and Tufano (1998). The main independent variables are Ln age, the logarithm of the fund's age in years as well as Top quintile, Middle quintiles and Bottom quintile, a piecewise decomposition of a fund's fractional performance rank defined as the fund's percentile past performance, represented by the four different performance measures Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh), relative to other funds within the same investment segment and month. In particular, the performance ranks are calculated according to the definitions in Sirri and Tufano (1998). Additional independent controls include Ln TNA family, Family focus, Ln TNA, Fund flow, Objective flow, Expense ratio, and Turnover ratio. Ln TNA family, is the logarithm of the fund family's total net assets under management. Family focus, represents the concentration of a fund family across investment segments defined as in Siggelkow (2003). Ln TNA, represents the logarithm of the fund's total net assets under management. Objective flow, is the average net-inflow of the funds in the same investment segment. Expense ratio, represents the fund's total expense ratio. Turnover ratio is the fund's yearly turnover ratio. All independent variables are lagged by one month. Regressions are run with fixed effects as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

cannot find any evidence that investors redeem their shares even if the fund belongs to the worst performers of their peer group. Hence, irrespective of a fund's stage of life investors do not vote with their feet when it comes to an underperformance of their fund investments.

Building on this observation we study a more direct link of an age-related difference in funds' shareholder structure and explore the probability of mature funds being populated by institutional investors. We obtain information on the primary investor group of a fund's share from Thomson Reuters Lipper (Lipper). Similar to Del Guercio and Reuter (2014) we classify a fund as an *Institutional fund* if more than 50 percent of the fund's assets are reflected through share classes sold to institutional investors. Then, we run the following logistic regression model:

$$Prob(Institutional\ fund_{i,t} = 1) = \Lambda(\alpha_0 + \beta Ln\ age_{i,t-1} + \gamma Z_{i,t-1} + A), \tag{4.5}$$

where *Institutional fund* is an indicator variable which equals one if fund $i$ is primarily populated by institutional investors in month $t$ and zero otherwise. $\Lambda(\bullet)$ indicates the logistic cumulative distribution function. Our main independent variable is *Ln age* to determine whether the likelihood of having an institutional fund increases or deteriorates with a fund's age. In addition, the vector $Z$ is the set of control variables (in month *t-1*) from Table 4.4 and fixed effects are represented by $A$.[65] We cluster standard errors at the fund level.

The coefficient on our main independent variable *Ln age* is negative and statistically significant. This indicates that the likelihood of a fund to be populated by an institutional majority deteriorates for mature funds. The magnitude of this effect suggests that a one-standard deviation increase in *Ln age* (0.9294) decreases the likelihood that a fund is an institutional fund by about 8.94 (-9.62 $\times$ 0.9294) percentage points. This is a notable effect considering that only about 25 percent of our fund-month observations belong to funds that are primarily populated by institutional investors.

[65] Note that, in this specification we refrain from including fund fixed effects because we are interested in whether mature funds are more or less populated by institutional investors. On the contrary, the use of fund fixed effects would alter the interpretation to mature funds being more or less likely to switch to a dominantly institutional shareholder structure. Hence, identification would come from changes at the fund level. However, results (not reported) with fund fixed effects are qualitatively the same.

Table 4.12: Fund age and the demand through institutional investors

| Dependent variable: | Institutional fund | |
|---|---|---|
| Ln age | -0.7160 *** | -0.6759 *** |
| | (0.0000) | (0.0000) |
| | [-9.6200] | [-8.1443] |
| Ln TNA family | -0.1918 *** | 0.0646 |
| | (0.0000) | (0.3606) |
| | [-2.5776] | [0.7789] |
| Family focus | -2.3029 *** | -0.4471 |
| | (0.0000) | (0.1893) |
| | [-30.9421] | [-5.3871] |
| Fund return | -0.1357 | 0.0048 |
| | (0.4095) | (0.9858) |
| | [-1.8229] | [0.0581] |
| Ln TNA | -0.1175 *** | -0.1590 *** |
| | (0.0002) | (0.0001) |
| | [-1.5790] | [-1.9165] |
| Fund flow | 0.0001 | 0.0007 *** |
| | (0.3072) | (0.0000) |
| | [0.0000] | [0.0081] |
| Expense ratio | -327.6299 *** | -473.9045 *** |
| | (0.0000) | (0.0000) |
| | [-4402.16] | [-5710.52] |
| Turnover ratio | 0.0245 | 0.2983 *** |
| | (0.1426) | (0.0000) |
| | [0.3296] | [-3.5950] |
| Family fixed effects | No | Yes |
| Incubation fund fixed effect | Yes | Yes |
| Segment fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Number of observations | 319,116 | 210,163 |
| Pseudo $R^2$ | 0.2318 | 0.5158 |

Notes: This table presents results from logistic regressions that analyze the impact of fund age on the probability of a fund being primarily populated by institutional investors. The dependent variable is Institutional fund, a binary variable which equals one if more than 50 percent of the fund's assets stem from fund shares that cater primarily to institutional investors and zero otherwise. The main independent variable is Ln age, the logarithm of the fund's age in years. Other independent variables are defined as in Table 4.4. Regressions are run with incubation, segment and time fixed effects as well as with and without family fixed effects. P-values reported in parentheses are based on robust standard errors clustered at the fund level. Average marginal effects in percentages are shown in square brackets. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

### 4.7.2 Style and performance extremity

Acknowledging that the type of shareholder changes during a fund's lifetime we touch in this section on what investors could stand to gain from investing in mature funds despite that they are unable to reinvent themselves over time and underperform their younger counterparts. Thereby, we analyze two implications arising from the differences in funds' age induced investment behavior. First, we explore in Panel A of Table 4.13 whether older funds take fewer large bets on specific investment styles, i.e., that the extremity of the funds' investment style deteriorates over time. Second, as a logical implication we test in Panel B of Table 4.13 whether mature funds deliver less extreme performance outcomes relative to their younger selves.

We measure the investment style of each fund $i$ in each month $t$ by the fund's Carhart (1997) factor sensitivities to the market factor (Market), value factor (HML), size factor (SMB) and momentum factor (MOM) obtained from 36-month rolling regressions. Then we estimate funds' style extremities as suggested by Bär, Kempf, and Ruenzi (2011) as:

$$SE_{i,t}^{S} = \frac{\left|\beta_{i,t}^{S} - \overline{\beta_{i,t}^{S}}\right|}{\frac{1}{N}\sum_{j=1}^{N}\left|\beta_{i,t}^{S} - \overline{\beta_{i,t}^{S}}\right|}, \tag{4.6}$$

where $S$ represents the analyzed investment style of the fund (Market, HML, SMB, MOM), $\beta$ is the factor exposure of fund $i$ in month $t$, and $\overline{\beta}$ is the average factor exposure of all funds in the same investment segment and month $t$ as fund $i$. Accordingly, style extremity is estimated as the absolute difference between a fund's style, represented by its beta loading to one of the four factors in the Carhart (1997) 4-factor model, and the average style of all funds in the same investment segment and month. This difference is then normalized by the average absolute difference of all funds so that style differentials become comparable across styles, investment segments, and time.

Similar to the style extremity measure above we calculate the performance extremity measure for each fund $i$ in each month $t$ as suggested by Bär, Kempf, and Ruenzi (2011) as:

$$PE_{i,t} = \frac{\left|P_{i,t} - \overline{P_{i,t}}\right|}{\frac{1}{N}\sum_{j=1}^{N}\left|P_{j,t} - \overline{P_{i,t}}\right|}. \tag{4.7}$$

Thereby, the performance extremity of a fund is estimated as the absolute difference between a fund's performance $P$, represented by the four different performance measures Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama-French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh), and the average performance of all funds in the same segment and month, $\overline{P}$, divided by the average absolute deviation of all funds in the same investment segment and month.

Results from Panel A of Table 4.13 show strong support for our hypothesis that mature funds pursue less extreme investment styles. These differences are statistically significant at the 1 percent level but also matter from an economic point of view. In particular, a doubling in a typical fund's age is associated with a decrease in the style extremity measure for the market factor of about 83 percentage points when compared to that of an average fund in the

Table 4.13: Impact of fund age on style extremity and performance extremity

**Panel A: Style extremity**

| Dependent variable: | Style extremity | | | |
|---|---|---|---|---|
| | Market | HML | SMB | MOM |
| Ln age | -0.8291 *** | -0.4176 *** | -0.5019 *** | -0.3033 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Ln TNA family | -0.0068 | -0.0038 | -0.0347 ** | 0.0001 |
| | (0.6264) | (0.7748) | (0.0137) | (0.9947) |
| Family focus | 0.1043 | 0.0251 | 0.0692 | 0.0856 |
| | (0.1102) | (0.6889) | (0.2928) | (0.2109) |
| Fund return | -0.0544 | 0.2292 *** | 0.0502 | 0.1304 * |
| | (0.5998) | (0.0085) | (0.5251) | (0.0943) |
| Ln TNA | -0.0004 | -0.0263 ** | 0.0126 | 0.0079 |
| | (0.9693) | (0.0105) | (0.2215) | (0.4272) |
| Fund flow | 0.0000 *** | 0.0000 *** | 0.0000 *** | 0.0000 *** |
| | (0.0001) | (0.0000) | (0.0000) | (0.0000) |
| Expense ratio | 1.9342 *** | -0.3814 | -0.2517 | 0.9643 |
| | (0.0016) | (0.5489) | (0.7820) | (0.2624) |
| Turnover ratio | -0.0088 | -0.0110 ** | -0.0069 | 0.0184 ** |
| | (0.2491) | (0.0133) | (0.2236) | (0.0268) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 353,217 | 353,217 | 353,217 | 353,217 |
| Adj. $R^2$ | 0.3141 | 0.2383 | 0.3305 | 0.3231 |

(*Continued*)

same investment segment and month. This differential becomes smaller but is still considerably large when we look at the differences in style extremity for the HML (SMB, MOM) factor that amounts to 42 (50, 30) percentage points.

In addition, results from Panel B of Table 4.13 clearly confirm our hypothesis that the extremity of performance outcomes deteriorates with fund age. Specifically, the decline in performance extremity associated with a doubling in a fund's age ranges from approximately 9 percentage points for the Jensen (1968) alpha up to 43 percentage points for the Pástor and Stambaugh (2003) 5-factor alpha.

Overall, the results from Section 4.7 suggest that funds cater to different groups of investors during their lifetime. In particular, our observations indicate that mature funds attract less performance sensitive and non-institutional investors by delivering more stable outcomes in terms of investment style and performance.

Table 4.13: Impact of fund age on style extremity and performance extremity (Continued)

**Panel B: Performance extremity**

| Dependent variable: | Performance extremity | | | |
|---|---|---|---|---|
| | Jensen | Fama French | Carhart | Pástor Stambaugh |
| Ln age | -0.0893 *** | -0.2767 *** | -0.3507 *** | -0.4275 *** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Ln TNA family | -0.0063 | -0.0131 * | -0.0128 * | -0.0161 * |
| | (0.2965) | (0.0683) | (0.0789) | (0.0659) |
| Family focus | 0.0551 * | 0.0677 ** | 0.0883 *** | 0.0693 * |
| | (0.0608) | (0.0329) | (0.0071) | (0.0547) |
| Fund return | -0.0808 | -0.0809 | -0.0938 | 0.0043 |
| | (0.4065) | (0.3750) | (0.3299) | (0.9638) |
| Ln TNA | -0.0123 *** | -0.0151 *** | -0.0190 *** | -0.0190 *** |
| | (0.0089) | (0.0048) | (0.0009) | (0.0023) |
| Fund flow | 0.0000 *** | 0.0000 *** | 0.0000 *** | 0.0000 *** |
| | (0.0001) | (0.0000) | (0.0000) | (0.0000) |
| Expense ratio | 3.4481 | 3.6833 | 4.7149 ** | 5.1692 *** |
| | (0.2026) | (0.1154) | (0.0302) | (0.0085) |
| Turnover ratio | 0.0096 *** | 0.0071 * | 0.0036 | 0.0015 |
| | (0.0075) | (0.0632) | (0.2760) | (0.6437) |
| Fund fixed effects | Yes | Yes | Yes | Yes |
| Family fixed effects | Yes | Yes | Yes | Yes |
| Incubation fund fixed effect | Yes | Yes | Yes | Yes |
| Segment fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 353,217 | 353,217 | 353,217 | 353,217 |
| Adj. $R^2$ | 0.1930 | 0.1827 | 0.1741 | 0.1590 |

Notes: This table presents results from pooled OLS regressions that analyze the impact of fund age on funds' style extremity (Panel A) and performance extremity (Panel B). We estimate funds' style and performance extremity based on the approach by Bär, Kempf, and Ruenzi (2011) as:

$$SE_{i,t}^{S} = \frac{\left|\beta_{i,t}^{S} - \overline{\beta_{i,t}^{S}}\right|}{\frac{1}{N}\sum_{j=1}^{N}\left|\beta_{i,t}^{S} - \overline{\beta_{i,t}^{S}}\right|} \quad ; \quad PE_{i,t} = \frac{\left|P_{i,t} - \overline{P_{i,t}}\right|}{\frac{1}{N}\sum_{j=1}^{N}\left|P_{j,t} - \overline{P_{i,t}}\right|}.$$

Thereby, for each fund and month style extremity (SE) is estimated as the absolute difference between a fund's style, that is represented by its sensitivity (beta loadings) to the market factor (Market), value factor (HML), size factor (SMB) as well as momentum factor (MOM) as in the Carhart (1997) 4-factor model, and the average style of all funds in the same segment and month. This difference is then divided by the average absolute difference of all funds in the same investment segment and month. Similarly the performance extremity (PE) is measured for each fund and month as the absolute difference between a fund's performance, that is represented by the four different performance measures Jensen (1968) alpha (Jensen), Fama and French (1993) 3-factor alpha (Fama French), Carhart (1997) 4-factor alpha (Carhart), and Pástor and Stambaugh (2003) 5-factor alpha (Pástor Stambaugh), and the average performance of all funds in the same segment and month divided by the average absolute deviation of all funds in the same investment segment and month. The main independent variable in both Panel A and Panel B is Ln age, the logarithm of the fund's age in years. Other independent variables and fixed effects are defined as in Table 4.4. P-values reported in parentheses are based on robust standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

## 4.8 Conclusion

The perception of age as something positive or negative is often determined by the valuation standard of the spectator. Learning theorists evaluate the passing of time as a positive since it can stand for more learning opportunities. On the contrary, physicians tend to consider aging as a negative due to the decline in one's physical capabilities. In the active managed world of the mutual fund industry the valuation standard is represented by funds' competence to beat their benchmark. However, the economics literature on mutual funds has mostly been a quest to identify investment skill cross-sectionally which neglects the role of time as another important determinant for a fund's performance.

Borrowing from the organization ecology's frameworks of the liability of newness and the liability of aging theory, we derive hypotheses on the impact of fund age on performance. Our results clearly support the liability of aging theory: funds' performance deteriorates as they mature due to a decline in innovative investment ideas. Hence, this confirms the existence of funds' diseconomies of life.

In particular, we document an age induced performance difference of up to 75 basis points per year for a doubling in fund age. This observation is robust to a broad range of controls that could contaminate the negative age-performance relation and is supported by tests that impose a relation to innovative investment behavior. Specifically, as funds grow older their trading strongly declines by up to 20 percent per year, they pursue less investment strategies that are predictors of superior future fund performance, and hold less stocks that are hard to value.

Nonetheless, our results indicate that the demand for mature funds stems from different investor groups than for younger funds. In particular, as funds grow older they are more populated by less performance sensitive and non-institutional investors that seem to put more emphasis on less extreme investment styles and more stable performance outcomes.

Taken together, our findings show that a fund's ability to beat its benchmark through the generation of influential ideas is subject to developments over time. This has important implications for mutual fund investors, that is, they need to be aware that funds' investment skills are not like wine and improve over time but are subject to a slow decay. This suggests a new dimension of mutual fund research. Specifically, avenues of future work should to take the evolutionary dimension into account when investigating investment skill.

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