Essays in Behavioral Finance and Investments

by

Shema Frédéric Mitali

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Declarations

I declare that Chapter 3 of this thesis is the product of work jointly produced by Dr. Constantinos Antoniou and myself. I declare that the work presented in this thesis has not been submitted for a degree at another university.

Abstract

This thesis studies the behavior of mutual fund managers. I explore the determinants of mutual fund performance heterogeneity, the drivers of their investment decisions with consequences for asset returns, and how they communicate with their investors.

Chapter 2 studies the relationship between U.S. mutual funds' common holdings and fund performance. In a network where funds are connected through portfolio overlap, degree centrality of each fund represents the level of similarity with peers. The results show that holdings similarity leads to lower abnormal fund returns. Further tests suggest that information asymmetry is a potential explanation for this relationship. The negative association between holdings similarity and fund performance widens in volatile markets. In uncertain times, mutual funds move towards their benchmark due to asset management constraints. This creates negative price pressure on commonly held assets. A portfolio based on stocks owned by low vs. high degree centrality funds yields abnormal returns of 7% per year. This chapter provides new evidence of the informational advantage hypothesis as a driver of fund performance. It also highlights negative externalities of asset management contracts.

In chapter 3, jointly with Dr. Constantinos Antoniou, we examine whether mutual fund managers invest more heavily in firms in which they have previously experienced higher returns. Using data from actively managed U.S. equity mutual funds, we find results that support this hypothesis. Experienced returns affect how managers rebalance their portfolios in response to flows, and influence investments at the style level. Experienced returns do not affect the investments of index-tracking funds. Experienced returns, when aggregated at the fund level across stocks, predict more aggressive trading behavior and lower fund returns, and when aggregated across managers at the stock level, predict lower stock returns.

Finally, chapter 4 measures the extent of economic policy uncertainty language in mutual fund communication and its effects on flows. I test the hypothesis that mutual funds communicating more about uncertainty do so to obfuscate financially relevant information. I find that the U.S. active mutual funds that use more words related to economic policy uncertainty tend to be risky and poorly performing funds. The use of uncertain economic terms has a positive effect on fund flows. The effect

is stronger for retail funds and in expansion periods. Initial fees become less salient when funds communicate more about economic uncertainty. The evidence presented in this chapter suggest that mutual fund communication matters for fund flows.

Chapter 1

Introduction

The research area of investment has been an active field for many years. The U.S. mutual fund industry has attracted the attention of researchers since the 1960s. Indeed, over the last decades this industry has grown rapidly representing almost $18 trillion at the end of 2018 according to the Investment Company Institute. As of 1994, mutual funds managed approximately $2 trillion (Gruber 1996). As a result, many researchers devoted their attention to the understanding of this growth rate and its rationale. More specifically, many studies explored the ability of mutual fund managers to deliver positive returns to their investors, in order to explain the growth of this industry.

Starting with Jensen (1968), the literature found little evidence of fund managers delivering positive performance over a benchmark (Malkiel 1995; Gruber 1996; Carhart 1997). On the other hand, a parallel list of studies found some evidence suggesting that fund managers have an ability to deliver abnormal positive returns to their investors (Grinblatt and Titman 1989, 1993; Grinblatt et al. 1995; Daniel et al. 1997).

Chapter 2 of this thesis aims at better understanding the heterogeneity of mutual fund performance. In their seminal paper, Grossman and Stiglitz (1980) explain that if agents can collect information at a cost, they should earn superior returns. Along these lines, several authors find indeed that informational advantage is a plausible explanation for heterogeneous performance. For example, Kacperczyk et al. (2005) find that mutual fund managers will concentrate their holdings on specific industries where they have an informational advantage. Cohen et al. (2008) find that mutual fund managers extract information from their social network and have concentrated holdings on stocks where they have educational connections with board members. As a consequence, they earn superior returns on their connected companies. In a similar spirit to Kacperczyk et al. (2005), Cici et al. (2018) show that fund managers will place larger bets on industries where they have gained human capital from previous work experience. This strand of literature shows that concentrated holdings and informational advantage are valid explanations for heterogeneous performance in the mutual fund industry.

Motivated by these findings, I measure, in chapter 2, concentrated holdings of fund managers, not with respect to an industry as in Kacperczyk et al. (2005) or a benchmark as in Cremers and Petajisto (2009), but by comparing fund managers to each other. I build a network of mutual fund portfolio overlap. I connect fund managers through the number of securities they have in common in their respective portfolios. When computing the degree centrality of this network (i.e., the extent of connectedness of the individual funds), I obtain a measure of holdings similarity at the fund level. Typically, a mutual fund with a high degree centrality will be highly connected to other mutual funds, i.e., it will own stocks that many of its peers also own. The first finding is that degree centrality is negatively related to fund performance. At the firm level, stocks owned by funds with low degree centrality earn around 7% of additional abnormal returns compared to stocks owned by mutual funds with high degree centrality. The results are robust to alternative measures of centrality and alternative sets of neighbors in the network (e.g., style peers). I also find that this effect is exacerbated in periods of market uncertainty, measured by stock market volatility, due to asset management contracts as motivated by Buffa et al. (2014).

I test the hypothesis that degree centrality relates to informational advantage. A fund manager that owns stocks disregarded by its peers, possibly does so because he has privileged information about these stocks. Using a change in regulation that forced fund managers to disclose their holdings more frequently, I find evidence that confirm this hypothesis.

A number of factors can explain fund managers heterogeneous investment decisions such as informational advantage as explained in chapter 2, but also prior work experience as in Cici et al. (2018). As fund managers over-invest in industries where they have acquired on-the-job experience, it links to a growing and important literature in behavioral economics on the effects of personal experience on economic decisions. Malmendier and Nagel (2011) show that households that experienced better stock market returns are more likely to participate in the stock market.

Kaustia and Knüpfer (2008) find that individual investors in Finland are more likely to subscribe to future initial public offering (IPO) if they have experienced good IPO outcomes in the past. Motivated by these evidence of reinforcement learning, Dr. Constantinos Antoniou and I study in chapter 3 the effect of experienced outcomes on future investment decisions for mutual fund managers.

In chapter 3, we test the hypothesis that mutual fund managers will favor stocks where they experienced good returns in the past. We measure stock-level experience for each fund manager as an exponentially weighted moving average of past stock returns for the periods when a fund manager was holding the stock. Using an exponentially weighted moving average allows us to account for the recency effect, often observed in studies on memory (e.g., Baddeley and Hitch 1993). Our results show that fund managers that experienced better returns on a given firm will place a larger bet of 0.01%. Unobserved time-varying firm of fund characteristics cannot explain this relationship. Aggregated across all stocks, fund managers allocate around $30M of capital in a quarter across firms on the basis of experience effects when considering the average fund size. We also document that these experience-driven investment decisions have important consequences for asset returns. Moreover, reinforcement learning does not lead to better performance for fund managers. As they experience better returns, they tend to become overconfident and more aggressive in their trading behavior, at the expense of future performance (Gervais and Odean 2001).

A possibility for the lack of ability of mutual fund managers to deliver positive returns is the cost of active investing. Fama and French (2010) found that fund managers can generate performance, however the latter becomes negative when considering expenses. Moreover, a potential explanation for investors delegating their capital to fund managers despite their poor returns is a failure to account for this cost of active investing. For example, Barber et al. (2005) found the investors are less sensitive to operating expenses compared to fees paid upfront.

The mixed evidence regarding performance found in the literature combined with the growth of the industry attracted the interest of regulators too. As almost half of U.S. households invest in mutual funds in 2016, according to the Investment Company Institute, regulators aim to protect households from a misunderstanding of fund fees for example. The Securities and Exchange Commission (SEC) wrote that the information provided by mutual funds to their investors in their prospectuses are often long and complex (Beshears et al. 2009).[1] This motivated the SEC to

[1] SEC Release No. 33-8861.

propose in late 2007 and adopt a summary prospectus, a form designed to simplify communication about mutual fund characteristics for investors. This opened the avenue of research related to mutual fund communication explored in the last chapter of this thesis.

In chapter 4, I explore the role of mutual fund communication in explaining the growth rate of the mutual fund industry. Mutual funds communicate with their investors through various channels including shareholders' reports (N-CSR SEC form). In these forms, mutual funds disclose their performance, risk, expenses, and also their vision of the economy. While the first parts are mandatory and regulated, there are no restrictions to what extent funds can express their views on the economy. I hypothesize that an emphasis on economic uncertainty in mutual fund communication will help mutual funds limiting outflows of capital. Indeed, if a mutual fund with poor performance express an uncertain economic environment, this can serve as a justification for the low returns delivered by the fund, and thus, investors will possibly punish less fund managers by taking money out of the fund.

I measure economic uncertainty in shareholders' reports following Baker et al. (2016) by counting the number of occurrences of words related to economic policy uncertainty. I find that poorly performing and risky funds are more likely to emphasize on economic uncertainty. Moreover, I find that increasing the number of words related to economic policy uncertainty leads to higher capital flows by approximately 4% per year, controlling for other fund characteristics such as performance, past flows, and expenses. The effect is stronger for mutual funds in the bottom of the performance distribution. Additionally, I find that upfront costs are less salient if mutual funds communicate more about economic uncertainty (Barber et al. 2005). This suggests that strategic communication can help obfuscate financially relevant information such as fund expenses.

To summarize, this thesis explores the determinants of mutual fund performance, investment decisions, and communication. As the size of this industry represented approximately $18 trillion according to the Investment Company Institute, it is important to understand their interactions with investors, as a significant part of them are households. The key findings show that informational advantage is an explanation for the observed differences in fund performance. Moreover, fund managers are influenced by their personal experience when they make investment decisions, which has consequences for asset prices. Finally, even in the presence of disclosure rules, fund managers have room for strategic communication. Using economic uncertainty in fund documents, which has been little studied so far, helps explaining the puzzling growth rate of this industry.

Chapter 2

Common Holdings and Mutual Fund Performance

2.1 Introduction

The asset management industry has grown at a remarkable pace in the last decades. In 2018, U.S. active equity mutual funds' total net assets represented around $18 trillion, and about 70 times less in 1980. Institutional investors have become more important for both regulatory bodies and households.[1] In the U.S., around 5% of the latter held mutual funds in 1980 and approximately 45% in 2018.[2] Yet, questions remain open about funds' ability to deliver performance and its drivers.

In a frictionless efficient market, institutional investors' performance would be homogeneous. The observed heterogeneity in trades and performance can be driven by informational advantage (e.g., Grossman and Stiglitz 1980; Hellwig 1980; Kyle 1985). Building on these theories, several studies show that concentration is optimal for well-informed investors. Kacperczyk et al. (2005) show that industry concentration leads to better performance. Van Nieuwerburgh and Veldkamp (2009) explain how informational advantage can explain the home bias. Previous studies have focused on inferring investors' informational advantage relative to a benchmark such as industries (Kacperczyk et al. 2005) or the market (Cremers and Petajisto 2009). In this study, I explore how comparing mutual funds' holdings to each other helps deducing informational advantage and superior performance.

[1] See "Asset Management and Financial Stability", Office of Financial Research, Department of the Treasury, 2013.

[2] Investment Company Institute.

In this chapter, I test the hypothesis that differences in mutual fund holdings is related to informational advantage. Using quarterly mutual fund holdings data from 1980:Q1 to 2016:Q4, I implement network analysis and connect actively managed U.S. equity mutual funds through their portfolio overlap (i.e., the number of stocks in common). The degree centrality of each mutual fund in the network at each quarter is measuring its holdings similarity with its peers.[3]

I find that mutual fund degree centrality has a negative and statistically significant effect on mutual fund performance. A one standard deviation increase in degree centrality leads to lower abnormal fund performance in the next quarter of roughly 0.2% (t-stat= -7.46) when performance is measured using the four-factor model (Carhart 1997). This main result cannot be explained by other fund characteristics (e.g., size, flows, or other measures of activeness relative to a benchmark such as active share or tracking error). Thus, mutual funds with low holdings similarity with peers perform better.

To investigate if degree centrality relates to informational advantage, I use a change in regulation as a quasi-natural experiment. In May 2004, the Securities and Exchange Commission (SEC) required more frequent portfolio disclosure from mutual funds.[4] Agarwal et al. (2015) find that more informed funds, proxied by high past abnormal performance, had their performance worsened following this regulation. If degree centrality relates to informational advantage, this result should hold for mutual funds with low degree centrality. I test this hypothesis following Agarwal et al. (2015). Results show that mutual funds with low degree centrality had their performance decreased by -6.7% (t-stat= -2.21) in the year 2004. This finding is consistent with a coordination in information acquisition and asset purchases (Veldkamp 2006). Fund managers' initial informational advantage disappears as other fund managers can learn about the same assets owned by the best performing managers, once their holdings are disclosed more frequently.

Previous literature shows that fund managers tend to group stocks into categories and focus on particular styles (Barberis and Shleifer 2003). To assess a mutual fund manager's holdings similarity with peers, it is thus also suitable to compare him with his style peers as opposed to the whole universe of managers. Using Morningstar

[3] For example, in a network composed of three funds (A, B, and C) where the first two have four stocks in common while the third fund does not share any position with the others, fund C's degree centrality will be 0 and 4 for A and B since this is their overlap (i.e., the weight associated to their connection).

[4] The portfolio disclosure frequency moved from semiannually to quarterly.

style classification, I group mutual funds into nine style groups.[5] At each quarter, there are nine networks composed of funds within each style category. I compute network degree centrality for each mutual fund within style clusters. I find a negative relationship of degree centrality on fund performance with the same magnitude as in the main results.

Investors give incentives to their mutual fund managers to be active. To do so, they base compensation contracts on relative performance to a benchmark. Tracking error constraints are often part of the terms. Thus, mutual fund managers cannot be as active as they want, especially in volatile markets. These institutional incentives can exacerbate price distortions (Buffa et al. 2014; Lines 2016).

Motivated by this mechanism, I study how holdings similarity changes in periods of uncertainty. I find that degree centrality increases in a volatile phase, defined by quarters when the Volatility Index (VIX) is in the top decile. This suggests that managers respond to their contract clause by moving closer to their peers when prices are volatile. Moreover, the negative relationship between degree centrality and fund performance is amplified in these phases. When facing volatility, mutual fund managers create negative price pressure on common assets. This creates spillovers on connected mutual funds. Thus, mutual funds with high degree centrality exhibit lower cumulative abnormal returns.[6]

Finally, I extend the analysis at the stock level. If mutual funds with low degree centrality earn higher abnormal fund returns due to informational advantage, their holdings should exhibit higher stock returns. Building a long-short portfolio based on stocks owned by mutual funds with low degree centrality on the long leg delivers abnormal return of 7% per year.

This study's contribution is threefold. First, this chapter relates to the large literature on mutual fund performance. Dating back to the late 60's, researchers have long examined and argued about the existence, determinants, and persistence of mutual fund performance (e.g., Jensen 1968; Gruber 1996; Carhart 1997). Cohen et al. (2005) show that managers who make decisions similar to distinguished peers do better. Cremers and Petajisto (2009) show that deviations from benchmark positively predict fund performance. Amihud and Goyenko (2013) find that mutual funds' R-squared obtained from multi-factor models negatively predict per-

[5] A 3×3 style box composed of small/mid/large-value/blend/growth funds.

[6] Chernenko and Sunderam (2017) show evidence of fire sales externalities for mutual funds. Moreover, mutual funds cannot internalize these externalities as they don't know precisely how many of their numerous peers follow the same strategies and buy the same stocks (Stein 2009).

formance.[7] Amihud and Goyenko (2013) explain that mutual funds with lower R-squared track factors less closely and thus relates to higher selectivity. This chapter differs from their study as lower degree centrality means that mutual funds follow less closely their peers, as opposed to factors. More recently, Hoberg et al. (2017) show that mutual funds outperforming their style peers tend to have larger abnormal performance going forward. The results presented in this chapter are consistent with the buy-side competition aspect of Hoberg et al. (2017). It suggests that mutual funds facing lower style competition can do better. This chapter differs as it builds on a different market friction as a source of fund performance difference, namely information asymmetry rather than the imperfect competition as emphasized in Hoberg et al. (2017). In a related work, Sun et al. (2012) show that hedge funds with more distinct historical returns relative to their peers have better subsequent performance. A hedge fund with a unique strategy will have a higher measure of distinctiveness. This study contributes to this literature by providing a new measure of holdings similarity to relates to informational advantage and is robust to existing measures of concentration (e.g., Cremers and Petajisto 2009).

Second, this chapter contributes to the growing literature on the adverse effects of benchmarking. Due to agency frictions, contracts link compensation to performance relative to a benchmark (Buffa et al. 2014). With volatile prices, fund managers are exposed to greater risks when being mismatched to the benchmark. Thus, they move towards the index in uncertain times and exacerbate price distortions. These externalities on asset prices have been documented by Lines (2016).[8] I provide new evidence on the negative effects of benchmarking on fund performance. It stems from negative price pressure exercised by mutual funds in uncertain times.

Finally, this study contributes to the extensive financial networks literature. Anton and Polk (2014) look at the asset pricing implications of securities' ownership structure. They show that shared ownership between stocks predicts cross-sectional variations in return correlation. Bartram et al. (2015) show that international stock returns can be affected by stocks connected by foreign ownership linkages. Ahern (2013) shows that central industries, in an inter-sectoral trade network, earn higher returns. At the fund level, Wahal and Wang (2011) look at the fees and flow compe-

[7]Other studies on performance drivers include for instance Kacperczyk et al. (2005), Titman and Tiu (2011), Jiang et al. (2014), and Doshi et al. (2015). More generally, deviation from peers can be due to skills, informational advantage, but also investment mandates, herding (Jiang and Verardo 2018) or unobserved actions of managers (Kacperczyk et al. 2006).

[8]Other studies on the link between asset management contracts and market outcomes include for instance Cuoco and Kaniel (2011), Basak and Pavlova (2013), Garleanu and Pedersen (2017), Ibert et al. (2017), and Ma et al. (2019).

tition among funds to attract investors in the case of new entrants. Recent studies found that a fund's importance in a information-based network is associated with higher performance (e.g., Ozsoylev et al. 2014, and Rossi et al. 2018).[9] In this study, I propose a network of mutual funds connected through portfolio overlap and show that degree centrality is disadvantageous in this context.

2.2 Data

I collect quarterly mutual fund holdings data from Thomson Reuters Mutual Fund Holdings database from 1980:Q1 to 2016:Q4. I obtain mutual fund characteristics (total net assets, monthly net returns, expense ratios, turnover ratios, and fund age) from the CRSP Survivor-Bias-Free U.S. Mutual Fund database. I aggregate variables for multiple share classes and aggregate monthly returns to obtain quarterly returns. I use MFLinks to merge the two databases.

Since the focus is on domestic actively managed equity mutual funds, I restrict the investment objective code reported by Thomson Reuters to be either aggressive growth, growth, growth and income, balanced, or unclassified following Lou (2012). Furthermore, I require total net assets (TNA) reported by CRSP to be minimum \$1 million, and restrict the CRSP investment objective code to start with "ED" (equity domestic).[10] Finally, I exclude index funds using the CRSP index flag. Table 2.1 on page 11 reports key summary statistics of the final database for the different summary statistics. The final dataset has 3,195 distinct mutual funds. We can also see from Figure 2.1 on page 12 an increase in the number of funds but also in asset under management over the years.

[9] Other related studies include for instance Hochberg et al. (2007) and Hochberg et al. (2010) who study venture capital firms (VCs) network and find that central VCs firms have significantly higher performance.

[10] The CRSP style objective code maps the existing investment objective codes (Wiesenberger, Strategic Insight, and Lipper Objective Codes) in order to have a continuous code. It is a four-characters code that correspond to four level of granularity. For example, the code "EDYG" denotes an equity (E) domestic (D) with style (Y) defined as growth (G). I specify the code for each fund to begin with ED in order to have domestic equity funds only and exclude short, hedged, and option income funds using this mapping.

Table 2.1: Summary Statistics

This table shows summary statistics of fund characteristics. The sample consists of U.S. active equity mutual funds from 1980:Q1 to 2016:Q4. *Degree* is the weighted degree centrality of the common holdings network. *Ret* is the quarterly fund net return. *Stocks* is the number of stocks in the portfolio. *Fund age* is the number of months since the fund's inception. *Flow* is the net growth of total net assets, winsorized at 1%. TNA (in millions of dollars) is total net assets. *Distance* is the Euclidean distance between each fund and its peers. The distance matrix is computed from the matrix of dollar positions invested by each fund in each asset divided by TNA. From the distance matrix, I compute fund-level distances as the average of distances with all peers. *Eigenvector* is the eigenvector centrality of the common holdings network.

	Obs	Mean	Std. Dev.	Min	Max
$Degree$	106,232	7,087.88	7,795.87	0	108,334
Ret	103,041	0.022	0.103	−0.616	0.924
$\ln(stocks)$	103,041	4.245	0.750	0.000	7.754
$\ln(fund\ age)$	102,962	4.888	0.894	1.099	7.006
$flow$	103,041	0.011	0.112	−0.294	0.804
$expense$	102,997	0.013	0.005	−0.005	0.170
$turnover$	97,675	0.852	1.256	0.000	91.500
TNA	106,232	1,254.47	5,252.73	1.001	195,806.90
$Distance$	103,604	0.213	0.060	0.115	1.057
$Eigenvector$	106,232	0.001	0.002	0.000	0.034

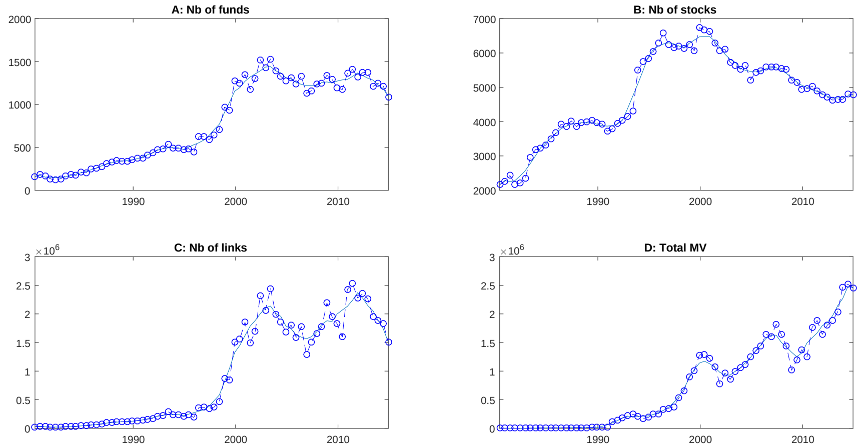

Figure 2.1: Evolution of summary statistics.

This figure represents the time evolution on the top left of the number of actively managed U.S. equity mutual funds in the sample from 1980:Q1 to 2016:Q4. On the top right is represented the evolution of the total number of stocks held by these funds. On the bottom left we have the total number of links or the sum of the network connections between all the funds for each quarter and finally the total market value of equity holdings of the U.S. equity mutual funds.

2.2.1 Other Data

Following Franzoni and Schmalz (2017), I compute net fund flow of fund i at quarter t as:

$$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + Ret_{i,t})}{TNA_{i,t-1}}, \tag{2.1}$$

where $Ret_{i,1}$ is the quarterly net return of fund i in quarter t. Due to the presence of extreme values in CRSP as mentioned in Elton et al. (2001) I winsorize the net fund flows at the 1% and 99% levels.

In the first set of results, I use other metrics of holdings concentration, namely active share and tracking error. These are obtained from the author's website (Cremers and Petajisto 2009, Petajisto 2013).[11]

I also use the daily CBOE Volatility Index (VIX) which is available from 1990. I compute the quarterly average VIX index and define a dummy variable whenever the VIX is in the top 10th percentile. This results in episodes that include the early 1990s recession, the 1997 Asian financial crisis, the 1998 Russian financial crisis, the downturn following the Dot-com bubble, and the financial crisis of 2008

[11] *http://www.petajisto.net/data.html*

for example. The use of a dummy is motivated by Cella et al. (2013) who use a *Turmoil* dummy, also defined from the VIX index, that captures market-level shocks. They find that institutional investors with a shorter trading horizon tend to amplify shocks by creating price pressure on assets. Since the use of the VIX index relates to the study of Cella et al. (2013), the related section of this chapter follows their methodology.

For further tests at the stock level, I obtain firm characteristics from different sources. I compute *Amihud* illiquidity ratio as the absolute value of firm j's daily stock return over the trading volume as reported by CRSP average over period t (Amihud 2002). I obtain analyst average recommendation from I/B/E/S. From Compustat, I compute asset growth, book-to-market ratio using the firm's book value, and the firm's profitability.[12] From CRSP, I obtain stock returns, compute stock return volatility, and market capitalization.

2.3 Network Analysis

With mutual funds holdings data, I use network analysis to obtain cross-sectional variations in holdings similarity. More specifically, I use the concept of centrality that graph theory defines as the most important nodes in a network. In social network analysis, central nodes are often associated to influential agents. Since the network analysis based on mutual fund holdings does not rely on social connections, a central fund will be defined as a mutual fund that is highly similar, in terms of holdings, to its peers.

The starting point of this analysis is an adjacency matrix. This square matrix $g \in \{0,1\}^{NxN}$ is the representation of a given graph, where $N = 5$ for instance, such as:

$$g = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Figure 2.2 shows the graph representation of the adjacency matrix g. First, we can see that the matrix g is symmetric and have zeros on the diagonal. Second, the graph

[12]Book value is total shareholders' equity (common plus preferred equity or assets minus liabilities) plus deferred taxes and investment tax credit minus the book value of preferred stock. Profitability is the operating income before depreciation divided by assets from the previous period.

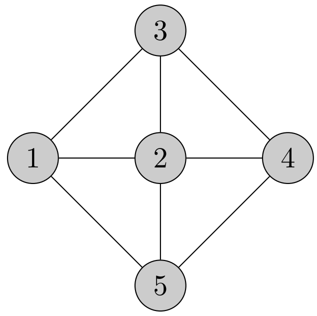

Figure 2.2: Graph representation of matrix g.

in Figure 2.2 on page 14 shows the difference in terms of centrality. Node 2 is more central in terms of degree/connections than the other nodes (4 edges compared to the other nodes that have 3 edges). If each connection has a weight (i.e., the strength of the link) this gives another dimension of cross-sectional variation.

The first challenge when applying network analysis in the setting of mutual fund holdings is that the data do not represent a square holdings matrix. The raw data can be defined by $W_{i,j,t}$, a bipartite matrix of holdings of mutual fund i in asset j at quarter t in weights (dollar value over TNA).[13] Following Gualdi et al. (2016), I map this matrix $W_{i,j,t}$ into a binary matrix $A_{i,j,t} = sign(W_{i,j,t})$ and project it into a monopartite adjacency matrix (i.e., one type of node: mutual funds):

$$O_{i,-i,t} = A_{i,j,t}A'_{i,j,t} - I_{N_t}\sum_{j}^{M_t} A'_{i,j,t}, \tag{2.2}$$

where I_{N_t} is the identity matrix of size N_t (the total number of mutual funds at quarter t) and M_t is the total number of firms at quarter t. This standard projection method allows us to obtain a mutual fund level portfolio overlap measure. Indeed, $O_{i,-i,t}$ is a square matrix where the entries represent the number of securities that a given mutual fund i has in common with any other mutual fund $-i$ but itself (i.e., zeros on the diagonal). For instance, if $O_{1,4,1984:Q3} = 20$, it means that mutual fund 1 and mutual fund 4 share 20 positions in common (among the M_t assets) in the third quarter of 1984. This will give us a weighted undirected network where the links between mutual funds will have an intensity/weight represented by the portfolio overlap between two nodes/funds.

Figure 2.3 on page 19 shows , as an example, the first quarter of the sample where red nodes represent mutual funds connected through portfolio overlap. The bigger

[13] A bipartite matrix is a network with two types of nodes, in this case mutual funds and firms.

the red node is, the more common holdings it has.

2.3.1 Style Network

The previous section presented the network of all actively managed U.S. equity mutual funds. However, as noted by Hoberg et al. (2017), it is relevant to investigate the performance of a given fund relative to its rivals in terms of style dimension. I refine the previous network by connecting mutual funds to their style-peers. This gives style clusters within the complete network. I classify funds within their style categories using data from Morningstar. Morningstar provides style classification for each fund based on their holdings. Each fund is classified based on two dimensions: size and book-to-market. For instance a large-value mutual fund is a fund with a significant amount of holdings in large-cap and high book-to-market stocks. Morningstar is widely used as a style identifier by practitioners and is therefore suitable for this part of the analysis (Teo and Woo 2004). I combine the original database with Morningstar style information using both fund Tickers and CUSIPs (Pástor et al. 2015).

2.3.2 Centrality

The next step in the analysis is to compute portfolio similarity measures at the mutual fund level. The centrality measure will identify mutual funds that have high or low holdings similarity with peers. It measures a node's importance in the network. A highly central fund has many positions overlapping with its peers and hence is less likely to have an informational advantage about particular firms according to the hypothesis tested in this chapter. In our network, the (weighted) degree centrality of a fund will be the sum of its overlaps with each neighboring node. More formally, we have:

$$Degree_{i,t} = \sum_{-i}^{N_t} o_{i,-i,t}, \tag{2.3}$$

where $o_{i,-i,t}$ is the overlap of fund i with fund $-i \neq i$ at quarter t. $Degree_{i,t}$ is the sum of the elements of row i of matrix $O_{i,-i,t}$, defined in equation (2.2) on page 14, and is the main measure of holdings similarity used in further analysis.

Other measures of centrality includes eigenvector centrality or betweenness centrality for instance. The eigenvector centrality looks at the importance of the nodes to which a given mutual fund is connected to (Bonacich 1987). Hence, this measures takes into account the second order of importance of centrality as pointed in Hochberg et al. (2007). If you consider a mutual fund connected to only a couple of other funds through common holdings, its degree centrality will be relatively low. However, if it is connected to few mutual funds that are central themselves, then eigenvector centrality will take this into account. More formally we have:

$$Eigenvector_{i,t} = \frac{1}{\lambda_t} \sum_{-i}^{N_t} o_{i,-i,t} e_{-i,t}, \tag{2.4}$$

where $\lambda_t \neq 0$ is a constant. Written differently we can notice that the eigenvector centrality will be associated to the left eigenvector in a spectral decomposition and λ_t as the largest eigenvalue of matrix $O_{i,-i,t}$:

$$\lambda_t e_t = O_{i,-i,t} e_t. \tag{2.5}$$

Other measures I don't consider include betweenness or closeness centrality for instance. I compute eigenvector centrality for each mutual fund i at each quarter t to test the robustness of centrality's effect on mutual fund performance.

2.3.3 Distance Matrix

The previous methodology uses matrix $O_{i,-i,t}$ for network analysis. However, it was obtained from the binary matrix $A_{i,j,t}$ where an element $a_{i,j,t}$ takes the value 1 whenever a fund i has a firm j in its portfolio. One potential concern with this methodology is to capture spurious effects as a fund might invest a non-significant amount in a given firm, yet takes the value 1 in matrix $A_{i,j,t}$ defined in equation (2.2) on page 14. To address this, I compute a distance matrix $D_{i,-i,t}$ from the original holdings matrix $W_{i,j,t}$:

$$D_{i,-i,t} = \sqrt{\sum_{j}^{M_t} (w_{i,j,t} - w_{-i,j,t})^2}, \tag{2.6}$$

where $w_{i,j,t}$ are elements of matrix $W_{i,j,t}$. $D_{i,-i,t}$ is a distance matrix that looks at the square difference of weights invested in each asset j by any two mutual funds i and $-i$. From this matrix, I compute a simple summary measure: the average distance for each mutual fund with its peers:

$$Distance_{i,t} = \frac{1}{N_t} \sum_{-i}^{N_t} d_{i,-i,t}, \tag{2.7}$$

where $d_{i,-i,t}$ are elements of matrix $D_{i,-i,t}$.

2.4 Results

2.4.1 Degree Centrality and Fund Performance

In this section, I test the effect of degree centrality on mutual fund performance using a regression approach. Controlling for fund characteristics, I run the following predictive regression:

$$\alpha_{i,t} = \beta_0 + \beta_1 Degree_{i,t-1} + \gamma Controls_{i,t-1} + F + T + \epsilon_{i,t-1}. \tag{2.8}$$

$Degree_{i,t-1}$ is the main independent variable. The dependent variable, $\alpha_{i,t}$ is the fund's abnormal performance. I estimate fund performance based on the CAPM (market premium), Fama and French three factors (market premium, size, book-to-market), and Carhart four-factor (market premium, size, book-to-market, and momentum) models. I estimate factor loadings using rolling-window regressions with 2 years of monthly data and use estimated betas to obtain the fund's estimated return for the next quarter.[14] Then, $\alpha_{i,t}$ is the difference between the realized fund return and the estimated return obtained from the factor models. Controls include *fund flow*, the natural logarithm of the number of stocks in the portfolio, fund size (TNA), and *fund age*, as well as *expense* ratio, past return, *turnover* ratio, but also other measures that predict performance such as *active share* or *tracking error*.

Table 2.2 on page 20 presents the results using a pooled OLS estimation approach with time and fund fixed effects and standard errors clustered by fund.[15] This methodology accounts for potential residual correlations within funds and also possible time trends. I find that fund *degree* centrality coefficients are negative and statistically significant at the 1% level in all specifications. For instance, column (1) of Table 2.2 on page 20 shows a coefficient of -0.004 (t-stat= -9.20) for degree when

[14] The results remain throughout with a longer rolling-window of 6 years as in chapter 4.
[15] Clustering at the quarter-level or without fund fixed effects doesn't affect the results.

controlling for fund characteristics. This means that, holding other variables constant, a one standard deviation increase in *degree* centrality (or a 7,087.88 increase in degree centrality, which corresponds to one standard deviation as shown in Table 2.1 on page 11) leads to a reduction of fund quarterly performance by -0.4% for the CAPM in column (1), -0.3% (t-stat= -8.94) for the Fama and French three-factor model in column (4), and -0.2% (t-stat= -7.46) for the Carhart four-factor model in column (7). Controls' coefficients show that a higher number of stocks in a portfolio, past fund returns, *turnover* ratio, and *fund age* tend to be positively associated to fund performance. Fund size, on the other hand, has the opposite effect which is consistent with a decreasing returns to scale hypothesis (Berk and Green 2004; Chen et al. 2004).

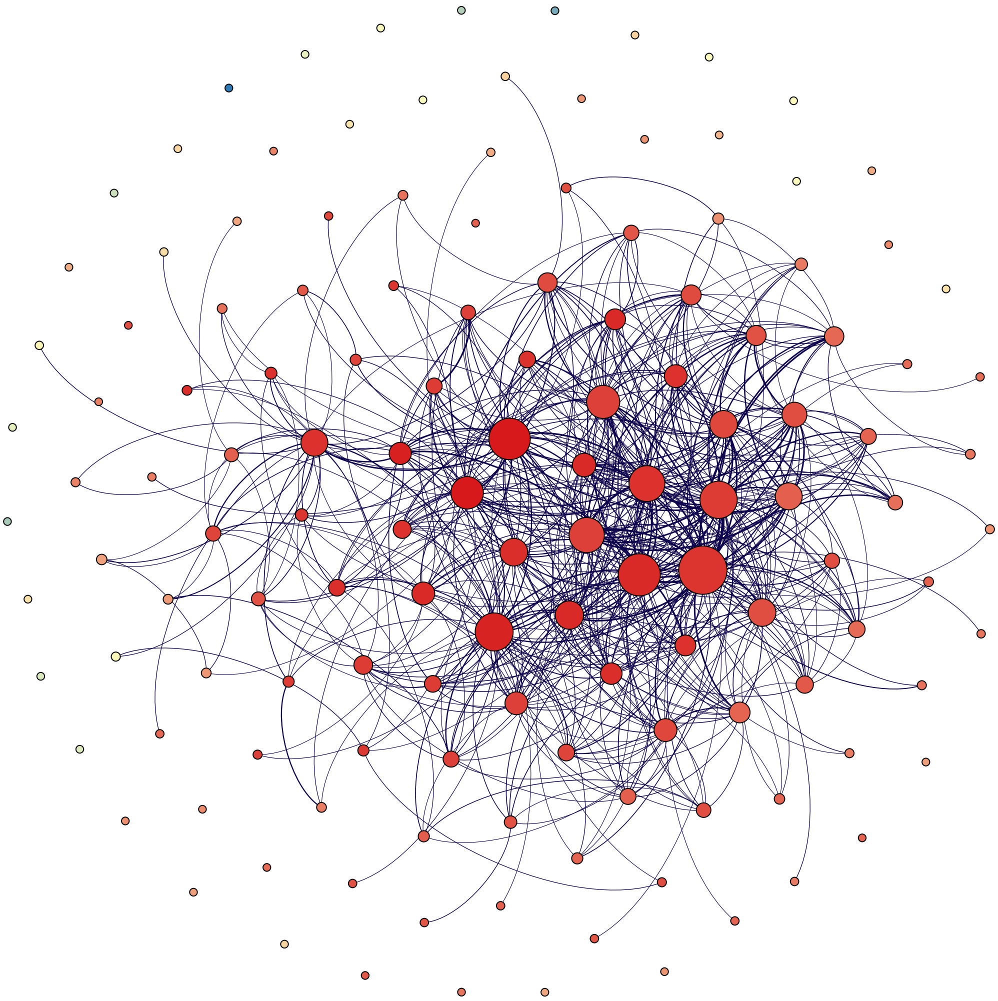

Figure 2.3: Monopartite network.

This figure represents the monopartite network with the first quarter of the sample (1980:Q1) as an example. Only links with a weight/overlap of at least 10 are represented.

Table 2.2: Degree Centrality and Fund Performance

This table shows the results of the effects of degree centrality on fund performance. The dependent variable is fund performance at quarter t. Three models are used to compute performance: $CAPM$, Fama-French three-factor model (Fama and French 1993; $FF3$), and Carhart four-factor (Carhart 1997; $FFC4$). The independent variables are measured at quarter $t-1$. The main independent variable is *Degree*. *Degree* is the weighted degree centrality of the common holdings network. TNA (in millions of dollars) is total net assets. *Ret* is the quarterly fund net return. *Flow* is the net growth of total net assets. *Stocks* is the number of stocks in the portfolio. *Fund age* is the number of months since the fund's inception. *Active share* is the difference between fund holdings with benchmark weights averaged across all assets in the portfolio (Cremers and Petajisto 2009). *Tracking error* is the volatility of the difference between fund returns and benchmark returns. All specifications include quarter and fund fixed effects, an unreported intercept, and standard errors are clustered at the fund level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$CAPM_{i,t}$			$FF3_{i,t}$			$FFC4_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Degree_{i,t-1}$	-0.004***	-0.005***	-0.005***	-0.003***	-0.003***	-0.004***	-0.002***	-0.002***	-0.002***
	(-9.20)	(-6.24)	(-7.71)	(-8.94)	(-5.26)	(-6.81)	(-7.46)	(-4.05)	(-5.02)
$active\ share_{i,t-1}$		0.002***			0.002***			0.001***	
		(3.17)			(3.29)			(2.65)	
$tracking\ error_{i,t-1}$			0.003***			0.003***			0.002***
			(5.60)			(5.50)			(5.98)
$\ln(TNA_{i,t-1})$	-0.002***	-0.004***	-0.004***	-0.000	-0.002***	-0.002***	0.000	-0.000	-0.001
	(-3.37)	(-5.02)	(-5.23)	(-0.99)	(-2.69)	(-2.88)	(1.06)	(-0.75)	(-0.94)
$Ret_{i,t-1}$	0.001***	0.002***	0.002***	-0.001***	-0.000	-0.000	-0.000	-0.000	-0.000
	(4.33)	(5.53)	(5.76)	(-3.35)	(-1.21)	(-0.90)	(-1.59)	(-0.38)	(-0.04)
$expense_{i,t-1}$	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.78)	(-0.65)	(-0.73)	(-0.96)	(-0.38)	(-0.45)	(-1.05)	(-0.36)	(-0.45)
$turnover_{i,t-1}$	0.001	0.002**	0.002**	0.001	0.001**	0.001*	0.001	0.001***	0.001**
	(0.94)	(2.48)	(2.33)	(0.82)	(2.06)	(1.91)	(1.02)	(2.64)	(2.45)
$flow_{i,t-1}$	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.42)	(0.49)	(0.40)	(-0.25)	(0.44)	(0.34)	(0.63)	(1.37)	(1.28)
$\ln(stocks_{i,t-1})$	0.003***	0.005***	0.005***	0.002***	0.003***	0.003***	0.002***	0.002***	0.002***
	(6.86)	(6.04)	(6.26)	(6.35)	(5.23)	(5.42)	(5.50)	(4.10)	(4.37)
$\ln(fund\ age_{i,t-1})$	-0.003***	-0.002*	-0.002	-0.002***	-0.001	-0.001	-0.002***	-0.001	-0.001
	(-3.73)	(-1.72)	(-1.61)	(-3.56)	(-1.06)	(-0.94)	(-4.16)	(-1.51)	(-1.38)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
# Obs	97,584	47,136	47,136	97,584	47,136	47,136	97,584	47,136	47,136
Adj R^2	0.804	0.829	0.829	0.878	0.896	0.897	0.904	0.916	0.916

Degree centrality measures, in the context of common holdings network, the extent to which a mutual fund is similar to its active peers. It can also capture a deviation from the norm in a similar fashion as the *active share* measure does (Cremers and Petajisto 2009).

I investigate the robustness of the main regression specification from Table 2.2 on page 20 to the *active share* measure and *tracking error*. *Active share* is defined as the sum of absolute differences between fund portfolio weights and benchmark weights while tracking error is defined as the variance of the difference between the fund portfolio return and the benchmark index return. Results show that *degree* centrality's coefficient is still negative and statistically significant when controlling for *active share*. It shows that centrality in common holdings network captures other relevant information missing in *active share*. When controlling for *active share*, a one standard deviation increase in *degree* centrality leads a reduction of quarterly fund performance (CAPM in column (2)) of -0.5% (t-stat= -6.24). The reduction is of -0.3% (t-stat= -5.26) for the Fama and French three-factor model in column (5) and -0.2% (t-stat= -4.05) for the Carhart four-factor model in column (8). The coefficients are of similar magnitude when controlling for *tracking error*. In these specifications the number of observations is lower as *active share* and *tracking error*, obtained from the author's website, stop in 2009. Fund characteristics' coefficients remain similar in these specifications.

2.4.2 Portfolio Disclosure

In this section, I investigate the impact of mandatory portfolio disclosure on fund performance for mutual funds with low holdings similarity to test the hypothesis that *degree* centrality relates to informational advantage. I used the mandatory portfolio disclosure regulation introduced in May 2004 by the SEC. I test the following specification:

$$\Delta\alpha_{i,2004:Q4-2003:Q4} = \beta_0 + \beta_1 DegreeDummy_{i,2003:Q4} + \gamma Controls_{i,t-1} + \epsilon_{i,t-1}. \quad (2.9)$$

Following Agarwal et al. (2015), I define a dummy that takes the value 1 for mutual funds in the bottom quartile of the *degree* centrality distribution in December 2003 ($DegreeDummy_{i,t-1}$).[16] The dependent variable is the change of abnormal performance in the year 2004, which includes the change of regulation. Controls include

[16] Agarwal et al. (2015) define a dummy for top performing funds as mutual funds in the top quartile of the distribution of fund performance in the prior year.

fund characteristics, as described in section 2.4.1, measured as of December 2003 and standard errors are clustered at the fund level.

Table 2.3: Portfolio Disclosure

This table reports results of the analysis on portfolio disclosure. The dependent variables are the changes of performance in the year when the SEC portfolio disclosure regulation was introduced (2004), it is the change of annual performance between December 2004 and December 2003. Independent variables are measured as of December 2003 and explained in the notes of Table 2.2. *DegreeDummy* corresponds to a dummy when a fund was in the bottom quartile of degree centrality distribution as of December 2003. Controls include TNA (in millions of dollars), which is total net assets; *Ret* (annual fund net return); $Flow$ (the net growth of total net assets); *stocks* (the number of stocks in the portfolio); *fund age* (the number of months since the fund's inception); *expense*, and *turnover*. All specifications include an unreported intercept, and standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$\Delta CAPM_{i,t-4:t}$	$\Delta FF3_{i,t-4:t}$	$\Delta FFC4_{i,t-4:t}$
	(1)	(2)	(3)
$DegreeDummy_{i,t-4}$	-0.051*	-0.052*	-0.067**
	(-1.91)	(-1.76)	(-2.21)
Controls	YES	YES	YES
# Obs	1,717	1,717	1,717
Adj R^2	0.014	0.007	0.005

Table 2.3 on page 23 shows that mutual funds with low holdings similarity suffered from the mandatory portfolio disclosure. Their performance decrease by -5.1 (t-stat= -1.91, for the CAPM in column (1)) to -6.7% (t-stat= -2.21, for the Carhart four-factor model in column (3)) following the introduction of the regulation.[17] The results presented in Table 2.3 on page 23 support the hypothesis of informational advantage.

[17]The results remain the same if $DegreeDummy_{i,t-1}$ is defined as mutual funds in the bottom tercile, quintile, or decile of the degree centrality distribution.

2.4.3 Style Degree Centrality and Fund Performance

So far I obtained mutual funds' degree centrality within a common holdings network composed of all U.S. active equity mutual funds. However, if an investor wants to invest in small-growth firms via a mutual fund, it will be more suitable for him to compare mutual funds within the same style category. In this section, I compute degree centrality for each fund in its respective style category as defined Morningstar.

As for Table 2.2 on page 20, I run a predictive regression of fund performance on style degree, controlling for fund characteristics. As in the previous analysis, I include both fund and time fixed effects and cluster standard errors at the fund level. I find in Table 2.4 on page 25 that a one standard deviation increase in style *degree* centrality leads to lower fund performance of -0.5% (t-stat= -11.14) for the CAPM model in column (1), -0.3% (t-stat= -10.46) for the Fama and French three-factor model in column (2), and -0.3% (t-stat= -8.54) for the Carhart four-factor model in column (3). The results suggest that comparing mutual funds with their style peers is as relevant as a comparison with the whole active equity fund universe. It could also be that links within the whole network are already representative of style links. For example a large-value fund will have few or no connections with a small-growth fund. Thus, the complete network and the style clusters are relatively similar as results reported in Table 2.4 on page 25 suggest.[18]

2.4.4 Degree Centrality in Uncertain Times

I investigate the idea that mutual funds with high holdings similarity tend to underperform even more at specific periods of market uncertainty as in Cella et al. (2013). In a volatile period, some mutual funds might need to reduce their holdings due to tracking error constraints for instance. The issue being that if many mutual funds do it at the same time, this will create negative price pressure on commonly held assets. A mutual fund with high *degree* centrality will be in further difficulties as it shares many positions in common with its peers. Motivated by this mechanism, I investigate the evolution of mutual fund *degree* centrality in periods of high volatility and its effect on fund performance.

Table 2.5 on page 27 studies mutual fund *degree* centrality in uncertain markets

[18]In unreported results, I find the same negative effect of style degree on fund performance, when fund's style is defined by its holdings rather than the Morningstar style classification. For example, if a fund holds at least 75% of its holdings of small-value stocks (defined using New York Stock Exchange or NYSE breakpoints), then it is a small-value fund.

Table 2.4: Style Degree Centrality and Fund Performance

This table reports the results of style network analysis using OLS regressions. The dependent variable is fund performance at quarter t. Three models are used to compute performance: $CAPM$, Fama-French three-factor model (Fama and French 1993; $FF3$), and Carhart four-factor (Carhart 1997; $FFC4$). The independent variables are measured at quarter $t-1$. The main independent variable is $StyleDegree$. It is the weighted degree centrality of the *style* common holdings network. Fund style is obtained from Morningstar where each mutual fund is categorized on the basis of size and book-to-market dimensions of its holdings. Each mutual fund falls within one of nine-style box (e.g., small-growth fund). The style common holdings network is composed only of mutual funds of the same category. Controls include TNA (in millions of dollars), which is total net assets; *Ret* (the quarterly fund net return); $flow$ (the net growth of total net assets); *stocks* (the number of stocks in the portfolio); *fund age* (the number of months since the fund's inception); *expense*, and $turnover$. All specifications include quarter and fund fixed effects, an unreported intercept, and standard errors are clustered at the fund level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$CAPM_{i,t}$	$FF3_{i,t}$	$FFC4_{i,t}$
	(1)	(2)	(3)
$StyleDegree_{i,t-1}$	-0.005***	-0.003***	-0.003***
	(-11.14)	(-10.46)	(-8.54)
Controls	YES	YES	YES
FE	YES	YES	YES
# Obs	84,037	84,037	84,037
Adj R^2	0.819	0.887	0.910

(as proxied by the Volatility index VIX) on fund performance. In Panel A, I explore how *degree* centrality evolves in periods of high volatility. I define a dummy that takes the value 1 whenever the VIX at quarter t is in the top decile of its distribution over time. The use of a dummy is motivated by Cella et al. (2013) who use a $Turmoil$ dummy, also defined from the VIX index, that captures market-level shocks. I regress *degree* centrality on the VIX dummy and find a positive and statistically significant effect. The coefficient in column (1) is 0.025 (t-stat= 5.40) when controlling for fund characteristics and a year fixed effect and 0.055 (t-stat= 16.25) when controlling for a fund $\times$ time fixed effect in column (2). This second specification allows me to control for any time-varying fund characteristic that could potentially affect *degree* centrality at the highly volatile quarter. In both specifications, I cluster standard errors at the fund level.[19] Figure 2.4 on page 28 also depicts how degree evolves around a highly volatile period. We can see from this figure, where the right y axis represents the average *degree* centrality for all funds, that degree tends to increase from period $m-6$ (6 months before the highly volatile event) until $m+3$ (three months after the event). The event in Figure 2.4 on page 28 is the third quarter of 2008 (Lehman Brothers). This suggests that mutual funds tend to move closer to each other in periods of high volatility. Based on this evidence, I investigate the effect of *degree* centrality on cumulative abnormal fund returns in the "surge" window (from quarter $t-2$ until quarter $t+1$).

Panel B of Table 2.5 on page 27 shows that being a mutual fund with high *degree* centrality, by one standard deviation, will lower your quarterly fund performance by approximately -0.33 percentage points (t-stat=-1.74) for the Carhart four-factor model (column (3)) around the volatile period, controlling for fund characteristics. These results suggest that, while *degree* centrality is generally not beneficial for fund performance, its negative effect is exacerbated in uncertain times as mutual funds get rid of volatile firms due to asset management contract terms and thus exercise negative price pressure on commonly held assets. This is consistent with the documented inefficiencies and unintended consequences of institutional incentives (Lines 2016).

[19] The results are robust to alternative dummy specification, i.e., top tercile, quartile, and quintile.

Table 2.5: Degree Centrality in Uncertain Times and Fund Performance

This table reports the results of common holdings' effects in uncertain times. In panel A, the dependent variable is $Degree$ measured at t. It is the weighted degree centrality of the common holdings network. The main independent variable is VIX. It is a dummy that takes the value 1 when the VIX index, in quarter t (event), is in the top decile of its distribution. Other controls, measured at t, include TNA (in millions of dollars), which is total net assets; *Ret* (the quarterly fund net return); $flow$ (the net growth of total net assets); *stocks* (the number of stocks in the portfolio); *fund age* (the number of months since the fund's inception), *expense*, and *turnover*. A quarter fixed effect is included in the first specification and a fund $\times$ time fixed effect is included in the second specification with no fund characteristics as controls. Standard errors are clustered at the quarter level. In panel B, the dependent variable is the cumulative abnormal fund return (CAR) in the window period (between quarter t-2 to t+1). Three models are used to compute abnormal return: $CAPM$, Fama-French three-factor model (Fama and French 1993; $FF3$), and Carhart four-factor (Carhart 1997; $FFC4$). The main independent variable is $Degree$ at time t. It is the weighted degree centrality of the common holdings network. Controls are the same in panel A. Panel B includes a fund fixed effect in all specifications. All specifications include an unreported intercept and standard errors are clustered at the fund level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

Panel A: Degree in Uncertain Times

	$Degree_{i,t}$	
	(1)	(2)
VIX_t	0.025***	0.055***
	(5.40)	(16.25)
Controls	YES	NO
FE	Year	Fund $\times$ Quarter
# Obs	79,624	83,257
Adj R^2	0.481	0.956

Panel B: Performance in Uncertain Times

	$CAPM_{i,t-2:t+1}$	$FF3_{i,t-2:t+1}$	$FFC4_{i,t-2:t+1}$
	(1)	(2)	(3)
$Degree_{i,t}$	-0.226**	-0.337*	-0.331*
	(-2.19)	(-1.84)	(-1.74)
Controls	YES	YES	YES
FE	YES	YES	YES
# Obs	73,000	73,000	73,000
Adj R^2	0.005	0.004	0.003

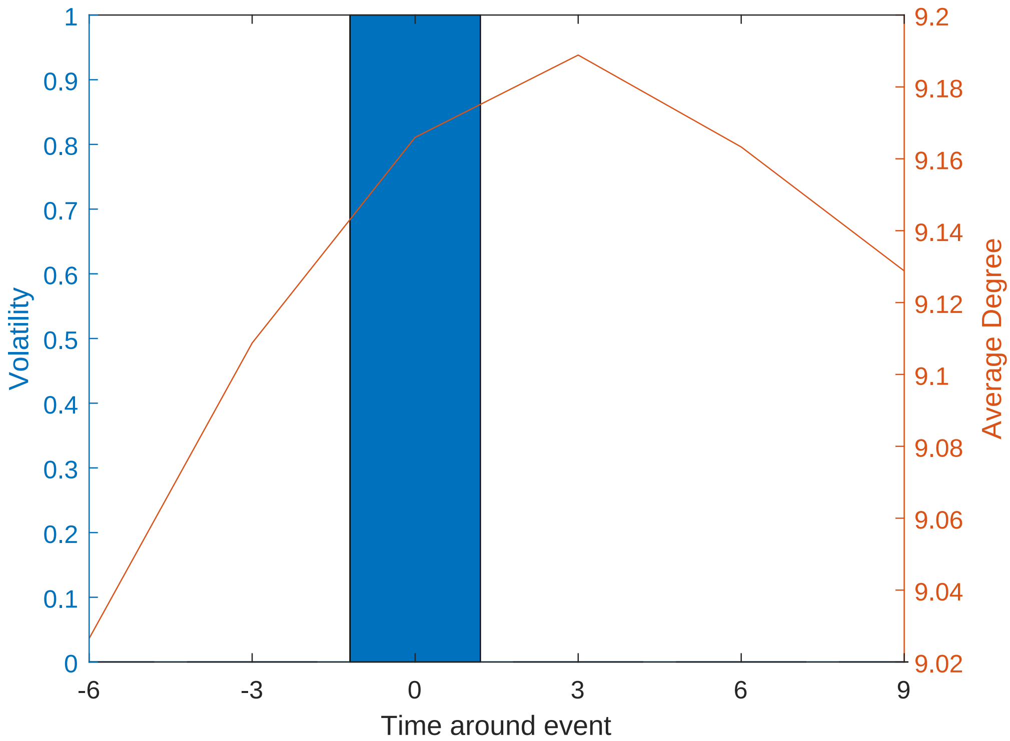

Figure 2.4: Average degree around a volatile event

This figure represents the average (natural logarithm) degree centrality of the right y-axis around a volatile event, which is defined as whenever the quarterly Volatility Index VIX (average monthly VIX) is in the top decile of its distribution. In this figure, the representative event is the third quarter of 2008 (Lehman Brothers).

2.4.5 Firm-level analysis

Owners' Degree Centrality and Stock Returns

In this section, I explore the effects of mutual fund *degree* centrality at the firm level. If mutual funds with low *degree* centrality have an advantage over their peers with high holdings similarity, mimicking their portfolio should exhibit higher returns. I investigate this aspect by constructing portfolios of stocks based the *degree* centrality of their mutual fund owners. I sort funds based on *degree* centrality and assign each fund in 10 groups at each quarter. I extract the holdings of each fund. Then, I compute the rounded average *degree* centrality decile portfolio across all funds for each stock (i.e., the simple average of all its owners' *degree* centrality decile). With ten portfolios of stocks based on the *degree* centrality of mutual fund owners, I construct a long-short portfolio where the long leg is on the low *degree* centrality stocks and compute the abnormal returns of the top, bottom, and long-short portfolios in the subsequent 12 months.

Table 2.6 shows the results of the univariate analysis at the firm level. The long-short portfolio exhibit in column (6) an abnormal return of 7% (t-stat= 3.40) annually with value-weighted portfolios, when abnormal return is obtained from the Carhart four-factor model. The difference between bottom and top stocks based on owners' *degree* centrality is almost 9% (t-stat= 4.37) for the three-factor model in column (5). These results suggests that mutual funds with low holdings similarity own stocks with higher abnormal returns. The results are weaker when forming equally-weighted portfolios. The difference is of 1.5% (t-stat= 1.88) annually for the CAPM in column (1) and 1.7% (t-stat= 2.27) for the three-factor model in column (2).

Table 2.6: Owners' Degree Centrality and Stock Returns

This table reports annual abnormal returns for portfolios sorted by fund degree centrality. Each quarter, mutual funds are sorted on the basis of *degree* centrality into ten portfolios. I extract holdings from mutual funds in the top and bottom decile for each centrality measure and compute equally-weighted and value-weighted portfolio returns composed of stocks owned by top and bottom decile mutual funds as well as a long-short portfolio where the long leg is in stocks owned by mutual funds with low *degree*. I regress returns of the top, bottom, and long-short portfolio returns in the subsequent year on $CAPM$, three-factor ($FF3$) and four-factor ($FFC4$) models and report the intercept of each model. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	Equally-weighted			*Value-weighted*		
	$CAPM$	$FF3$	$FFC4$	$CAPM$	$FF3$	$FFC4$
	(1)	(2)	(3)	(4)	(5)	(6)
1	-0.006	-0.017*	-0.000	0.205**	0.225***	0.195***
	(-0.39)	(-1.62)	(-0.08)	(7.50)	(9.97)	(8.33)
10	-0.020*	-0.033***	-0.008	0.136***	0.139***	0.125***
	(-1.79)	(-4.21)	(-1.06)	(6.24)	(7.45)	(6.37)
1-10	0.015*	0.017**	0.008	0.070***	0.086***	0.070***
	(1.88)	(2.27)	(0.89)	(3.51)	(4.37)	(3.40)

Owners' Degree Centrality, Stock Returns, and Uncertain Times

Previous results show that mutual funds with high *degree* centrality suffer more in uncertain periods. However, this does not directly show negative price pressure on common assets or spillovers effects. To disentangle from common information at the firm level that might make mutual funds sell assets, I investigate the effect of *degree* centrality in uncertain periods at the stock level.

I compute *degree* centrality at the stock level as the value-weighted average of a stock's owners' degree. Stocks with owners that have a high *degree* centrality should exhibit more negative returns in uncertain periods if these mutual funds exercise negative price pressure, controlling for firm characteristics. To verify this, I focus on periods of uncertain markets defined as quarters where VIX is in the top decile of its distribution as before and focus on the "surge period" as shown in Figure 2.4 on page 28 (i.e., from quarter $t-2$ until quarter $t+1$).

Table 2.7 on page 31 shows the results of the effect of centrality in uncertain periods at the stock level. A firm owned by mutual funds that are one standard deviation higher in terms of *degree* centrality will have lower cumulative abnormal returns of -0.5 percentage points (t-stat= -2.81) during the uncertain period for the CAPM model in column (1). In this specification, I control for various firm characteristics to exclude other explanations that might cause the stock to decrease in value (e.g., past return, analysts' recommendation, illiquidity, stock return volatility), as well as firm fixed effects.[20] The results suggest that owners' portfolio similarities have a significant effect on stock returns in uncertain times. The results are weaker for the Fama and French three-factor model in columns (3) and (4), and insignificant for the Carhart four-factor model in columns (5) and (6). Including a firm fixed effect also weakens the significance.

2.4.6 Further tests

In this section I investigate if the relationship between *degree* centrality and fund performance still holds using alternative centrality and similarity measures. I first choose *eigenvector* centrality as it takes into account a second order type of importance within a network. Namely, a mutual fund with high *eigenvector* centrality means that it is connected to mutual funds that also have many connections. In this

[20] These characteristics have been shown in prior literature to affect stocks returns (Banz 1981; Rosenberg et al. 1985; Fama and French 1993; Jegadeesh and Titman 1993; Falkenstein 1996; Haugen and Baker 1996; Barber et al. 2001; Amihud 2002; and Cooper et al. 2008).

Table 2.7: Owners' Degree Centrality, Stock Returns, and Uncertain Times

This table reports the results of common holdings' effects for stocks in uncertain times. The dependent variable is the cumulative abnormal stock return (CAR) in the window period (between quarter t-2 to t+1). Quarter t is the period when the VIX is in the top decile of its distribution. Three models are used to compute stock abnormal returns: CAPM, Fama-French three-factor model, and Carhart four factor (Fama and French 1993; Carhart 1997). The main independent variable is *Degree* at the stock level defined as the value-weighted average of a stock's mutual fund owners degree. Controls include *Amihud* illiquidity ratio, *analyst* average recommendation, *asset* growth, book-to-market ratio (B/M), firm *size*, profitability (*profit*), past stock return (*Ret*), and stock return volatility (*vol*). All specifications include an unreported intercept, and standard errors are clustered at the quarter level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$CAPM_{j,t-2:t+1}$		$FF3_{j,t-2:t+1}$		$FFC4_{j,t-2:t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Degree_{j,t}$	-0.499***	-0.191	-0.142*	-0.090	-0.545	-0.393
	(-2.81)	(-0.78)	(-1.92)	(-1.07)	(-1.52)	(-1.23)
$Amihud_{j,t}$	0.000	0.000	0.001	0.002	0.001	0.002
	(0.09)	(0.52)	(0.46)	(0.35)	(0.12)	(0.07)
$analyst_{j,t}$	-0.002	-0.000	0.022	0.047	-0.056	-0.011
	(-1.41)	(-0.60)	(0.46)	(0.96)	(-0.34)	(-0.07)
$asset_{j,t}$	0.006***	0.005***	0.107**	0.093**	0.292*	0.260*
	(3.97)	(3.70)	(2.18)	(2.05)	(1.88)	(1.78)
$\ln(B/M_{j,t})$	-0.006**	-0.002	0.123	0.176*	0.430	0.574*
	(-2.03)	(-0.56)	(1.20)	(1.69)	(1.19)	(1.80)
$\ln(size_{j,t})$	0.007	0.019***	0.476**	0.698**	2.061***	2.682***
	(1.43)	(2.80)	(2.23)	(2.41)	(2.86)	(2.86)
$profit_{j,t}$	0.001	0.001	-0.005	-0.014	0.008	-0.020
	(0.99)	(0.77)	(-0.19)	(-0.46)	(0.08)	(-0.18)
$Ret_{j,t}$	0.001	0.000	0.006	0.009	-0.034	-0.029
	(1.24)	(0.80)	(0.22)	(0.29)	(-0.30)	(-0.22)
$vol_{j,t}$	-0.001	0.000	0.079	0.061	0.609	0.620
	(-0.45)	(0.04)	(0.66)	(0.35)	(1.17)	(0.82)
Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	151,651	151,651	151,651	151,651	151,650	151,650
Adj R^2	0.903	0.903	0.880	0.880	0.841	0.841

section, I use the same regression approach as in equation (2.8) on page 17 with the same controls, including *active share*, fixed effects and clustered standard errors at the fund level. When using *eigenvector* as a measure of mutual fund holdings similarity, quarterly fund performance (CAPM) is lower by -0.1% (t-stat= -2.73) when *eigenvector* centrality is changed by one standard deviation (see Table 2.8 on page 33). This effect disappears using other factor models (three-factor and four-factor). The effect of *eigenvector* centrality is also present when computed in style networks and its effect is also amplified in periods of uncertainty.

Then I use a *distance* measure that computes holdings similarity between mutual funds using the proportion invested in each asset with respect to the size of the fund.[21] This methodology addresses the fact that I used dummies in the original network; links were created whenever a mutual fund invests in a firm irrespective of the amount. This serves as a robustness test to see if this binary network misses information from the dollar proportion invested by each fund in each firm. Overall, I find that the main hypothesis still holds. A larger *distance* of one standard deviation leads to higher fund performance (a coefficient of 0.1% and t-stat= 2.73 for the CAPM), controlling for fund characteristics. This effect disappears using other factor models (Fama and French three-factor and Carhart four-factor). The *distance* measure shows similar results when computed against style peers. However, *distance* does not seem to show any negative impact in periods of high volatility.

The *distance* measure is less robust, typically when controlling for *active share*. A possible reason is that if there are many closet indexing mutual funds (i.e., funds that invest weights close to market weights), *distance* will be similar to computing the *active share* of a mutual fund. Thus, it is less informative than a fund's *degree* as to how it differs from its peers.

Finally, I investigate the effect of *degree* centrality on fund performance in subperiods and sub-groups. I split the sample into two subperiods: before and after the May 2004 SEC regulation that made portfolio disclosure mandatory for mutual funds. I find that the effect is much weaker or absent in the post period. This suggests that mutual funds with low holdings similarity potentially had an informational advantage as they held stocks disregarded by their peers. After the regulation, mutual funds with low *degree* centrality lost their advantage as their holdings became more frequently public. The effect of *degree* centrality on fund performance is present among funds in the large stocks style category and growth stocks category.

[21] I compute the distance matrix from the bipartite network of mutual funds (See Section 2.3 for more details on the *distance* measure).

The absence of effect in the small and value style categories could be explained by the large number of small stocks.

Table 2.8: Further Tests

This table reports further results of OLS regressions. The dependent variable is abnormal return at quarter t. Three models are used to compute performance: $CAPM$, Fama-French three-factor model (Fama and French 1993; $FF3$), and Carhart four-factor (Carhart 1997; $FFC4$). The main independent variables are *Eigenvector* and *Distance*. *Eigenvector* is the eigenvector centrality of the common holdings network. *Distance* is the Euclidean distance between each fund and its peers. The distance matrix is computed from the matrix of dollar positions invested by each fund in each asset divided by TNA. From the distance matrix, I compute fund-level distances as the average of distances with all peers. When *Style* is specified, *Eigenvector* and *Distance* are measured with respect to fund style peers as opposed to the whole active mutual fund universe. When *VIX* is specified, the dependent variable is the cumulative abnormal return around the event quarter (when VIX is in the top decile). Controls include TNA (in millions of dollars), which is total net assets; *Ret* (the quarterly fund net return); $flow$ (the net growth of total net assets); *stocks* (the number of stocks in the portfolio); *fund age* (the number of months since the fund's inception); *expense*, and *turnover*. Pre (Post) -Disclosure corresponds the effect of *Degree* on fund performance in the sub-period prior (post) to the May 2004 SEC regulation. The last four rows correspond to sub-groups of funds according to their style category, as specified by Morningstar style box. All specifications include an unreported intercept, and quarter and fund fixed effects, except for the uncertainty test (VIX) where the specifications include a fund fixed effect only. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$CAPM_{i,t}$	$FF3_{i,t}$	$FFC4_{i,t}$	Controls	FE
$Eigenvector_{i,t-1}$	-0.001***	-0.001***	-0.001***	YES	YES
	(-2.73)	(-2.78)	(-3.57)		
$Distance_{i,t-1}$	0.001***	0.001**	0.001	YES	YES
	(2.73)	(2.17)	(1.61)		
$StyleEigenvector_{i,t-1}$	-0.001**	-0.001**	-0.000*	YES	YES
	(-2.00)	(-1.97)	(-1.79)		
$StyleDistance_{i,t-1}$	0.020***	0.015***	0.011***	YES	YES
	(3.85)	(3.60)	(3.11)		
$Eigenvector_{i,t-1}$ (VIX)	-0.181**	-0.345**	-0.372**	YES	YES
	(-2.36)	(-2.27)	(-2.28)		
$Distance_{i,t-1}$ (VIX)	0.006	0.012	0.014	YES	YES
	(0.84)	(0.86)	(0.91)		
Pre-Disclosure	-0.011***	-0.008***	-0.006***	YES	YES
	(-4.76)	(-4.43)	(-3.80)		
Post-Disclosure	-0.002***	-0.001	0.001	YES	YES
	(-2.41)	(-1.00)	(1.09)		
Large	-0.004***	-0.004***	-0.004***	YES	YES
	(-7.93)	(-9.23)	(-9.23)		
Small	-0.000	0.001	0.001	YES	YES
	(-0.06)	(0.58)	(0.95)		
Growth	-0.009***	-0.007***	-0.006***	YES	YES
	(-6.59)	(-6.96)	(-6.08)		
Value	-0.002	0.001	0.003**	YES	YES
	(-1.16)	(0.69)	(2.44)		

2.5 Summary

In this chapter, I build a holdings similarity measure from common holdings network that captures informational advantage. I document that *degree* centrality is significantly associated to lower fund performance in a sample of actively managed U.S. equity mutual funds from 1980:Q1 to 2016:Q4. This main result holds across alternative holdings similarity measure (e.g., eigenvector centrality, distance) or when computed within style cluster networks.

Mutual funds face institutional constraints such as limited deviation from a benchmark. If facing a turbulent period, a fund manager will sell his volatile stocks in order to respect his contract terms. This will create negative price pressure on assets that are commonly held by many peers. Hence, a mutual fund with high holdings similarity suffers more in periods of high volatility.

This chapter complements the large literature in mutual fund performance and its drivers. This new measure supports the idea that differences in mutual fund performance might be driven by informational advantage. It also contributes to the growing literature on asset management contracts that has highlighted the negative effects and unintended consequences of benchmarking on asset prices for instance.

Chapter 3

Do Experienced Returns Affect Mutual Fund Managers' Investment Decisions?

3.1 Introduction

In September 2015, the mutual fund Fidelity Advisors Growth Opportunities invested approximately 1.6% of its capital in Microsoft, while at the same time Calamos Growth Fund took a much larger bet in Microsoft, investing 3% of its assets in this company. Such differences, which are common among mutual funds, highlight that the signals used by mutual fund managers to actively allocate capital in excess of $15 trillion across U.S. equities are considerably heterogeneous. What factors contribute to this heterogeneity? Are these factors indicative of stock-picking skill? Do these factors have any general asset pricing implications? These questions are central to the debate pertaining to active portfolio management and stock market efficiency.

Previous studies show that differences in investment strategies across funds arise because managers' extract information from their own social network (Cohen et al. 2008; Gerasimova 2016), or from personal industry-related experiences (Kempf et al. 2016; Cici et al. 2018). Other studies highlight a preference of managers to invest in companies that are situated close to them (Coval and Moskowitz 1999). We add to this literature, examining whether managers' investment decisions in specific companies are affected by their firm-specific experienced returns.

Our hypothesis is motivated from findings in behavioral economics, that people view a random process more favorably if they experienced more positive outcomes from this process in the past (Barron and Erev 2003; Ludvig et al. 2015). Such findings are commonly attributed to reinforcement learning (Erev and Roth 1998; Camerer and Ho 1999). Recent experimental work shows that the expectations held by an individual about the payoffs of a specific asset are overly optimistic, if this asset performed well for this individual in the past (Jiao 2017). Collectively, these findings highlight that personal experience matters for decision-making under risk, which suggests that reinforcement learning is a promising framework to analyze the stock-level investment decisions of mutual fund managers. Our hypothesis is that mutual managers will invest more heavily in a firm if their return experience with this firm is better.

In our baseline analysis, the experienced return of a given manager with a specific company is a weighted average of the past returns generated by this firm whilst held by the manager, with weights decaying exponentially with time. This function captures the well-known recency effect, whereby observations experienced in the more recent past are more vividly recalled (e.g., Baddeley and Hitch 1993). To determine the speed of decay, we follow a procedure similar to Malmendier and Nagel (2011), estimating our model on a tightly spaced grid of different rates of decay, and selecting the value that minimizes the model's sum of squared residuals. Our estimates suggest that the recency effect is not extreme, and that return experiences in the distant past also influence investment decisions.

In a regression framework, controlling for various manager and firm characteristics that may influence investment decisions (including past stock returns), we find that a one standard deviation increase in experienced returns is associated with a 0.01% (t-stat= 12.45) larger weight in this firm, relative to the size of the fund, which constitutes 2.8% of the average weight on a stock in our sample. In economic terms, this amounts to an increased investment of roughly $614K in this firm. When aggregated across all stocks for each fund and each quarter, this estimate implies that on average $30M worth of investments is allocated according to experienced returns, which amounts to about 1.55% of the size of the average mutual fund. This finding supports our hypothesis, that reinforcement learning affects the stock-level investment decisions of mutual fund managers.

We conduct various robustness checks. For example, to ensure that our results are not driven by an omitted variable related to either the firm or the fund, we also estimate a model that includes firm $\times$ time and fund $\times$ time fixed effects. We find that the coefficient on experienced returns continues to be positive and highly significant in this model. We also conduct a placebo test with passively managed index funds. Such funds provide an ideal setting for such a test, since their managers are not trading based on their expectations about future stock returns. Therefore, according to our hypothesis, the coefficient on experienced returns in this sample should be statistically insignificant. We indeed find that it is (coefficient= -0.00, t-stat= -0.40), which supports the view that our baseline results capture the effect of experienced returns on the expectations and trades of actively managed mutual funds.

Several studies argue that investors simplify their investment decisions assigning stocks in specific categories, and engage in style investing (e.g., Barberis and Shleifer 2003; Teo and Woo 2004). Motivated by this observation, we examine whether reinforcement learning affects investment decisions on the style level. We sort stocks according to styles, based on various attributes such as market value or book-to-market ratio, and examine whether the average weight placed on a stock in a given style is positively related to managers' style-level experienced returns. We find that a one standard deviation increase in style-level experienced returns is associated with an increased investment in firms that belong in this style by around 0.02% (t-stat= 4.93). When aggregated across stocks, this estimate implies that roughly 3.06% of the assets of the average fund are allocated according to style-level experienced returns.

We also estimate a model with an alternative definition of experienced returns based on Malmendier and Nagel (2011), which allows managers with shorter tenure to exhibit a larger recency effect. With this specification, we find that the effect of experience returns on investment decisions is larger compared to our baseline case, amounting to roughly 5.5% of the assets of the average fund being allocated according to tenure-weighted experienced returns (or 8.8% when we use tenure-weighted experienced returns to estimate the style-level model).

Experienced returns influence the way mutual fund managers rebalance their portfolio in the presence of flows. Specifically, we find that when managers are faced with inflows, they invest more of the new capital in stocks with higher experienced returns. Similarly, when faced with outflows, they reduce their positions in stocks with higher experienced returns less. These findings provide additional support to our hypothesis, that managers are more inclined to invest in a specific firm, if their experienced return with this firm is better.

Does reinforcement learning in this context reveal stock-picking skills? If so, then managers with better overall experienced returns are better stock pickers, and thus their funds would earn higher returns going forward.[1] Moreover, since stocks with higher experienced returns receive larger weights in mutual fund portfolios, information-based trading implies that experienced returns, when aggregated across managers for a specific stock, constitute a profitable trading signal, which positively predicts stock returns.

To test the managerial skill hypothesis, we aggregate experienced returns on the fund level ($AggExpRet_{Fund}$) and examine whether it predicts future fund returns. We find that the coefficient on $AggExpRet_{Fund}$ is *negative* and significant, with a one standard deviation increase in $AggExpRet_{Fund}$ being associated with a 0.1% reduction in fund returns. This result suggests that experienced returns not only do not reflect managerial skill, but that they distort managers' trades in a way that is detrimental to fund performance. One possible distortion is that higher experienced returns make managers more overconfident, which leads to more aggressive trading behavior (Gervais and Odean 2001). We indeed find some support for this hypothesis, as managers with higher $AggExpRet$ tend to have higher turnover, active share and tracking error.

A different distortion is highlighted by Kempf et al. (2016), who suggest that investors learn better when they experience negative return shocks. According to this argument, managers with higher $AggExpRet$ had relatively fewer learning opportunities, and thus make less profitable trades. To test this idea, we define separate variables for positive and negative aggregate experienced returns ($AggExpRet^+_{Fund}$ and $AggExpRet^-_{Fund}$, respectively) and re-estimate the model. We find that, whereas $AggExpRet^+_{Fund}$ is insignificant, $AggExpRet^-_{Fund}$ is negative and highly significant, with a one standard deviation increase in $AggExpRet^-_{Fund}$ being associated with a 0.25% reduction in quarterly fund returns. This finding supports the argument in Kempf et al. (2016), that the absence of negative return experiences distorts managerial learning.

To test the "good" signal hypothesis, we aggregate experienced returns on the stock level ($AggExpRet_{Firm}$), and examine whether this variable predicts future earnings shocks and stock returns. We find that $AggExpRet_{Firm}$ does not predict earnings shocks or returns around earnings announcements. Moreover, in a portfolio setting,

[1] This conjecture assumes that investors do not allocate capital across funds according to aggregate experienced returns (i.e., Berk and Green 2004). Note that experienced returns are not directly observed by investors.

we find that stocks with higher $AggExpRet_{Firm}$ *underperform* stocks in the opposite of the spectrum by about 8% per year. This finding is in line with literature showing that the trades of mutual fund managers can induce price pressure, and cause misvaluations in the cross-section of stock returns (i.e., Coval and Stafford 2007; Frazzini and Lamont 2008; Lou 2012; Akbas et al. 2015). In our setting, it is possible that stocks with higher aggregate experienced returns, which are overweighted in mutual find portfolios, become over-priced. Conversely, stocks with lower experienced returns become under-priced. With the passage of time, as prices converge to fundamental levels, the latter will outperform the former.

Our work contributes to the literature analyzing the subjective factors that influence the trades of mutual fund managers. Along these lines, previous studies emphasize the role of business and social connections (e.g., Ritter and Zhang 2007; Cohen et al. 2008; Massa and Rehman 2008), as well as the importance of previous industry-related experiences (e.g., Kempf et al. 2016; Cici et al. 2018). The factors highlighted by these studies can be seen as information-based, since they are typically associated with higher fund returns. Our work extends this literature, showing that the stock-level investment decisions of mutual fund managers are affected by their firm-specific experienced returns, consistent with reinforcement learning. However, contrary to these studies, our results suggest that reinforcement learning distorts managers' trades, since it is associated with lower fund returns.

Other studies examine whether mutual fund managers display any behavioral biases. For example, Bernile et al. (2017) show that managers who experience natural disasters are less inclined to take on risk. Shu et al. (2017) show that the trades of managers who experience bereavement due to parental loss are less profitable. Akepanidtaworn et al. (2018) show that managers make profitable trades when they buy stocks, but lose money when they sell, a finding they attribute to limited attention spent on sells. Bai et al. (2019) show that the birth of month of a fund manager, which determines whether a manager starts school earlier, influences fund performance. Our work extends this literature, showing that managers' stock-specific trades are affected by reinforcement learning. Moreover, on the manager level, reinforcement learning seems to cultivate overconfidence, which is damaging to fund performance.

Our results also contribute to the literature on the effect of past experiences on the economic decisions of various participants in financial markets, such as individual investors (Kaustia and Knüpfer 2008; Malmendier and Nagel 2011), members of the Federal Open Market Committee (Malmendier et al. 2017), and portfolio managers in credit markets (Chernenko et al. 2016). We extend this literature, showing that mutual fund managers invest more heavily in stocks that generated better returns for them in the past. This finding also contributes to the broader literature that discusses how investors' stock return expectations are extrapolative (Lakonishok et al. 1994; Greenwood and Shleifer 2014; Da et al. 2018), highlighting a particular form of extrapolation: investors form stock-specific return expectations by extrapolating their own return experience with these firms.

Finally, our paper links to the literature on the potential of arbitrage to be "destabilizing" to pricing efficiency (Stein 2009; Lou and Polk 2012; Huang et al. 2016). A closely related study is by Akbas et al. (2015), who show that cross-sectional mispricing is larger when mutual funds are more capitalized. The results from our cross-sectional asset pricing tests add to this literature, showing that the experienced returns of mutual fund managers, which determine the extent to which a stock is overweighted or underweighted in mutual fund portfolios, can lead to mispricing and cross-sectional return predictability.

3.2 Data & Methodology

In this section we describe our sample selection criteria, and define our variables and econometric model.

3.2.1 Sample Specification

Our data come from different sources. The data on mutual fund size (total net assets: TNA), fund age, and fund returns are from the CRSP Survivor-Bias-Free U.S. Mutual Fund database. The data on mutual fund holdings are from the Thomson Reuters Mutual Fund Holdings database from 1980 to 2016. We group multiple share classes and merge CRSP fund characteristics with mutual fund holdings using MFlinks. The data on fund managers' names and histories as well as fund style categories are from Morningstar.

Thomson Reuters Mutual Fund Holdings data are given on a quarterly basis, starting in 1980:Q1. We assign individual manager information to each fund and its associated style category using Morningstar data, which start in 1991. We merge CRSP and Morningstar data using funds' Ticker first and subsequently using funds' CUSIP for non-matched funds, following Pástor et al. (2015). We manually screen for potential typos in managers' names. Overall, we match more than 80% of the managers in the Morningstar sample to the CRSP database.

Consistent with prior studies (e.g., Lou 2012), we retain funds with a minimum fund size of $1 million, and focus only on U.S. actively managed equity mutual funds.[2]

The data on firms' market value, stock prices, and returns are from CRSP, and book values are from Compustat. We exclude from our sample stocks in the bottom New York Stock Exchange (NYSE) size decile, or stocks with a price lower than $5 per share, which tend to be avoided by mutual funds due to their potential illiquidity (i.e., Falkenstein 1996). This filter is designed to mitigate any microstructural biases associated with very small stocks, and is commonly used in empirical finance studies (e.g., Jegadeesh and Titman 2001; Lou 2012).

In Section A of the Appendix, we explain in detail how we compute each of the variables. Table 3.1 on page 47 summarizes the final database. We have 6,329 different managers for 2,054 mutual funds and 8,347 stocks from 1991:Q1 to 2016:Q4.

3.2.2 Experienced Returns

To measure the experienced return of the manager of fund i in firm j at quarter t, we use an exponentially weighted moving average of past returns, as follows:

$$Experience_{i,j,t} = \sum_{k=0}^{T} (1-\phi)^k \phi R_{j,t-k} I_{[w_{i,j,t-k}>0]}, \tag{3.1}$$

In the above expression, $R_{j,t-k}$ is the return on firm j at period $t-k$. $I_{[w_{i,j,t-k}>0]}$ is an indicator variable that equals to 1 if the manager of fund i invests in firm j at time $t-k$ and 0 otherwise (i.e., when the fund managed by this manager has a positive weight on this stock $w_{i,j,t-k} > 0$, where $w_{i,j,t-k}$ is the dollar amount invested divided by the total net assets of the managed fund). In the sum, T indicates the number of quarters since stock j was first purchased by the manager of fund i, where

[2] We select mutual funds with an investment objective code, as reported by the Thomson Reuters Mutual Fund Holdings database, to be either aggressive growth, growth, growth and income, balanced, or unclassified, excluding index funds. We also restrict funds to those that have a Morningstar Category Group of "U.S. Equity."

k indicates an arbitrary past quarter.[3,4] This calculation in equation (3.1) on page 42 is done at the manager level, i.e., we calculate the experienced return of the manager of fund i for firm j, regardless in which funds this manager has worked in the past. Moreover, if fund i is managed by a team of managers (about 66% of our sample), we take a tenure-weighted average of experienced returns in firm j at time t, using the date that each manager first appeared in the Morningstar database to estimate their tenure in the industry.[5]

The parameter ϕ in equation (3.1) on page 42 captures the rate of decay in the weights attached on past return observations. It reflects the weight that is placed on the most recent return observation, which then accordingly determines the weights on all other past return observations. Drawing on the results of Malmendier and Nagel (2011), we consider a function with decreasing weights (i.e., a recency effect where the weight on the most recent observation is the highest), captured with the parameter $0 < \phi < 1$. To illustrate, Figure 3.1 on page 44 shows various functions for different values of ϕ. As ϕ gets closer to 1, the function gets steeper, indicating that experienced returns are mostly affected by recent observations. As ϕ decreases, the function becomes flatter, and the weight attached on more distant returns increases. However, in all cases, the weight attached on the most recent experiences is higher, consistent with a recency effect on mental representations.

Because there is no theoretical guidance on what ϕ should be, we estimate it from the data using a procedure similar to that in Malmendier and Nagel (2011). Specifically, we estimate our model described below on a tightly spaced grid of different values for ϕ, which correspond to different experienced return specifications, and retain the version that minimizes the regression's sum of squared residuals.[6]

[3]In the period that a stock was first purchased k=T, and $k = 0$ indicates the current time period, t. Note that with this specification, we assume that each stock provides its return during the full quarter that it is held by a fund, which implies that it was bought at the closing price at the end of the previous quarter.

[4]Note that, if a fund manager held a stock at some point in the past, then completely sold it, and then bought it again at a later date, our experienced returns measure assigns a value of zero to the intermittent periods that the stock was not held.

[5]This specification assumes that managers with larger tenure are more senior, and therefore influence investment decisions more strongly. However, our results are robust to using an equally-weighted average instead.

[6]For a fixed value of ϕ, the model is linear in its parameters, and can thus be estimated using ordinary least squares.

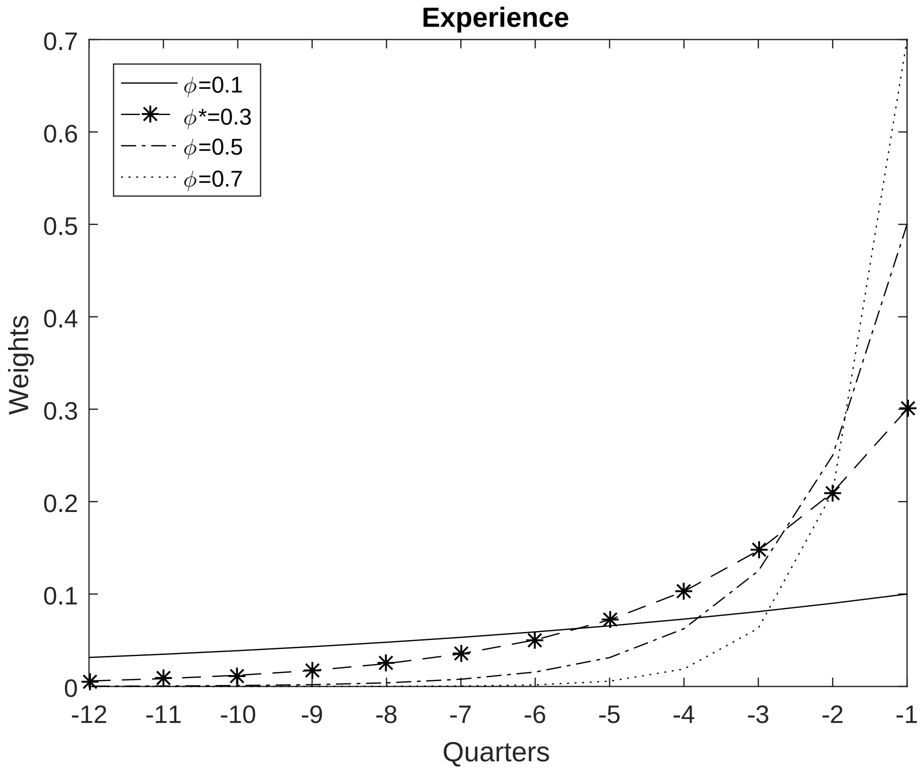

Figure 3.1: *Experience* decay factor
This figure shows the weights on past returns for the exponentially weighted moving average for different values of the decay parameter ϕ.

3.2.3 Model Specification

The dependent variable in our models is the weight placed on firm j by fund i at quarter t, $w_{i,j,t}$, defined as the dollar amount invested divided by the total net assets of the managed fund. Such a measure is commonly used when studying the investments decisions of mutual fund managers (e.g., Coval and Moskowitz 1999; Cohen et al. 2008; Gerasimova 2016). Because $w_{i,j,t}$ changes as the market value of firm j changes, we adjust it following the method in Kacperczyk et al. (2005), to capture the "active" investment decision by the manager of fund i on firm j, as follows:

$$Weight^{adj}_{i,j,t} = w_{i,j,t} - \tilde{w}_{i,j,t}, \tag{3.2}$$

where

$$w_{i,j,t} = \frac{\$holding_{i,j,t}}{TNA_{i,t}} \quad \text{and} \quad \tilde{w}_{i,j,t} = \frac{w_{i,j,t-k}\prod_{k=0}^{K}(1+R_{j,t-k})}{\sum_j w_{i,j,t-k}\prod_{k=0}^{K}(1+R_{j,t-k})}.$$

The variable $\tilde{w}_{i,j,t}$ reflects the weight that fund i would place on firm j at time t had this fund bought this stock in the past (at time $t-K$) and never traded it. Therefore, the adjustment shown in equation (3.2) on page 44, subtracts from the weight on firm j the hypothetical buy-and-hold weight reflecting the variation in firm j's value over time, thus capturing the manager's active investment decision in this firm ($Weight^{adj}$).

Note that, in our estimations, if a specific stock is not held by a mutual fund manager at a given quarter, it does not enter in our estimations for that specific fund for that quarter, i.e., it does not receive a weight of zero.[7] In our setting, stocks that were never held by a manager would also have zero experienced returns, so entail no variation than can be used to test our hypothesis.

Equation (3.3) below is our baseline model:

$$\begin{aligned} Weight^{adj}_{i,j,t} &= c + \beta Experience_{i,j,t-1}(\phi) + \gamma FundControl_{i,t-1} \\ &+ \delta FirmControl_{j,t-1} + S \times T + \epsilon_{i,j,t}. \end{aligned} \tag{3.3}$$

In terms of fund-level controls, our models include fund alpha with respect to the Carhart four-factor model (*fund alpha*; Carhart 1997), fund flows (*flow*, calculated as the percentage change between two quarters of total net assets after taking into account fund returns), the natural logarithm of fund age (ln(*fund age*), calculated as the number of months since fund inception), and the natural logarithm of the total net assets (ln(*TNA*)) of the fund. To control for the fact that funds invest in firms with different market values (MV) and book-to-market (B/M) ratios according to their designated style, we control for the variable *%Style*, proposed by Cohen et al. (2008), calculated as the portion of a fund's TNA invested at quarter $t-1$ in the style in which firm j belongs, depending on its MV and B/M ratio.[8] We also control for fund turnover ($turnover$), calculated as the minimum of the absolute values of

[7]Note that in our descriptive statistics table, the indicated minimum weight of 0 is just a rounded value of a very small positive weight.

[8]To classify firms into styles, we use NYSE breakpoints on firm size (MV) and B/M ratios. For each quarter, firms in the bottom (top) 30th (70th) MV percentile are classified as small (large) stocks. Firms in the bottom (top) 30th (70th) B/M percentile are growth (value) stocks. Firms in-between the 30th-70th percentiles for MV (B/M) are classed as mid-size (blend).

sales and purchases of securities in a quarter, divided by the total net assets of fund i, as in Wermers (2000) and Brunnermeier and Nagel (2004). *Manager tenure* is the number of months since the first appearance in the Morningstar database. For team-managed funds, *manager tenure* is an equally-weighted average of the tenure of each manager. The dummy variable *team* equals 1 if fund i is managed by a team of managers and 0 otherwise.

We also include in the model fund style $\times$ time fixed effects, denoted in equation (3.3) on page 45 by $S \times T$. We use the Morningstar classification to assign funds into styles, where a fund can belong in one of nine styles (3×3, according to MV and *B/M* orientations). Thus, $S \times T$ equals 1 if fund i at quarter t belongs in a specific style category. These fixed effects capture aggregate shocks that may influence the investment decisions of managers, due to factors such as correlated capital inflows or outflows (e.g., Teo and Woo 2004).

At the firm level, in our models we control for the natural logarithm of firm MV and book-to-market ratio B/M, and four lags of past quarterly stock returns (ret_{t-k}, where $k \in \{1, .., 4\}$). Moreover, to account for any correlation in the residuals for the same firm at a given time, in all our models we cluster standard errors at the firm $\times$ time level. All the independent variables in the model enter on a lagged basis.

Table 3.1 on page 47 provides descriptive statistics for the different variables. On average, we have 1,899 firms and 925 funds per quarter, with roughly 79 funds investing in each firm. There are more large-cap funds, than mid-cap and small-cap funds. On average, the weight placed on a firm, $w_{i,j,t}$, is 0.64% relative to fund TNA and 0.39% for the adjusted weight. Our experienced returns measure (with $\phi = 0.3$) is equal to 4% on average, with a standard deviation of 9%.

The average fund in our sample has an average quarterly return of 2%, an α of -0.98%, a TNA of around \$5,578M, is 15 years old, with a flow of 2%, and an annual turnover ratio of 80%. These statistics are comparable to studies that use this data (e.g., Agarwal et al. 2015; Doshi et al. 2015; Pástor et al. 2015). On average each manager in our sample has a tenure of 10 years. Table 3.2 on page 48 shows correlations for the main variables, namely $Experience$, *fund alpha*, $flow$, *fund age*, TNA, *%Style*, *turnover*, *manager tenure*, *team*, MV, B/M, and four lags of stock returns (ret). As expected, the highest correlations are between experienced returns and lagged stock returns. For this reason, our model controls for past stock returns at different lags.

Table 3.1: Summary Statistics

This table presents summary statistics of our main variables. The sample is composed of actively managed mutual funds in the U.S. from 1991:Q1 to 2016:Q4. Data on fund manager names and histories, and data on fund styles are from Morningstar. Firm-level data are from CRSP and Compustat, and fund-level data are from the CRSP Survivorship-Bias-Free U.S. Mutual Fund database and Thomson Reuters Mutual Fund Holdings database. Variable definitions are in Table A1 in the Appendix. The experienced returns measure (*Experience*) is calculated assuming a decay parameter ϕ equal to 0.3.

	Mean	Std. Dev.	Min	Max	P25	P50	P75
Panel A: Observations							
Firms by quarter	1899.3	182.9	1022	2336	1798	1904	2007
Funds by firm & quarter	78.79	63.14	1	410	34	60	106
Funds by quarter	925.16	235.74	134	1223	892	978	1059
Large blend	175.77	41.47	31	234	165	184	198
Large growth	202.58	48.51	42	267	191	213	232
Large value	130.96	34.33	19	182	122	136	155
Mid blend	53.3	16.75	4	76	47	58	65
Mid growth	97.31	24.22	21	129	96	102	113
Mid value	37.07	13.23	1	55	31	39	48
Small blend	79.57	25.67	3	110	71	82	102
Small growth	105.3	27.31	8	138	102	114	121
Small value	43.3	13.35	3	56	41	49	53
Panel B: Fund characteristics							
Weight (%)	0.64	0.79	0	4.31	0.07	0.3	0.94
$Weight^{adj}$ (%)	0.39	0.77	-11.89	4.31	-0.04	0.08	0.62
Experience (ϕ=0.3)	0.04	0.09	-0.42	0.76	-0.01	0.03	0.08
Large blend	0.03	0.07	-0.36	0.68	0	0.03	0.07
Large growth	0.04	0.08	-0.36	0.69	0	0.04	0.08
Large value	0.03	0.07	-0.42	0.7	-0.01	0.03	0.06
Mid blend	0.03	0.07	-0.36	0.68	0	0.03	0.07
Mid growth	0.04	0.08	-0.36	0.69	0	0.04	0.08
Mid value	0.03	0.07	-0.42	0.7	-0.01	0.03	0.06
Small blend	0.03	0.07	-0.36	0.68	0	0.03	0.07
Small growth	0.04	0.08	-0.36	0.69	0	0.04	0.08
Small value	0.03	0.07	-0.42	0.7	-0.01	0.03	0.06
fund alpha (%)	-0.98	0.12	-14.96	15.06	-1.02	-0.97	-0.92
flow	0.02	0.14	-0.5	1.96	-0.03	0	0.04
fund age	185.98	158.31	1	1106	85	147	230
TNA	5577.79	27,024.28	1.1	498,117.1	165.4	576.5	1927.89
%Style	36.7	24.17	0	175.95	15.22	34.39	57.35
turnover	0.8	0.8	0	1.11	0.2	0.7	0.94
manager tenure	114.83	69.88	0	336	60	106.5	162
fund return	0.02	0.09	-0.81	0.92	-0.02	0.03	0.08
Panel C: Firm characteristics							
MV	5281.07	19,956.85	11.32	724,773.4	409.05	1012.72	3013.1
B/M	0.09	0.24	0	14.23	0.03	0.05	0.08
Ret	0.04	0.18	-0.9	12.64	-0.06	0.04	0.13

Table 3.2: Correlations of Model Variables

This table presents correlations between the main independent variables: *Experience*, which is an exponentially weighted moving average of past stock returns experienced by manager of fund i on stock j from the time this manager invested in this firm until period $t-1$ with a decay parameter ϕ equal to 0.3, the tenure-exponentially weighted experience measure is based on Malmendier and Nagel (2011) (*TW-Experience*), with a decay parameter θ equal to 2.4. Other variables include the fund Carhart four-factor alpha, net fund flows, fund age in months, total net assets, the percentage invested by manager i in the style category corresponding to stock j, turnover ratio, manager tenure (we take an equally-weighted average for team-managed funds), a team dummy, firm size (MV), firm book-to-market (B/M) ratio, and four lags of firm stock quarterly returns. See Table A1 in the Appendix for detailed variable definitions.

	Experience	*TW-Experience*	*fund alpha*	*flow*	*fund age*	TNA	*%Style*	*turnover*	*manager tenure*	*team*	MV	B/M	Ret_{t-1}	Ret_{t-2}	Ret_{t-3}	Ret_{t-4}
Experience	1															
TW-Experience	0.212	1														
fund alpha	0.204	0.058	1													
flow	0.039	-0.037	0.085	1												
fund age	-0.002	0.169	0.009	-0.145	1											
TNA	0.001	0.250	0.009	-0.001	0.160	1										
%Style	-0.071	0.173	-0.051	-0.067	0.104	-0.005	1									
turnover	0.091	-0.129	0.022	-0.071	-0.002	-0.126	-0.121	1								
manager tenure	-0.004	0.437	0.012	-0.116	0.352	0.180	0.118	-0.008	1							
team	-0.004	-0.026	0	-0.045	0.002	-0.148	0.023	0.111	0.040	1						
MV	0.039	0.214	-0.001	-0.047	0.165	0.019	0.526	0.002	0.091	0.018	1					
B/M	-0.024	-0.071	-0.001	0.018	0.017	-0.015	-0.197	-0.003	-0.102	-0.022	0.030	1				
Ret_{t-1}	0.494	0.100	0.258	0.028	0	-0.001	-0.074	0.064	0.007	0.003	0.026	-0.014	1			
Ret_{t-2}	0.365	0.086	0.057	0.025	-0.005	-0.004	-0.034	0.043	-0.003	0.008	0.006	-0.014	-0.030	1		
Ret_{t-3}	0.197	0.054	-0.018	0.007	-0.003	-0.004	-0.025	0.039	-0.005	-0.003	0.002	-0.013	-0.033	-0.028	1	
Ret_{t-4}	0.137	0.047	-0.015	0.007	-0.007	-0.003	-0.024	0.025	-0.011	-0.003	-0.008	-0.013	-0.031	-0.022	-0.007	1

3.3 Results

In this section we present our baseline results and various robustness checks. Moreover, we conduct some additional tests related to our hypothesis.

3.3.1 Baseline Model

Table 3.3 on page 50 shows the results. We introduce the control variables sequentially. In line with the reinforcement learning hypothesis, we find that the coefficient on experienced returns is positive and highly significant. As shown by column (4), where the regression includes the full set of controls, a one standard deviation increase in experienced returns in a firm leads to a larger active investment in it equal to 0.01% (t-stat= 12.45), which corresponds to roughly \$0.6M.

As shown in column (4) of Table 3.3 on page 50, the rate of decay ϕ is equal to 0.24, which suggests that the recency effect is not extreme, and that returns experienced further back in time also influence investment decisions. A similar finding is reported by Malmendier and Nagel (2011), who study the effect of experienced market returns on the decisions of households to invest in equities.

In terms of firm controls, the coefficients on MV and B/M are positive and significant, indicating that fund managers, on average, prefer large stocks, perhaps for their higher liquidity, and stocks with higher B/M ratios, which have lower price multiples and tend to yield a value premium. The coefficients on lagged stock returns are all positive and significant, indicating that fund managers trade on momentum, consistent with the results in Carhart (1997).

3.3.2 Robustness Checks

We discuss various robustness checks in this subsection, with the results shown in Table 3.4 on page 51. For the first test, we examine whether our results capture the effect of an omitted variable, in either the fund or the firm. We do so by replacing firm-level controls with a firm $\times$ time fixed effect, which controls for all information about a specific firm that is common to all managers. Moreover, we replace all fund-level controls with a fund $\times$ time fixed effect, which controls for time-varying manager characteristics, such as risk aversion or "sentiment." In column (3) of Table 3.4 on page 51 we present the results when both these fixed effects are included in the model, and find that the coefficient on experienced returns is positive and

Table 3.3: Experienced Returns and Investment Decisions

This table presents the results of the effect of experienced firm returns on investment decisions. The dependent variable is $Weight^{adj}_{i,j,t}$. The main independent variable is *Experience*. When a fund is team-managed, we take a tenure-weighted average of *Experience* in firm j by each manager, where tenure is based on the date that each manager first appeared in the Morningstar database. We estimate the model on a tightly spaced grid of different values of *Experience*, corresponding to different decay parameters (ϕ), and select the model that minimizes the regression's sum of squared residuals. For definitions of the variables, see Table A1 in Appendix. All specifications include a fund style $\times$ time fixed effect and an unreported intercept. Standard errors are clustered by firm $\times$ time. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$Weight^{adj}_{i,j,t}$			
	(1)	(2)	(3)	(4)
$Experience_{i,j,t-1}$	0.017***	0.018***	0.008***	0.011***
	(18.56)	(14.79)	(13.17)	(12.45)
Fund Controls				
$fund\ alpha_{i,t-1}$		-0.014***		-0.012***
		(-17.56)		(-15.74)
$flow_{i,t-1}$		0.004***		-0.001***
		(9.84)		(-3.36)
$\ln(fund\ age_{i,t-1})$		0.130***		0.107***
		(216.52)		(205.34)
$\ln(TNA_{i,t-1})$		-0.172***		-0.146***
		(-272.89)		(-293.97)
$\%Style_{i,j,t-1}$		0.098***		-0.043***
		(68.55)		(-36.21)
$turnover_{i,t-1}$		0.038***		0.002***
		(66.57)		(3.98)
$manager\ tenure_{i,t-1}$		0.022***		0.017***
		(43.89)		(34.69)
$team_{i,t-1}$		-0.030***		-0.023***
		(-37.78)		(-31.21)
Firm Controls				
$\ln(MV_{j,t-1})$			0.361***	0.398***
			(147.67)	(130.18)
$\ln(B/M_{j,t-1})$			0.161***	0.162***
			(89.69)	(78.22)
$ret_{j,t-1}$			0.022***	0.009***
			(24.78)	(9.43)
$ret_{j,t-2}$			0.015***	0.003**
			(17.18)	(2.51)
$ret_{j,t-3}$			0.016***	0.004***
			(14.48)	(3.42)
$ret_{j,t-4}$			0.010***	0.004***
			(12.40)	(4.03)
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time
Parameter	0.34	0.40	0.19	0.24
#Obs	6,771,424	5,294,297	6,672,128	4,576,988
Adj R^2	0.093	0.155	0.189	0.240

significant (0.005, t-stat= 9.56).[9] Overall these results suggest that our findings are not capturing the effect of an omitted firm- or fund-level variable.

Table 3.4: Robustness Checks

This table presents the results of different regressions, following the procedures explained in the notes for Table 3. In the regression for column (1), we replace all fund controls with a fund $\times$ time fixed effect. In the regression for column (2), we replace all firm controls with a firm $\times$ time fixed effect. In column (3) we replace all fund and firm controls (except *%Style*) with these fixed effects. In the regression for column (4), the dependent variable is the percentage change in shares held by manager i in stock j from quarters $t-1$ to t, adjusted for stock splits (*ChangeShares*). In the regression for column (5), our baseline model includes with $Weight^{adj}_{i,j,t}$ as the dependent variable in a sample of index funds (as indicated in the Morningstar database). For definitions of the variables, see Table A1 in Appendix. All regressions include an unreported intercept. Standard errors are clustered by firm $\times$ time. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level respectively.

	Active				Passive
		$Weight^{adj}_{i,j,t}$		$ChangeShares_{i,j,t}$	$Weight^{adj}_{i,j,t}$
	(1)	(2)	(3)	(4)	(5)
$Experience_{i,j,t-1}$	0.017***	0.004***	0.005***	0.003***	-0.000
	(20.98)	(6.35)	(9.56)	(8.11)	(-0.07)
Fund Controls	YES	NO	NO	YES	YES
Firm Controls	NO	YES	NO	YES	YES
Fixed Effects	Firm x Time	Fund x Time	Fund x Time	Style x Time	Style x Time
Fixed Effects			Firm x Time		
Parameter	0.28	0.19	0.25	0.07	0.09
# Obs.	5,282,186	6,671,751	6,761,640	5,254,100	1,274,938
Adj R^2	0.304	0.578	0.616	0.019	0.083

We estimate our baseline model of equation (3.3) on page 45 using the percentage change in the number of shares held in firm j by fund i from quarter $t-1$ to quarter t, *ChangeShares*, as the dependent variable. This variable, since it is not affected by variations in the value of firm j, is an alternative way to capture managers' active investment decisions. Using our baseline specification from equation (3.3) on page 45, we find in column (4) of Table 3.4 that the coefficient on experienced returns is positive and significant (0.003, t-stat= 8.11).

In additional robustness checks, we estimate our baseline model using the unadjusted weight placed on a given stock ($w_{i,j,t}$), or using market-adjusted stock returns to estimate experienced returns. In both cases our key results continue to hold. For brevity we do not report these results, which are available from the

[9] In these models we include the variable *%Style*, since it not subsumed by time varying firm or fund fixed effects.

authors on request.

Our next robustness check is a placebo test using the investment decisions of the managers of index funds. The trades of such managers aim to replicate specific stock indices, and so are not based on expectations about future stock returns.[10] Therefore, in this sample, we expect that the coefficient on experienced returns is statistically insignificant. The results in column (5) of Table 3.4 on page 51 show that the coefficient on experienced returns is indeed statistically insignificant (-0.000, *t*-stat= -0.07), a finding which provides support to our claim that our baseline findings capture the effect of experienced returns on the stock return expectations of active mutual funds' managers.

3.3.3 Additional Tests

In this section we examine whether our findings are different for team-managed vs. single-manager funds, or depend on managerial tenure.

Individual vs. team-managed funds

Many of the funds in our sample are managed by teams of managers, and for our analysis the experienced return of the manager of fund i reflects a tenure-weighted average of these managers' experienced returns for firm j. However, our findings may differ for team-managed funds. One view, according to the "wisdom of crowds," suggests that groups make better decisions. Assuming that experienced returns do not carry any value-relevant information, this view suggests that group-managed funds would maintain a more forward-looking perspective, and thus display a weaker experienced returns effect.[11] However, research in psychology suggests that the opposite may also be true. For example, Kahneman and Tversky (1973) show that people become more confident about a certain opinion when faced with multiple signals that support it. This is because people use a simple "counting heuristic," and do not fully process the extent to which the signals are correlated. In our setting, this finding might predict a stronger effect for team-managed funds, where different managers discuss their (correlated) views on the same stocks.

To examine whether team size matters, we estimate our baseline model of equation

[10] We identify index funds using the relevant indicator from Morningstar.

[11] In section 4.1 we conduct tests to examine whether experienced returns reflect value-relevant information. We do not find any evidence to support this view.

(3.3) on page 45 while interacting the experienced returns variable with the dummy variable *team*. The results are shown in Table 3.5 on page 55. In column (1), the coefficient on experienced returns, which amounts to single-manager funds, is 0.009 (t-stat= 9.00). The corresponding coefficient for team-managed funds is 0.012 (= 0.009 + 0.003), and the incremental effect is statistically significant (t-stat= 3.78). We conduct an additional test, whereby we split team-managed funds into two groups (cutting at the median) according to the number of managers, and then estimate our baseline model of equation (3.3) on page 45 separately in each group. The results in Table A.3 in the Appendix show that the coefficient on experienced returns for the high number of managers group is 0.017 (t-stat= 15.01), whereas for the small number of managers group it is 0.013 (t-stat= 10.29). The difference between these coefficients is statistically significant. Collectively, these results are in line with the view that experienced returns are more influential for team-managed funds.

Managerial Tenure

Thus far our results reflect the effect of experienced returns using a decay factor ϕ that best fits the data across all managers. However, managers with more experience in the industry may have a "longer" memory, and thus display a weaker recency effect. Indeed, Malmendier and Nagel (2011) show that older households have longer memories of stock market returns. To examine whether managerial tenure influences the effect of experienced returns, we construct an alternative tenure-weighted experienced return measure (*TW-Experience*) based on Malmendier and Nagel (2011), as follows:

$$TW\text{-}Experience_{i,j,t} = \sum_{k=1}^{tenure_{i,t}-1} \omega_{i,t}(k,\theta) R_{j,t-k} I_{[w_{i,j,t-k}>0]}, \tag{3.4}$$

where

$$\omega_{i,t}(k,\theta) = \frac{(tenure_{i,t}-k)^{\theta}}{\sum_{k=1}^{tenure_{i,t}-1}(tenure_{i,t}-k)^{\theta}}.$$

With this specification, the rate of decay is captured by θ, where $\theta > 0$ captures the recency effect. The variable $tenure_{i,t}$ reflects the experience of the manager of fund i in the mutual fund industry, and is calculated based on the first date that this manager appears in the Morningstar database. *TW-Experience* implies that managers with shorter tenure will exhibit a larger recency effect. To illustrate, in Figure 3.2 we plot the weights attached on past experienced returns, by a manager with 24 quarters of experience, and another with 8 quarters of experience, assuming that $\theta = 2.8$. As seen from Figure 3.2, the junior manager puts a higher weight on more recent observations, relative to the more senior manager.[12] As θ increases, both managers would demonstrate a stronger recency effect, but in all cases the more senior manager would exhibit weaker recency. As in our baseline analysis, we estimate our model on a tightly spaced grid for different values of θ, and select the model that minimizes the regressions sum of squared residuals.

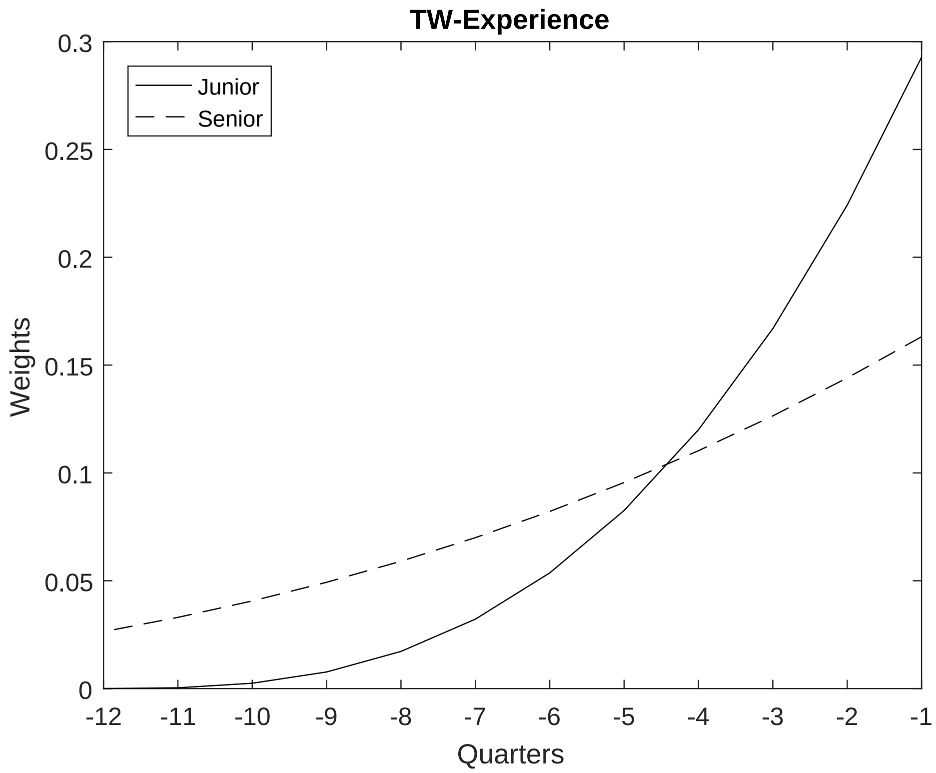

Figure 3.2: *TW-Experience* decay factor

This figure shows the weights on past returns for our tenure-weighted experienced return measure (*TW-Experience*) based on Malmendier and Nagel (2011) with decay parameter θ=2.8. We compare two managers with two years of tenure (junior) and a manager with six years of tenure (senior).

The results are shown in columns ((2)-(4)) in Table 3.5 on page 55. For this estimation we used a grid of θ values between -1 and 5, where $\theta = 0$ reflects the case where there is no "time"-related effect on the way returns are coded in memory, and thus

[12] We can also note from Table 2 that, as expected, *manager tenure* has a strong positive correlation with *TW-Experience*, while its correlation with our measure *Experience* of equation (1) is close to zero.

experienced return just reflects the simple average return for a specific stock since time of purchase. Since our results indicate that a $\theta > 0$ best explains the data, this estimation provides evidence that a recency effect does influence the mental representation of experienced returns.[13]

Consistent with our previous results in Table 3.3 on page 50, we find that the coefficient on *TW-Experience* is positive and significant, ranging from around 0.02% to 0.04%, depending on the specification. The larger coefficient obtained in this case relative to our baseline results in Table 3.3 on page 50, especially when allowing for time-varying firm and fund fixed effects, suggests that junior managers display a stronger recency effect compared to more senior managers.

Table 3.5: Experience, Teams, and Tenure

This table presents the results of the effect of experienced returns on investment decisions for team-managed funds and managers with different tenure, following the procedures explained in the notes for Table 3.3. The dependent variable is $Weight^{adj}_{i,j,t}$. In the regression for column (1), we estimate our baseline model while interacting *Experience* with a dummy that flags team-managed funds. In the regressions for columns ((2)-(4)), we use an alternative measure for experienced returns, following Malmendier and Nagel (2011), which allows managers with shorter tenures to exhibit a stronger recency effect (*TW-Experience*). For definitions of the variables, see Table A1 in Appendix. All specifications include an unreported intercept. Standard errors are clustered by firm $\times$ time. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level respectively.

		TW-Experience		
	(1)	(2)	(3)	(4)
$Experience_{i,j,t-1}$	0.009***	0.015***	0.043***	0.039***
	(9.00)	(20.75)	(57.70)	(82.13)
$Experience_{i,j,t-1}$x $Team_{i,t-1}$	0.003***			
	(3.78)			
$Team_{i,t-1}$	-0.024***			
	(-30.31)			
Fund Controls	YES	YES	NO	NO
Firm Controls	YES	YES	YES	NO
Fixed Effects	Style x Time	Style x Time	Fund x Time	Fund x Time
Fixed Effects				Firm x Time
Parameter	0.33	2.8	2.2	2.6
# Obs.	5,254,116	5,254,100	6,671,708	6,761,469
Adj R^2	0.241	0.372	0.579	0.632

[13]Our estimate of θ is around 2.5, which is larger than the 1.5 reported by Malmendier and Nagel (2011), who analyze how memories of a single asset (i.e., the stock market return) affect future stock market participation decisions. In our setting, we model managers' investments and memories over many individual stocks, a setting where the recency effect can be stronger due to memory constraints.

3.3.4 Changes in Shares Held and Response to Flows

In this subsection we examine whether managers, when faced with capital inflows or outflows, rebalance their portfolios according to their experienced returns from different stocks. Following Lou (2012), we use the following regression specification:

$$\begin{aligned} ChangeShares_{i,j,t} = {} & \alpha + \beta ExperienceDummy_{i,j,t-1} \\ & + \gamma ExperienceDummy_{i,j,t-1} \times flow_{i,t} + \delta Control_{i,j,t-1} \\ & + S \times T + \epsilon_{i,j,t}, \end{aligned} \tag{3.5}$$

where $ChangeShares$ is the percentage change in the number of shares held in firm j by fund i from quarter $t-1$ to t. As in Lou (2012), we estimate the model separately for outflow and inflow funds. With this specification the coefficient on $flow$ indicates whether managers buy or sell shares proportionately when faced with inflows or outflows.[14]

We include an experienced returns dummy variable (*ExperienceDummy*) in the model that equals to 1 if fund i is in the top 33%, 25%, or 20% in the distribution of experienced returns for firm j at time $t-1$. The key variable of interest in this model is *ExperienceDummy* $\times$ $flow$, an interaction variable that examines whether experienced returns influence how managers expand or liquidate their positions when faced with inflows or outflows. If experienced returns influence this decision according to reinforcement learning, the coefficient on the interaction variable should be positive for the inflow sample, and negative for the outflow sample.[15]

In the model, we also include three control variables, following the analysis of Lou (2012). Specifically, we control for *own*, the percentage of shares outstanding of firm j that is held by the manager of fund i at the end of quarter $t-1$; *illiq*, the absolute value of the firm j's daily stock return over the trading volume as reported by CRSP, averaged over quarter $t-1$ (Amihud's illiquidity ratio); and an interaction of these variables with $flow$. As in our baseline regression of equation (3.3) on page 45, we include time-varying style fixed effects and cluster standard errors at the firm

[14] For example, a coefficient on $flow$ equal to 1 for the inflow (outflow) sample indicates that all existing shares are scaled up (down) proportionately after capital additions (withdrawals). If the coefficient is less than 1 for the inflow sample, then this means that some new money go toward scaling up existing stocks, and some toward buying new stocks or toward increasing cash holdings. Similarly, for the outflow sample, a coefficient less than 1 implies that funds partly finance redemptions using their cash holdings.

[15] We express the effect of experienced returns using a dummy variable because with this specification the coefficient on the interaction term can be interpreted as dollar deviations from proportional changes in holdings due to experienced returns.

$\times$ time level.

The results are shown in Table 3.6 on page 58. In line with our previous results, the coefficient on the experienced return dummy is positive and significant for both samples, and increases monotonically as the dummy captures higher experienced returns, ranging from 1.7% to 4.6%. Consistent with our hypothesis, we find that the coefficient on the interaction between the $ExperienceDummy$ and $flow$ is negative for the outflow subsample and positive for the inflow subsample. For example, the results in column (2) suggest that for every dollar of outflow, managers are less willing to sell shares in stocks with high experienced returns, by about 5 cents (t-stat= -3.74). Similarly, the results in column (5) suggest that for every dollar of inflow, managers are more willing to buy shares in stocks with higher experienced returns, by about 5 cents (t-stat= 6.57).

3.3.5 Style-Level Experience

In this subsection, we examine whether experienced returns affect investment decisions based on the style level of the fund.

The first style categorization is based on Teo and Woo (2004), who sort stocks into nine MV and B/M portfolios (3×3).[16] We use size and book-to-market categorizations as they have been demonstrated to matter to investors (Kumar 2009). Moreover, Morningstar itself classifies funds according to these dimensions, thus further strengthens this type of categorization in the market. For our second style classification, we assign firms into one of the 125 portfolios based on MV, B/M, and return momentum, as proposed by Daniel et al. (1997) (DGTW). This categorization adds the dimension of return momentum, which fund managers tend to employ (Carhart 1997). Finally, since fund managers extract information from their industry experiences (Kempf et al. 2016), our third and fourth styles are based on Fama and French's 12 or 48 industries (Fama and French 1997).

After assigning each stock to a style group for each quarter, we take an average of our previously computed experienced returns measure at the style level for each fund and quarter, and then examine whether this style-specific experienced return relates to the weight attached to the specific style in the following quarter. The dependent

[16] To do this classification, we use the NYSE breakpoints based on firm MV and firm B/M. Firms in the bottom (top) 30th (70th) MV percentile are small (large) stocks. Firms in the bottom (top) 30th (70th) B/M percentile are growth (value) stocks. Firms in-between the 30th-70th MV (B/M) percentiles are classed as mid-sized (blend) stocks.

Table 3.6: Changes in Shares Held and Response to Flows

This table presents the results of the effects of experienced returns on investment decisions in the presence of flows. The dependent variable is the percentage change in shares held by the manager of fund i in stock j from quarters $t-1$ to t, adjusted for stock splits (*ChangeShares*). The main independent variable is an experience measure dummy, which equals 1 if the manager of fund i is in the top 20%, 25%, or 33% in terms of experienced returns (*Experience* for firm j at $t-1$ across all funds. In this table, the decay parameter ϕ is set to 0.25, which is the estimate obtained in column (3) of Table 3.4. When a fund is team-managed, we take a tenure-weighted average of *Experience* in firm j by each manager, where tenure is based on the date that each manager first appeared in the Morningstar database. $flow$ is capital inflows or outflows as a proportion of the fund's TNA. We follow the specification in Lou (2012), controlling for the proportion fund i owns in firm j with respect to the total number of shares outstanding ($own_{i,j,t-1}$), the Amihud's illiquidity ratio ($illiq_{j,t-1}$), as well as the interaction of these two variables with $flow$. For definitions of the variables, see Table A1 in Appendix. We estimate the model separately for outflows ($flow < 0$) and inflows ($flow > 0$). All specifications include a fund style $\times$ time fixed effect and an unreported intercept. Standard errors are clustered by firm $\times$ time. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level respectively.

	Outflow			Inflow		
	Top 33%	Top 25%	Top 20%	Top 33%	Top 25%	Top 20%
	(1)	(2)	(3)	(4)	(5)	(6)
$ExperienceDummy_{i,j,t-1}$ x $flow_{i,t}$	-0.081***	-0.050***	-0.030**	0.065***	0.051***	0.042***
	(-6.49)	(-3.74)	(-2.04)	(9.19)	(6.57)	(4.92)
$ExperienceDummy_{i,j,t-1}$	0.018***	0.033***	0.044***	0.017***	0.033***	0.046***
	(20.64)	(33.23)	(39.42)	(20.99)	(33.87)	(40.59)
$flow_{i,t}$	0.483***	0.475***	0.472***	0.815***	0.821***	0.823***
	(57.77)	(59.89)	(61.62)	(193.00)	(204.35)	(210.93)
Characteristics						
$own_{i,j,t-1}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(11.23)	(11.76)	(12.20)	(16.03)	(16.60)	(17.08)
$own_{i,j,t-1}$ x $flow_{i,t}$	-0.095***	-0.095***	-0.095***	0.011**	0.011***	0.011***
	(-15.11)	(-15.15)	(-15.19)	(3.23)	(3.20)	(3.15)
$illiq_{j,t-1}$	-0.001***	-0.001***	-0.001***	-0.000	-0.000	-0.000
	(-4.15)	(-4.17)	(-4.15)	(-0.60)	(-0.60)	(-0.61)
$illiq_{j,t-1}$ x $flow_{i,t}$	0.010	0.010	0.010	-0.023***	-0.023***	-0.023***
	(1.58)	(1.56)	(1.50)	(-4.57)	(-4.58)	(-4.56)
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time	Style x Time	Style x Time
Parameter [fixed]	0.25	0.25	0.25	0.25	0.25	0.25
#Obs	3,315,788	3,315,788	3,315,788	3,199,253	3,199,253	3,199,253
Adj R^2	0.008	0.009	0.009	0.051	0.051	0.051

variable in the model is $Weight^{adj}$, averaged for each fund and quarter at each style level. We control for various fund-level characteristics, as in our baseline models for Table 3.3 on page 50 and described in equation (3.3) on page 45. Moreover, we include a *style* $\times$ *time* fixed effect, which controls for all information about a given style that is common across all managers, as well as a fund fixed effect.

The results are in Table 3.7 on page 60. The coefficients on style-level experienced returns are positive and significant, at approximately 0.02%. We re-do the test using the tenure-weighted experienced returns measure from equation (3.4) on page 53 and report the results in Table A.4 in the Appendix. Again we find positive and significant coefficients, which range from approximately 0.06% to 0.07%. In both cases, the coefficients on experienced returns are larger, relative to our baseline firm-level analysis from equation (3.3) on page 45, which suggests that experienced returns matter more on the style level. One possible explanation for this result is memory constraints. Perhaps it is easier to recall return experiences that are associated with broader styles as opposed to individual stocks. This is precisely the motivation behind style-level thinking, as outlined in Barberis and Shleifer (2003), i.e., it simplifies information processing when making portfolio decisions.

3.4 Do Experienced Returns Reflect Managerial Skill?

Is the effect of experienced returns information-based? It is possible that experienced returns on the fund level (i.e., averaged across stocks for a given fund) reveal the skill of the manager in picking stocks. Therefore, managers with better overall experienced returns are better stock pickers. Moreover, the fact that managers place larger bets on firms with higher experienced returns, may indicate that experienced returns on the stock level (i.e., averaged across funds for a given stock) constitute a "buy" signal that positively predicts future stock returns. In this section we investigate these important issues.

3.4.1 Fund Performance

To investigate whether experienced returns reveal the skill of the manager, we average experienced returns for fund i and quarter t across all stocks owned by this fund, ($AggExpRet_{Fund}$), and examine whether this aggregate variable can predict future fund returns. According to the skill-based hypothesis, and as long as investors do

Table 3.7: Style-Level Experience

This table presents the results of the effect of experienced returns on investment decisions at the style level, following the procedures explained in the note to Table 3.3. The dependent variable is $Weight^{adj}_{i,j,t}$, averaged equally for specific styles for fund i and quarter t. The key independent variable is *Experience*, value-weighted averaged at the style level. We consider four different style categorizations: a split of all stocks according to MV and B/M (3×3 sorts) (column (1)), a categorization based on Daniel et al. (1997), where stocks are sorted in $5 \times 5 \times 5$ portfolios based on MV, B/M, and return momentum (column (2)), and industry categorizations using 12 or 48 industries, using Fama/French definitions (columns (3)-(4)). All specifications include a style $\times$ time fixed effect, a fund fixed effect, and an unreported intercept. For definitions of the variables see Table A1 in Appendix. Standard errors are clustered at the style $\times$ time level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level respectively.

	Morningstar	DGTW	F-F 12 Industries	F-F 48 Industries
	(1)	(2)	(3)	(4)
$Experience_{i,s,t-1}$	0.019***	0.022***	0.020***	0.022***
	(4.93)	(23.14)	(9.45)	(16.53)
Fund Controls				
$fund\ alpha_{i,t-1}$	-0.009**	-0.009***	-0.010***	-0.010***
	(-1.99)	(-7.80)	(-3.89)	(-6.10)
$flow_{i,t-1}$	-0.018***	-0.015***	-0.018***	-0.015***
	(-10.11)	(-25.30)	(-16.20)	(-19.56)
$\ln(fund\ age_{i,t-1})$	0.004	0.002	-0.008**	-0.005**
	(0.78)	(1.19)	(-2.57)	(-2.38)
$\ln(TNA_{i,t-1})$	-0.113***	-0.075***	-0.079***	-0.074***
	(-24.79)	(-48.89)	(-28.65)	(-38.58)
$turnover_{i,t-1}$	-0.012***	-0.017***	-0.025***	-0.022***
	(-4.91)	(-20.97)	(-17.37)	(-21.97)
$manager\ tenure_{i,t-1}$	-0.002	-0.008***	-0.006***	-0.008***
	(-0.69)	(-6.51)	(-2.67)	(-5.14)
$team_{i,t-1}$	0.006	0.005***	0.005	0.005**
	(1.31)	(2.92)	(1.52)	(2.25)
Fixed Effects	Style x Time	Style x Time	Industry x Time	Industry x Time
Fixed Effects	Fund	Fund	Fund	Fund
Parameter	0.46	0.41	0.37	0.35
#Obs	255,469	2,180,382	659,180	1,452,527
Adj R^2	0.486	0.459	0.464	0.445

not allocate capital across funds according to $AggExpRet_{Fund}$ (i.e., Berk and Green 2004), the coefficient on this variable should be positive.

To measure fund performance, we estimate the Carhart four-factor model using two years of past fund monthly returns (Carhart 1997). Then, we compute the expected return for each fund from the factor model, and subtract it from the fund's realized return. We control for fund characteristics as in the regression for Table 3.3 on page 50: *flow*, ln(*fund age*), ln(*TNA*), *turnover*, the number of stocks held in a fund, *manager tenure*, *team*, and up to four lags of past fund returns. We also include *active share* as an additional control variable, which is designed to capture performance (Cremers and Petajisto 2009), as well as fund and fund style fixed effects.

The results, shown in Table 3.8, indicate that the coefficient on $AggExpRet_{Fund}$ is *negative* and statistically significant. In column (1), the coefficient suggests that a one standard deviation increase in $AggExpRet_{Fund}$ is associated with an approximate 0.18% reduction in quarterly abnormal returns, statistically significant at the 1% level. When we add a fund fixed effect to the model, the coefficient on $AggExpRet_{Fund}$ is reduced to 9.5 basis points, and is statistically significant on the 10% level. This result suggests that the behavior of managers with higher aggregated experienced returns is distorted in some way that is detrimental to fund performance.

One possible distortion is biased learning, as discussed in Gervais and Odean (2001). According to this theory, better past outcomes cultivate overconfidence due to biased self-attribution. This leads to more "aggressive" behavior from traders, and thus a deterioration in the quality of their future decisions. To test this hypothesis, we examine whether a higher $AggExpRet_{Fund}$ is positively related to three variables that capture the aggressiveness of trading behavior, namely turnover (Barber and Odean 2000), active share, and tracking error. Active share, proposed by Cremers and Petajisto (2009), reflects the sum of absolute deviations from the benchmark index.[17] A higher active share, therefore, indicates more aggressive trading in the sense that the manager's conviction in the quality of his private signals is high. Tracking error is the standard deviation of the difference between the return of the fund and the return of the benchmark index. A higher tracking error implies that the manager's portfolio differs from the benchmark portfolio, which is another indicator of the manager's conviction in the quality of his private signals.

[17]We obtain active share and tracking error data from Antti Petajisto's website at *http://www.petajisto.net/data.html*. We thank him for making this data publicly available.

The results are shown in Table 3.8 on page 63. We focus the discussion on the models that include a fund fixed effect, which we test the hypothesis using within fund variation in $AggExpRet_{Fund}$. Consistent with the theory of Gervais and Odean (2001), the coefficient on $AggExpRet_{Fund}$ is positive and significant for all three measures in columns (4), (6), and (8), suggesting that higher aggregated experienced returns make managers trade more aggressively. An alternative explanation could also related to mean-reversion in returns. Indeed it is also possible that the documented results stem from the negative long-term effect of fund performance as illustrated by the persistent negative estimates of past fund returns at the third and fourth lags.

A second distortion that may be associated with higher aggregate experienced returns is suggested by Kempf et al. (2016), who show that managers who experience an industry shock conduct more profitable trades in the future. They suggest that this result arises because trading in adverse situations presents learning opportunities for mutual fund managers. In our setting, higher values for $AggExpRet_{Fund}$ imply a relative absence of negative return experiences, and thus inferior learning opportunities. To test this hypothesis, we calculate two different aggregate experienced returns measures, one for positive and one for negative experience stocks ($AggExpRet^{-}_{Fund}$ and $AggExpRet^{+}_{Fund}$, respectively), expecting that the effect of the latter variable on fund returns is more significant. The results in column (10) of Table 3.8 on page 63 show that the coefficient on $AggExpRet^{+}_{Fund}$ is statistically insignificant, whereas the coefficient on $AggExpRet^{-}_{Fund}$ is negative and highly significant, with a one standard deviation increase in $AggExpRet^{-}_{Fund}$ being associated with a 0.25% reduction in next quarter's fund returns. The results support the findings of Kempf et al. (2016), suggesting that the absence of negative return experiences are costly to future fund performance.

Overall the results suggest that higher experienced returns are not reflective of managerial skill, and that they entail distortions that are detrimental to future fund performance.

3.4.2 Stock Returns

To investigate whether experienced returns reveal fundamental information about the stock, we average experienced returns for stock j and quarter t across all managers ($AggExpRet_{Firm}$), and examine whether this aggregated variable can predict future earning shocks and returns.

Table 3.8: Experienced Returns and Fund Performance

This table presents the results of the effects of experienced returns on fund performance, turnover, active share, and tracking error. The main independent variable is aggregated experienced return at the fund level, $AggExpRet_{Fund}$, which is a value-weighted average of stock-level experienced returns for fund i at time t. Fund return performance (dependent variable in the regressions for columns (1), (2), and (9) is calculated using the Carhart four-factor model. We use two years of past fund return data to obtain factor loadings, which we then use to obtain a fund's abnormal return in quarter t. The dependent variable in columns ((3)-(4)) is the fund i's *turnover* ratio, *active share* in columns ((5)-(6)), and *tracking error* in columns ((7)-(8)). In column (9), we aggregate experienced returns on the fund level, separately for positive and negative *experience* stocks, forming $AggExpRet^{+}_{Fund}$ and $AggExpRet^{-}_{Fund}$, respectively. Other fund controls include the previous quarter natural logarithm of total net assets (TNA) at time $t-1$, the natural logarithm of *fund age* in months, the natural logarithm of the number of stocks in the fund portfolio at quarter $t-1$, net fund $flows$, *manager tenure* (we take an equally-weighted average for team-managed funds), a *team* dummy, *turnover* ratio, and *fund return* at quarters $t-1$, $t-2$, $t-3$, and $t-4$. For detailed descriptions of all variables, see Table A1 in the Appendix. All specifications include an unreported intercept, fund style and time fixed effect. Standard errors are clustered by fund. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	$Performance_{i,t}$		$Turnover_{i,t}$		$Active\ Share_{i,t}$		$Tracking\ Error_{i,t}$		$Performance_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AggExpRet_{Fund_{i,t-1}}$	-0.175***	-0.095*	0.023***	0.005***	0.004***	0.002***	0.002***	0.001***	
	(-3.69)	(-1.78)	(13.13)	(5.69)	(2.40)	(3.76)	(4.35)	(3.39)	
$AggExpRet_{Fund^{+}_{i,t-1}}$									-0.027
									(-0.40)
$AggExpRet_{Fund^{-}_{i,t-1}}$									-0.252***
									(-2.81)
$active\ share_{i,t-1}$	0.290***	0.599***							
	(6.33)	(4.81)							
$flow_{i,t-1}$	0.055	0.010	-0.009***	-0.005***	0.005***	0.004*	0.001***	0.000	0.008
	(1.15)	(0.18)	(-7.11)	(-5.90)	(3.07)	(1.65)	(2.66)	(0.27)	(0.14)
$\ln(fund\ age_{i,t-1})$	0.050	0.450***	0.001	0.009*	0.010**	0.020***	0.000	0.000	0.447***
	(1.26)	(2.68)	(0.25)	(1.91)	(2.49)	(4.27)	(0.04)	(0.11)	(2.67)
$\ln(TNA_{i,t-1})$	-0.177***	-1.662***	-0.009***	-0.013***	0.003	-0.009***	0.001	0.001	-1.665***
	(-5.18)	(-16.60)	(-3.30)	(-5.04)	(0.78)	(-2.92)	(0.91)	(1.22)	(-16.66)
$turnover_{i,t-1}$	0.015	0.096*			0.011***	0.003*	0.001*	0.000	0.093*
	(0.43)	(1.90)			(4.34)	(1.85)	(1.65)	(0.91)	(1.85)
$\ln(nb\ stocks_{i,t-1})$	0.207***	0.229**	-0.017***	-0.040***	-0.150***	-0.045***	-0.019***	-0.009***	0.235**
	(4.39)	(2.47)	(-6.81)	(-9.46)	(-27.05)	(-11.23)	(-29.61)	(-11.57)	(2.54)

(Continued)

Table 3.8 Continued

	Performance		*Turnover*		*Active Share*		*Tracking Error*		*Performance*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$manager\ tenure_{i,t-1}$	0.006	-0.023	-0.004	-0.003	0.026***	0.008***	0.003***	0.001	-0.025
	(0.20)	(-0.30)	(-1.48)	(-0.88)	(6.45)	(2.92)	(4.51)	(1.23)	(-0.33)
$team_{i,t-1}$	-0.057	0.163	0.012***	0.002	0.013**	0.008*	-0.002	-0.000	0.158
	(-0.97)	(1.34)	(2.66)	(0.54)	(1.97)	(1.82)	(-1.41)	(-0.26)	(1.29)
$fund\ return_{i,t-1}$	0.863***	0.611***	-0.012***	-0.006***	0.002	-0.001	0.000	0.000	0.610***
	(10.33)	(6.48)	(-7.17)	(-4.93)	(1.61)	(-0.85)	(0.19)	(0.21)	(6.49)
$fund\ return_{i,t-2}$	0.160**	-0.050	-0.007***	-0.003***	0.006***	0.001**	0.001	0.001*	-0.049
	(2.55)	(-0.77)	(-5.93)	(-3.32)	(4.69)	(2.33)	(1.08)	(1.69)	(-0.76)
$fund\ return_{i,t-3}$	-0.113**	-0.230***	-0.005***	-0.002*	0.006***	0.001***	0.001***	0.001***	-0.232***
	(-2.10)	(-4.10)	(-4.88)	(-1.73)	(5.31)	(2.67)	(3.39)	(3.49)	(-4.13)
$fund\ return_{i,t-4}$	-0.258***	-0.360***	-0.003***	-0.001	0.005***	0.002***	0.002***	0.001***	-0.360***
	(-4.79)	(-6.78)	(-3.49)	(-1.14)	(5.30)	(3.52)	(4.15)	(3.84)	(-6.78)
Fixed Effects	Time	Time	Time	Time	Time	Time	Time	Time	Time
Fixed Effects	Style	Style	Style	Style	Style	Style	Style	Style	Style
Fixed Effects		Fund		Fund		Fund		Fund	Fund
Parameter	0.46	0.51	0.35	0.45	0.60	0.37	0.09	0.05	0.49
#Obs	29,588	29,588	29,990	29,990	29,727	29,667	29,724	29,990	29,588
Adj R^2	0.757	0.760	0.149	0.558	0.633	0.943	0.555	0.558	0.760

Earnings announcements

For our first test we examine whether $AggExpRet_{Firm}$ can predict the earnings surprise in the next quarter, which we estimate using the seasonal random walk model, or cumulative market-adjusted stock returns in the days surrounding the earnings announcement. In these models we use the firm-level control variables used in previous tests, namely the natural logarithm of MV and B/M, and four lags of past quarterly stock returns. Moreover, when the dependent variable in the model is the cumulative stock return in the earnings announcement period, we also control for the earnings surprise, SUE. Under the information-based hypothesis we expect that the coefficient on $AggExpRet_{Firm}$ is positive and significant in these models.

The results are shown in Table 3.9 on page 66. In column (1) the dependent variable is the earnings shock, and in columns ((2)-(4)) the return in different windows around the earnings announcement. As seen from all columns of Table 3.9, the coefficient on $AggExpRet_{Firm}$ is statistically insignificant, a finding which does not support the information-based hypothesis.

A portfolio-based test

For our second test we examine whether $AggExpRet_{Firm}$ can predict stock returns in a portfolio setting. Each quarter, we sort stocks into quintile portfolios according to this variable, which we hold for the next quarter. We risk-adjust the returns of these portfolios using two benchmark models, the Fama-French three- and five-factor models (Fama and French 1993; Fama and French 2015), both augmented with the momentum factor, resulting in four- and six-factor models, respectively.[18] Moreover, since stock return predictability is typically stronger for smaller firms (e.g., Zhang 2006), where limits to arbitrage are more binding, we first split the sample into two groups based on firm size, cutting at the median NYSE market value, and then form quintile portfolios separately in each group.

The results are shown in Table 3.10 on page 67. Panel A presents the results for small stocks. Contrary to the information-based hypothesis, for the four-factor model, we find that average returns decrease monotonically as we move through the $AggExpRet_{Firm}$ quintiles, ranging from 1.37% for Q1 to -0.78% for Q5. The return

[18] Data on the factors are from Kenneth French's data library at *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*. We thank him for making the data publicly available.

Table 3.9: Experience and Earnings Announcements

This table presents the results of the effects of experienced returns on returns around earnings announcements. For this test, the decay parameter ϕ is set to 0.25, which is the estimate obtained in column (3) of Table 3.4. When a fund is team-managed, we take a tenure-weighted average of *Experience* in firm j by each manager, where tenure is based on the data that each manager appeared in the Morningstar database. To conduct the test, we first take a value-held weighted average of *Experience* for stock j across all funds in each quarter t, $AggExpRet_{Firm}$. Our dependent variables are earnings surprise ($SUE_{j,t}$, calculated using the seasonal random walk model) and cumulative market-adjusted returns ($CAR_{j,t}$) around earnings announcements in a window *(t-1,t+1)*, *(t-2,t+2)*, or *(t-1,t+3)*. Firms controls include lagged MV, B/M, and four lags of stock returns. When CAR is the dependent variable, we also control for $SUE_{j,t}$. For detailed descriptions of all variables, see Table A1 in the Appendix. All specifications include an unreported intercept, and a time fixed effect. Standard errors are clustered by firm. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence levels, respectively.

	SUE	*CAR(-1;+1)*	*CAR(-2;+2)*	*CAR(-1;+3)*
	(1)	(2)	(3)	(4)
$AggExpRet_{Firm_{j,t-1}}$	-1.768	0.000	0.000	0.000
	(-0.91)	(0.98)	(0.57)	(0.79)
$SUE_{j,t}$		0.000***	0.000***	-0.000
		(7.60)	(3.06)	(-1.63)
$\ln(MV_{j,t-1})$	-1.297	-0.000**	-0.000	-0.001**
	(-0.97)	(-1.99)	(-1.28)	(-2.09)
$\ln(B/M_{j,t-1})$	1.983	0.002***	0.003***	0.002***
	(0.95)	(7.35)	(8.68)	(6.95)
$ret_{j,t-1}$	9.164	-0.001**	-0.002***	-0.001***
	(1.00)	(-2.11)	(-4.43)	(-2.92)
$ret_{j,t-2}$	-0.644	-0.001*	-0.001***	-0.001***
	(-1.29)	(-1.77)	(-3.89)	(-3.23)
$ret_{j,t-3}$	1.288	-0.001***	-0.001***	-0.001***
	(1.31)	(-2.86)	(-4.10)	(-3.12)
$ret_{j,t-4}$	-1.004	-0.001**	-0.001***	-0.001*
	(-1.02)	(-2.49)	(-3.56)	(-1.67)
Fixed Effects	Time	Time	Time	Time
# Obs.	191,439	191,438	191,439	191,438
Adj R^2	0.000	0.004	0.007	0.006

differential between the high and low $AggExpRet_{Firm}$ portfolios is equal to 2.15% per quarter, and is highly statistically significant (t-stat= 4.42). The result is very similar when using the six-factor model, where the return differential is 2.06% per quarter (t-stat= 4.06).

Table 3.10: Experienced Returns and the Cross-Section of Stock Returns

This table presents the results of the effects of experienced returns on stock returns. For this test, the decay parameter ϕ is set to 0.25, which is the estimate obtained in column (3) of Table 3.4. When a fund is team-managed, we take a tenure-weighted average of *Experience* in firm j by each manager, where tenure is based on the data that each manager appeared in the Morningstar database. To conduct the test, we first take a value-held weighted average of *Experience* for stock j across all funds in each quarter, $AggExpRet_{Firm}$. We then split firms into two groups based on market value of equity (Small vs. Large), using the median NYSE market capitalization as the cut-off to form the two groups. We then sort stocks into quintile portfolios, separately for small and large stocks, based on $AggExpRet_{Firm}$. We obtain the equally-weighted return on these portfolios for the next quarter, as well as the hedge portfolio Q1-Q5. The excess returns on these portfolios is then regressed on the Fama-French 3 or 5 factors, including the momentum factor (MOM). Standard errors are computed using the Newey-West correction for 4 lags. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence levels, respectively.

	Quintile					
	1	2	3	4	5	1-5
Panel A: Small firms						
FF3+MOM α(%)	1.37***	0.80**	0.43	0.15	-0.78**	2.15***
	(2.64)	(2.07)	(1.42)	(0.50)	(-2.07)	(4.42)
FF5+MOM α(%)	1.11***	0.17	0.01	-0.30	-0.95**	2.06***
	(2.63)	(0.57)	(0.05)	(-1.10)	(-2.27)	(4.46)
Panel B: Large firms						
FF3+MOM α(%)	1.13***	0.70***	0.30	-0.20	-1.53***	2.66***
	(3.58)	(2.83)	(1.17)	(-0.74)	(-4.08)	(5.98)
FF5+MOM α(%)	0.71***	0.18	-0.09	-0.40	-1.06***	1.77***
	(2.55)	(0.94)	(-0.45)	(-1.13)	(-2.61)	(4.64)

In Panel B of Table 3.10, we present results for large stocks. Using the four-factor model, we find that holding period returns decrease monotonically across the quintiles, ranging from 1.13% for Q1 to -1.53% for Q5. The return differential between the high and low $AggExpRet_{Firm}$ portfolios is equal to 2.66% per quarter, and is highly statistically significant (t-stat= 5.98). The corresponding return differential when using the six-factor model is 1.77% per quarter (t-stat= 4.64).

These results do not support the view that fund-manager experienced returns reveal fundamental information about the stock. Rather, these results are in line with literature showing that the trades of mutual fund managers can induce price pressure, and cause misvaluations in the cross-section of stock returns (i.e., Coval and Stafford 2007; Frazzini and Lamont 2008; Lou 2012; Akbas et al. 2015). In our setting, it is possible that stocks with higher experienced returns, which are preferred by mutual fund managers, become over-priced. Conversely, stocks with lower experienced returns become under-priced. With the passage of time, as prices converge to fundamental levels, the latter will outperform the former.[19]

Overall, the results in this section suggest that the effect of experienced returns on the trades of mutual fund managers is not information-based. Moreover, and perhaps more worryingly, experienced returns do not seem to be a mere side-show. Rather, they seem to be associated with distortions on the fund level that are costly to fund performance, and with mispricings in the cross section of stocks.

3.5 Summary

We examine whether mutual fund managers invest more heavily in stocks in which they have experienced better returns in the past. The results support this hypothesis. Moreover, managers are less willing to sell stocks with high experienced returns when faced with outflows, and more willing to "top-up" these stocks when faced with inflows. Experienced returns do not influence the trading decisions of the managers of index funds, which further supports our hypothesis.

We also examine whether experienced returns reflect managerial skill. We find that higher aggregated experienced returns are associated with lower future fund returns. Moreover, we find that higher aggregated experienced returns are associated with higher turnover, active share, and tracking error. These findings suggest that managers with higher experienced returns become more overconfident, trade more aggressively, and earn lower returns. Finally, we find that stocks with higher experienced returns, which are overweighted in mutual fund portfolios, subsequently underperform stocks with lower experienced returns.

[19]A different possibility is that experienced returns in this setting capture long-run reversals, documented by De Bondt and Thaler (1985). However, this is less likely since we risk-adjust returns using multi-factor models, which can price the long-run reversal effect (Fama and French 1996).

Whereas the canonical asset pricing model assumes that the perception of risk for individual companies is "objective," recent work suggests that risk perception is subjective, as it is influenced by investors' personal experiences with these companies. Our work highlights that this effect is pervasive, influencing the portfolio decisions of sophisticated investors as well. These findings suggest that, to better understand outcomes in financial markets, it is fruitful to further study how subjective factors influence the behavior of different market participants.

Chapter 4

Economic Uncertainty in Mutual Fund Communication

4.1 Introduction

When a seller provides information about a commodity, it can serve as a tool for a potential buyer to assess its quality (Stigler 1987). Consequently, information quality can affect the buyer's propensity to purchase the commodity, and ultimately consumer welfare. Information precision has been studied in a number of context such as political campaign (e.g., Coate 2004, Prat 2006) or marketing (Johnson and Myatt 2006). However, surprisingly few studies explore the role of information provision in the context of U.S. mutual funds, despite their economic importance. As of 2018, the size of this industry represented approximately $18 trillion according to the Investment Company Institute. This chapter contributes to a large literature on information economics by providing evidence of the role of communication in the mutual fund industry.

In this chapter, I explore how mutual funds' use of terms in their communication channels related to economic policy uncertainty can affect their investors' assertion of their products. Mutual funds are required by the SEC to report to their investors on a semiannual and annual basis about their performance, risk, and expenses in a shareholders' report. They are free to discuss extensively about the general state of the economy in different sections of the report. This gives them room for strategic communication. I hypothesize that increasing discussion about economic uncertainty will decrease the signal precision of fund quality, i.e., performance.

Using a dictionary-based text analysis, I count the number of occurrences of words related to economic policy uncertainty following the list of words of Baker et al. (2016) in U.S. fund companies shareholders reports from 2003 to 2018. I find that an increase of economic policy uncertainty language leads to higher fund flows. In economic terms, a one standard deviation increase in economic uncertain words leads to a 4% increase in flows, or approximately $30M considering the average fund size. Fund flows are important for financial markets. Greenwood and Thesmar (2011) show that fund flows can make asset prices fragile and predict volatility. As fund flows affect stock prices, it is important to better understand its drivers.

To understand the relationship between uncertain language and fund flows, Johnson and Myatt (2006)'s framework provides insights regarding the optimality of signal precision. When a firm targets a mass market, it is optimal to provide imprecise signals about their product. In the context of mutual funds, it is difficult for an investor to be appealed by specific characteristics of a fund product as most of the funds offer similar services. Thus, the U.S. active equity fund industry will resemble a mass market where product will have a plain-vanilla design.[1] In the context of a mass market strategy, it is optimal to provide noisy signals as this will increase the funds' revenues (Johnson and Myatt 2006).

The fact that economic uncertainty language leads to higher flows helps understand why the average fund with zero excess returns would still receive inflows. However, this does not shed light on the fact that poor performing funds receive lower outflows than predicted by workhorse models (e.g., Berk and Green 2004). To investigate this puzzle, I test the effect of economic uncertainty language on flows conditional on bad performance and find that the positive effect on flows is stronger for bad funds. Mullainathan et al. (2008) model offers general insights to understand this result. They document that during market downturns, mutual funds advertize less their own performance. Thus, a poorly performing fund would be better off increasing economic uncertain language when its own performance is bad.

In the next test, I explore the channels through which language affects fund flows. To disentangle economic uncertainty language from sentiment measures, I control for the tone of the document using dictionaries from Loughran and McDonald (2011). I find that a negative tone will negatively affect flows, consistent with findings from Hillert et al. (2014), but cannot explain the economic uncertainty results nor the

[1] Johnson and Myatt (2006) explain that a precise signal would be optimal in a niche market. This could for example correspond to financial institutions catering to investors through product design as in Célérier and Vallée (2017).

size of the document.

One explanation for language to influence investors decision is limited attention. It is possible that investors will face more difficulties processing information in a large document that contains more words related to economic uncertainty as in limited information processing models (e.g., Sims 2003). To test this possibility, I explore the role of economic policy uncertainty language on flows separately for retail funds and institutional funds. Retail funds are investment vehicles targeted specifically to retail investors according to Morningstar. Prior research shows that retail investors are more subject to behavioral biases such as overconfidence (Odean 1999). I find that the documented effect of economic uncertainty is stronger for retail funds.

Companies might communicate strategically to obfuscate financially relevant information (Persson 2018). Barber et al. (2005) show that front-end load fees are relevant for investors and more salient than other expenses. As a result, investors tend to avoid funds with high front-end load fees. If mutual funds communicate more about economic policy uncertainty, this might make front-end load fees less salient. I find results that corroborate this hypothesis.

This chapter's contribution is threefold. First, it contributes to the large literature on mutual fund performance and the active fund puzzle. Gruber (1996) explains that the growth of the active fund management industry represents a puzzle given the lack of evidence of performance. Chevalier and Ellison (1997) and Sirri and Tufano (1998) show that flows to funds are strongly related to past performance. Later, Berk and Green (2004) provide a model to explain this flow-performance relationship. However, it is still difficult to explain why an average fund with zero excess returns would receive positive flows. This study provides an alternative explanation to this puzzle building on the effects of mutual fund communication on investors' behavior.

Second, this chapter contributes to a large and growing literature on text analysis in finance. Many studies have looked at the effect of news media (Tetlock 2007), language in firms' 10-Ks (e.g., Loughran and McDonald 2011; Jegadeesh and Wu 2013; Loughran and McDonald 2014) on asset prices. While many researchers have focused on firms reports, surprisingly few have looked at the institutional investors reporting language. In a related study, Hillert et al. (2014) look at sentiment measures in fund communication and find that positive tones positively affect fund flows. This chapter contributes to the literature on text analysis in finance and focuses on economic uncertainty in communication rather than sentiment measures.

Third, this study contributes to an extensive literature on information economics and communication. Many researchers have studied asymmetric information between economic agents its consequences on strategic communication (e.g., Grossman 1981; Milgrom 1981; and Crawford and Sobel 1982). Thus communication between two parties can be a useful tool for an information receiver (Stigler 1961), but also a strategic one for the sender (Lippmann 1922). Bertrand et al. (2010) show that consumers can be persuaded to take up loans in the context of direct-mail solicitations in South Africa. In politics, DellaVigna and Kaplan (2007) show that having access to Fox News made voters more likely to choose the Republican party in 2000. In financial markets, Engelberg and Parsons (2011) show that local trading responds to local coverage of earnings announcements. This chapter shows how investors are influenced by the way mutual fund communicate with consequences on fund flows and industry size.

4.2 Institutional Background

Registered management investment companies have to complete and file with the Securities and Exchange Commission the N-CSR Form according to the Investment Company Act of 1940. Management investment companies are firms that sell fund shares to the public. Fund companies file the N-CSR, also called shareholders' report, on a semiannual (Form N-CSRS) and annual basis (Form N-CSR).

The N-CSR Form typically includes a shareholders' letter, usually signed by the CEO of the investment company. It also includes a performance summary, economic and market overview, investment, manager's discussion, details about the expenses, portfolio composition as well as other information regarding the financial statements. Thus, the N-CSR is akin to a firm's 10-Ks and is the most comprehensive SEC Form for mutual funds.

Details and examples related to fees are mandatory in shareholders' report. Other sections related to performance, portfolio composition, discussion of fund performance are also mandatory. However, there are no requirements regarding the length of these discussions. Thus, even in the presence of disclosure mandate, information overload can arise, potentially at the expense of consumers (Persson 2018).

Mutual funds communicate via others channels. Typically, they are also required to file summary prospectuses (Form 497) which was proposed in late 2007. The goal was to simplify disclosure of fund information to investors. It includes information regarding the investment objective, fees and expenses, historical turnover, returns, and risks, among other items. However, as its name indicates, the summary prospectus is much shorter and thus gives less room for the fund company to communicate strategically. Moreover, Beshears et al. (2009) find that simplified disclosure does not affect investors' choices of funds. Mutual funds also communicate using advertising channels such as in news media outlets (Mullainathan et al. 2008). This chapter does not cover fund communication in these alternative channels.

4.3 Data and Methodology

In this section I describe the various data sources and variables used in the empirical test performed.

4.3.1 Mutual Fund Characteristics

I obtain mutual fund characteristics from the CRSP Mutual Fund Database. Namely, I collect information on fund size (total net assets; TNA), returns, age, turnover ratio, and expense ratio.

I focus on U.S. active domestic equity universe by using the CRSP investment objective code.[2] Following Lou (2012), I impose funds to have a minimum size of $1 million.

I compute annual flows as the percentage change of fund size on top of fund returns. More specifically, flows is computed as follows:

$$flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{4.1}$$

where $TNA_{i,t-1}$ and $TNA_{i,t}$ are fund i's total net assets at the end of year $t-1$ and t, respectively, while $R_{i,t}$ is fund i's return over the year t.

To measure fund performance, I follow prior studies (e.g., Kacperczyk et al. 2005; Ben-David et al. 2018) and define it as the difference between a fund's realized return and its return predicted by a factor model. I use the Carhart (1997) four-factor model using monthly data. With a rolling window of 60 months as in Ben-David et al. (2018), I estimate factor loadings and use the estimates without the intercept the obtain the predicted return. More specifically, I estimate the following

[2] I restrict the CRSP investment objective code to start with "ED", where the "E" stands for equity and the "D" stands for domestic.

four-factor model for fund i at month t:

$$R_{i,\tau} - Rf_{\tau} = a_{i,t} + \beta_{i,t}(MKT_{\tau} - Rf_{\tau}) + s_{i,\tau}SMB_{\tau} + h_{i,\tau}HML_{\tau} + u_{i,\tau}UMD_{\tau} + \epsilon_{i,\tau}, \tag{4.2}$$

where $\tau = t-60, ..., t-1$, $R_{i,\tau}$ is the fund i's net return in month τ, Rf is the one month Treasury bill, MKT (market), SMB (size), HML (value), and UMD (momentum) are the four factors as in Carhart (1997). Then, I define fund performance α as follows:

$$\alpha_{i,t} = R_{i,t} - Rf_t - [\hat{\beta}_{i,t}(MKT_t - Rf_t) + \hat{s}_{i,t}SMB_t + \hat{h}_{i,t}HML_t + \hat{u}_{i,t}UMD_t], \tag{4.3}$$

where the coefficient denote by a hat are estimated from equation (4.2). Monthly performance is aggregated at the year level by cumulating monthly α to obtain annual fund performance.

To proxy for a fund's propensity to take risk, such as deviating from a benchmark, I use the factor loading on the market factor from the CAPM (β from equation (4.2) but based on the CAPM, that is, without the factors SMB, HML, and UMD). This measure is a useful proxy of systemic risk for active managers as it represents the extent to which a fund's returns respond to those of the market (in this case all firms from the NYSE, AMEX, or NASDAQ).

4.3.2 Mutual Fund Communication

I collect mutual fund communication from the SEC Edgar database. I obtain fund companies' CIK (central identifier key; which is the identifier for the SEC Edgar database) from the CRSP Mutual Fund database and use it to scrape mutual fund shareholders' reports. Mutual funds communicate about their performance through various forms which include summary prospectuses (form 497), shareholders' reports (form N-CSR), but also voluntary disclosure such as advertising in the media. The advantage of using shareholders' reports is that they are more comprehensive than summary prospectuses and more readily available than advertising campaigns. Moreover, mutual funds sometimes strategically do not communicate about their performance in advertising as shown by Mullainathan et al. (2008). In shareholders reports they are required to do so but are free to communicate as much as they want about other topics such as the economic environment.

The documents are cleaned following Gentzkow et al. (2017). I first remove all elements of the text other than words (e.g., html tags, numbers, punctuations).

Then, I remove stop words using Porter (1980).[3]

4.3.3 Measuring Economic Uncertainty

To measure economic uncertainty in mutual fund shareholders' reports, I use a dictionary-based method following Baker et al. (2016). The authors measure the frequency of articles in top U.S. newspapers that contain the words "economic" or "economy"; "uncertain" or "uncertainty"; and "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". With this list of words, the authors created an index that captures economic policy uncertainty and correlates with other uncertainty measures, such as stock market volatility and spiked at major events such as 9/11 attacks and Presidential elections.

Using this method in the context of mutual fund communication is relevant for several reasons. As the measure proposed by Baker et al. (2016) correlates with stock market volatility, it allows the fund companies to emphasize the degree of uncertainty by using more words taken from the list proposed by the authors. As it echoes the words used by journalists in top U.S. newspapers, it amplifies the degree of uncertainty of investors who potentially read both shareholders' report and U.S. newspapers. For these reasons, I measure economic uncertainty (EU) as follows:

$$EU_{i,t-1} = c_{i,t-1}, \tag{4.4}$$

where $c_{i,t-1}$ is the raw count of words in the list: "economic", "economy", "uncertain", "uncertainty", "congress", "deficit", "Federal Reserve", "legislation", "regulation" and "White House" in all reports published by the investment company of fund i in year $t-1$. Appendix B shows an example of content from a N-CSR form with the counted words highlighted.

Table 4.1 on page 77 summarizes the variables used in this study. The N-CSR coverage before 2003 is sparse. Thus, the sample starts from 2003 to 2018 and contains 7,228 distinct funds and an average of 4,076 funds per year and 731 fund companies. The average count of uncertain words is more than 7,198 per companies in a year. The average fund has flow of 1%, is 14 years old, and an annual turnover of 70%.

[3] Stopwords include words such as "the", "a", or "and".

Table 4.1: Summary Statistics

This table presents summary statistics of our main variables. The sample is composed of U.S. actively managed mutual funds from 2003 to 2018. Fund documents are obtained from the S.E.C. and other fund characteristics are obtained from the CRSP Mutual Fund Database. *Age* is expressed in years. Total net assets (TNA) are measured in millions. *Expense* and *turnover* ratio are in percentage. Fund documents are at the year-fund company level, while other variables are at the year-fund level.

	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
Fund by year	35,303	4075.7	1553.75	888	6115	2772	4283	5395
Company by year	35,303	542.91	88.29	296	632	476	575	623
Fund by company	35,303	32.76	36.25	1	164	8	19	44
EU	28,075	7197.9	15,873.15	37	98572	569	1765	5415
$flows$	35,295	0.01	0.47	-0.94	2.73	-0.18	-0.07	0.07
age	35,303	14.22	9.72	1	94	8	12	17
TNA	35,295	725.22	1949.88	1.3	14101.2	28.1	118.2	492.6
$turnover$	27,715	0.7	0.54	0.13	1.84	0.27	0.53	0.98
$expense$	27,850	0.05	0.18	0	1.12	0.01	0.01	0.02
$fund\ return$	28,075	0.11	0.2	-0.44	0.49	0.02	0.12	0.25

4.4 Results

In this section I present the results of the various tests performed to explore the hypothesis that economic uncertainty affects investors' behavior.

4.4.1 Attributes of Funds with High Economic Uncertainty Language

Before investigating the effects of language on fund flows, I explore the determinants of funds with high economic uncertainty language. For this purpose, I regress the economic uncertainty language measure, EU, on fund characteristics:

$$EU_{i,t} = \beta_0 + \beta_1 X_{i,t-1} + F + T + \epsilon_{i,1}. \tag{4.5}$$

$X_{i,t-1}$ is a matrix that contains the following fund characteristics: annual fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), annual fund returns, annual turnover ratio, expense ratio, fund performance measured with the Carhart (1997) four-factor model, and fund risk as measured by the beta coefficient from the CAPM model. To account for potential correlation in the residuals at the fund and time level, I include fund and time (year) fixed effects and double-cluster standard errors by fund and time.

Table 4.2 on page 79 shows the results. The first observation is that most variation in economic uncertainty comes from unobservables, i.e., fund fixed effects. Indeed, the adjusted R^2 goes from 3% to approximately 88% when adding fixed effects. The second observation is that funds with high economic uncertainty language tend to be risky, poorly performing, and expensive funds. As hypothesized in the previous sections, a fund that will be inclined to provide an unprecise signal will do so to obfuscate information that could hurt in terms of fund flows. Thus, an expensive funds will provide more details to the report in order to potentially distract the reader from the fee section and similarly for bad performance and risk. Finally, the results show that young funds tend to have higher economic uncertainty language. A possible explanation for this finding is the career concerns of fund managers (Chevalier and Ellison 1999). Fund age is correlated with manager tenure as shown in chapter 3 (Table 3.2 on page 48). Younger managers tend to take on more risk as documented by Greenwood and Nagel (2009) and thus potentially attempt to hide risk with economic uncertainty language. Other fund characteristics (size, returns, and turnover) do not seem to be statistically related to economic uncertainty language.

4.4.2 Fund Flows and Economic Uncertainty Language

To investigate the role of economic uncertainty language in mutual fund communication on fund flows, I use a regression approach. I test if higher economic uncertainty in reports published in year $t-1$ leads to higher flows in year t as hypothesized in the previous sections. More specifically, I use the following regression specification as the main test:

$$flows_{i,t} = \beta_0 + \beta_1 EU_{i,t-1} + \beta_2 X_{i,t-1} + F + T + \epsilon_{i,1}. \tag{4.6}$$

The dependent variable is the percentage change in fund size from the end of year $t-1$ to the end of year t on top of fund returns (see equation (4.1) on page 74). The main independent variable (EU) is the count of words related to economic uncertainty according to Baker et al. (2016) in all shareholders' reports published in year $t-1$ by the company of fund i. To disentangle from other fund characteristics that might affect fund flows, I control for various variables denoted by matrix $X_{i,t-1}$. The set of controls include annual fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), annual fund returns, annual turnover

Table 4.2: The Determinants of Economic Uncertainty

This table presents estimates from panel regressions of mutual funds' *% Economic uncertainty* on fund characteristics. All regressions include year fixed effects. The regressions include as lagged fund-level characteristics: *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM model, *expense* ratio, quarterly fund *flow*, the natural logarithm of *fund age* , annual *fund return*, the natural logarithm of fund size (TNA), *expense* ratio, and *turnover* ratio. Where specificed, a fund and fund company fixed effect are included. Standard errors are double-clustered by fund-year. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$EU_{i,t}$			
	(1)	(2)	(3)	(4)
$flow_{i,t-1}$	268.047***	277.996***	300.474***	-20.345
	(2.98)	(3.02)	(3.19)	(-0.46)
ln(*fund age*$_{i,t-1}$)	-1.1e+03***	-1.1e+03***	-1.1e+03***	-1.0e+03***
	(-12.98)	(-13.27)	(-13.32)	(-6.34)
ln($TNA_{i,t-1}$)	881.782***	895.365***	923.540***	225.328*
	(8.48)	(8.37)	(8.55)	(1.85)
fund return$_{i,t-1}$	83.621	-99.889	-289.831	30.805
	(0.65)	(-0.65)	(-1.44)	(0.35)
$turnover_{i,t-1}$		-38.766	-73.534	90.903
		(-0.49)	(-0.90)	(1.40)
$expense_{i,t-1}$		-678.177***	-665.392***	1.1e+04**
		(-12.28)	(-11.95)	(2.35)
$alpha_{i,t-1}$			32.320	-72.426*
			(0.36)	(-1.86)
$beta_{i,t-1}$			283.634***	-290.987***
			(3.58)	(-5.06)
Yes FE	Yes	Yes	Yes	Yes
Fund FE	No	No	No	Yes
# Obs	28063	27486	27201	26572
Adj R^2	0.026	0.030	0.030	0.876

ratio, expense ratio, fund performance measured with the Carhart (1997) four-factor model, the squared of fund performance to account for the convexity of the flow-performance relationship (Chevalier and Ellison 1997), and fund risk as measured by the beta coefficient from the CAPM model. All independent variables are measured at $t-1$. Finally, I include fund and year fixed effects and double-cluster standard errors by fund and time to mitigate issues related to correlation of residuals across funds and time.

Table 4.3 on page 81 shows the main results. The coefficient on economic uncertainty EU is positive and statistically significant (0.041; t-stat= 4.60) for the specification that includes all controls and fixed effects. This confirms the hypothesis that a higher use of words related to economic uncertainty in shareholders' reports leads to higher flows. To give an economic interpretation of the results, a one standard deviation increase in EU leads to an increase of flows of 4%, which represents approximately $30M for the average fund. Other controls are consistent with prior literature. Fund flows are persistent, that is lagged flows positively predicts future flows. Moreover, investors are highly responsive to performance. They punish poorly performing funds with outflows and reward good performing funds with inflows.[4] Old and large funds receive less flows which is consistent with the decreasing returns to scale explanation (Berk and Green 2004).

In a recent study, Ben-David et al. (2018) show that investors are highly responsive to fund rankings (Morningstar ratings). In the Appendix, I show that economic uncertainty is robust to Morningstar ratings in explaining fund flows (see Table B.1 on page 104). Moreover, measuring economic uncertainty relative to style-peers gives similar results (see Table B.2 on page 105 in the Appendix).[5] Finally, in unreported results I find that the main results reported in Table 4.3 on page 81 are robust to additional controls related to the investment company (i.e., family flow, and family fixed effects).

Further Results on Language Channels

Following the confirmed hypothesis that economic uncertainty language correlates with higher fund fund flows, I examine the channel through which uncertainty lan-

[4] Estimating fund performance with a shorter rolling window, i.e., 2 years as in chapter 2, does not affect the results presented in this chapter.

[5] The motivation for this test is that if a given large-value fund communicates more about economic uncertainty it is possibly because large value companies perform badly. Thus, it is relevant to adjust EU with the style average.

Table 4.3: Document Economic Uncertainty and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$EU_{i,t-1}$	0.040***	0.039***	0.039***	0.041***
	(6.76)	(4.48)	(4.45)	(4.60)
ln($fund\ age_{i,t-1}$)		-0.019	-0.029**	-0.035**
		(-1.33)	(-1.99)	(-2.38)
ln($TNA_{i,t-1}$)		-0.295***	-0.293***	-0.296***
		(-19.03)	(-18.60)	(-18.55)
$flow_{i,t-1}$		0.030***	0.031***	0.029***
		(5.59)	(5.55)	(5.20)
$fund\ return_{i,t-1}$		0.067***	0.075***	0.018
		(8.77)	(9.37)	(1.47)
$turnover_{i,t-1}$			-0.003	-0.004
			(-0.48)	(-0.57)
$expense_{i,t-1}$			-0.047	-0.134
			(-0.22)	(-0.46)
$alpha_{i,t-1}$				0.040***
				(7.93)
$alpha^2_{i,t-1}$				-0.001
				(-0.31)
$beta_{i,t-1}$				0.012
				(1.44)
Year FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
# Obs	32797	27464	26863	26572
Adj R^2	0.276	0.334	0.339	0.343

guage leads to higher fund flows. Higher economic uncertainty language could be driven by longer shareholder reports or negative tone for instance. To distinguish the effect of economic uncertainty from these alternative explanations, I estimate the regression described in equation (4.6) on page 78 and control for additional characteristics related to fund language. To control for the sentiment of the document, I control for positive and negative tone of the shareholders' reports following Loughran and McDonald (2011).[6] I also control for other measures that could relate to the difficulty of information processing for readers, namely document length or file size and average word length. Loughran and McDonald (2014) show that file size is simple measure of document readability. Word length is also a proxy for complex words.

Table 4.4 on page 83 presents the results on language channels. When controlling for all additional document measures, namely negative document tone ($Tone^{-}_{i,t-1}$), positive document tone ($Tone^{+}_{i,t-1}$), document length ($DocLength_{i,t-1}$), and average word length ($WordLength_{i,t-1}$). The main independent variable of economic uncertainty EU is robust to other document measures. The coefficient decreases from 4% to 3.2% and remains statistically significant with a t-statistic of 3.52. A negative (positive) document tone negatively (positively) affects fund flows, which is consistent with findings by Hillert et al. (2014). Finally, other measures of readability positively affect fund flows. This confirms the hypothesis that document uncertainty benefits fund flows and does not capture other document-related measures.

4.4.3 Fund Flows, Bad Performance, and Economic Uncertainty Language

Thus far, Table 4.3 on page 81 gives an explanation as to why the average fund receives flows higher than predicted by standard models of delegated asset management (e.g., Berk and Green 2004). However, it does not explain the convexity of the flow-performance relationship, that is bad funds experience less outflows than they should. To explore if fund communication can explain this convexity, I use the same approach as the main model presented in equation (4.6) on page 78 conditional on bad performance. More precisely, I estimate the following regression:

$$flows_{i,t} = \beta_0 + \beta_1 PerfDummy_{i,t-1} * EU_{i,t-1} + \beta_2 X_{i,t-1} + F + T + \epsilon_{i,1}. \quad (4.7)$$

[6]The authors created a list of words related to positive and negative sentiment specific to financial applications.

Table 4.4: Further Results on Language Channels

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). All regressions include fund and year fixed effects. Various additional controls are included related to fund documents: positive and negative tone of the documents, document and word length following Loughran and Mcdonald (2011). I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$EU_{i,t-1}$	0.040***	0.033***	0.040***	0.037***	0.032***
	(4.53)	(3.75)	(4.59)	(4.26)	(3.53)
$Tone^{-}{}_{i,t-1}$	0.010				-0.140***
	(0.78)				(-4.52)
$Tone^{+}{}_{i,t-1}$		0.046***			0.089***
		(3.63)			(3.48)
$DocLength_{i,t-1}$			0.023***		0.024***
			(4.09)		(3.90)
$WordLength_{i,t-1}$				0.033**	0.069*
				(2.30)	(1.73)
Fund Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
# Obs	26572	26572	26572	26572	26572
Adj R^2	0.343	0.344	0.344	0.343	0.344

I define $PerfDummy_{i,t-1}$ as an indicator variable that takes the value 1 whenever fund i is in the bottom decile of the performance distribution as of the end of year $t-1$. The set of controls in $X_{i,t-1}$ is the same as in the main regression specification of equation (4.6) on page 78, namely annual fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), annual fund returns, annual turnover ratio, expense ratio, fund performance measured with the Carhart (1997) four-factor model, the squared of fund performance to account for the convexity of the flow-performance relationship (Chevalier and Ellison 1997), and fund risk as measured by the beta coefficient from the CAPM model. Moreover, I also include in the set of controls $X_{i,t-1}$ the two terms of the interaction separately ($PerfDummy_{i,t-1}$ and $EU_{i,t-1}$). As in the main analysis, I include firm and year fixed effects and double-cluster standard errors by fund and year.

Table 4.5 on page 85 presents the results. The interaction term shows a positive and statistically significant coefficient (0.022; t-stat= 2.25). This shows that the effect of economic uncertainty language is stronger for funds with bad performance. In economic terms, a fund with bad performance relative to its peers will have higher flows by approximately \$45M if it increases its economic uncertainty language by one standard deviation. Typically, instead of being punished for bad performance by \$100M of outflows, a fund will experience only \$55M of outflows if its company focuses the discussion on economic uncertainty language in its shareholders' reports. Other controls have similar effects on flows as documented earlier. That is, lagged flows and performance positively affects flows while age and size have a negative effect.

4.4.4 Fund Flows, Business Cycles, and Economic Uncertainty Language

Figure 4.1 on page 86 shows that mutual funds' asset under management decreased substantially during the 2008 financial crisis. At the same time, the length of shareholders' reports peaked at a record high (see Figure 4.2 on page 87). As Baker et al. (2016) show, economic uncertainty was also at its highest around that period. Thus, it is worth investigating how investors responded to economic uncertainty language in periods of recessions as opposed to expansion periods.

Table 4.5: Document Economic Uncertainty, Performance, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). *PerfDummy* is a dummy for each fund that has an annual performance (*alpha*) in the bottom decile of the performance distribution. All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$PerfDummy_{i,t-1}*EU_{i,t-1}$	0.016	0.025**	0.026***	0.022**
	(1.60)	(2.50)	(2.61)	(2.25)
$EU_{i,t-1}$	0.040***	0.038***	0.038***	0.038***
	(6.62)	(4.23)	(4.19)	(4.26)
$PerfDummy_{i,t-1}$	-0.078***	-0.052***	-0.049***	0.003
	(-8.39)	(-5.09)	(-4.69)	(0.21)
ln($fund\ age_{i,t-1}$)		-0.018	-0.027*	-0.035**
		(-1.23)	(-1.90)	(-2.39)
ln($TNA_{i,t-1}$)		-0.296***	-0.294***	-0.296***
		(-19.06)	(-18.64)	(-18.57)
$flow_{i,t-1}$		0.030***	0.030***	0.029***
		(5.50)	(5.50)	(5.20)
$fund\ return_{i,t-1}$		0.056***	0.062***	0.018
		(6.53)	(6.83)	(1.48)
$turnover_{i,t-1}$			-0.002	-0.004
			(-0.36)	(-0.57)
$expense_{i,t-1}$			-0.045	-0.140
			(-0.21)	(-0.48)
$alpha_{i,t-1}$				0.042***
				(7.30)
$alpha^2_{i,t-1}$				-0.003
				(-0.63)
$beta_{i,t-1}$				0.012
				(1.47)
Year FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
# Obs	32797	27464	26863	26572
Adj R^2	0.277	0.335	0.340	0.343

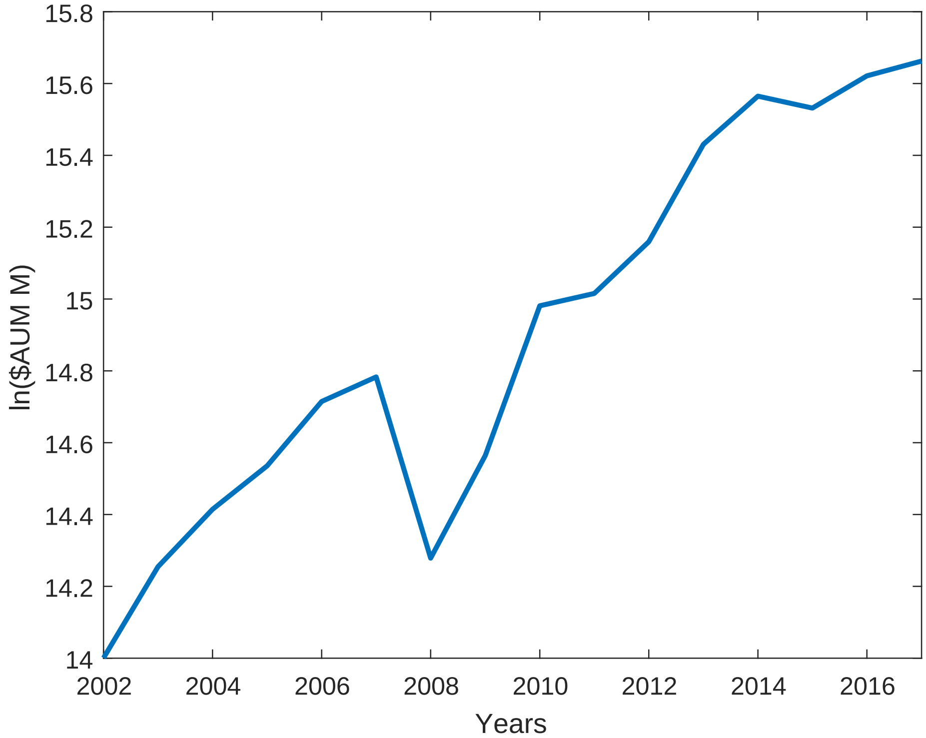

Figure 4.1: Mutual funds' assets under management.
This figure shows the evolution of the natural logarithm of U.S. active equity mutual funds total assets under management in million U.S. dollars.

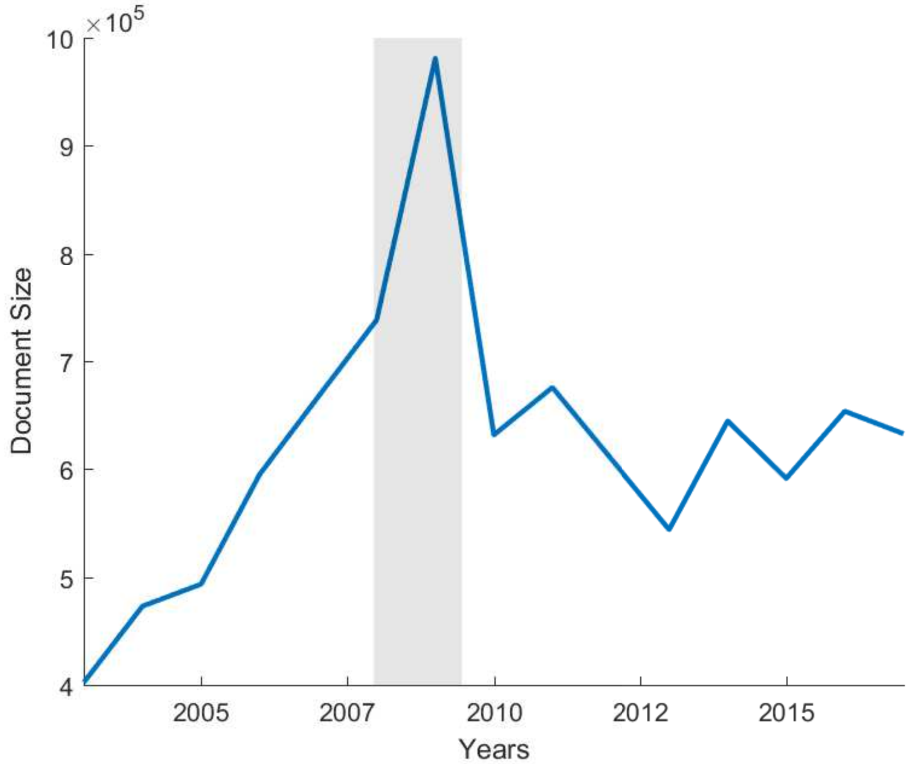

Figure 4.2: Mutual funds' documents size.
This figure shows the evolution of the average U.S. active equity mutual funds N-CSR forms length in number of characters. The grey area represents the recession period.

To investigate this question, I estimate the following regression specification

$$flows_{i,t} = \beta_0 + \beta_1 recession_{t-1} * EU_{i,t-1} + \beta_2 X_{i,t-1} + F + T + \epsilon_{i,1}. \qquad (4.8)$$

$recession_{t-1}$ is a dummy indicating if a recession occurred in year $t-1$. It is obtained from the Federal Reserve Bank of St. Louis. $EU_{i,t-1}$ as defined earlier is a the count of words related to economic uncertainty in fund i's company shareholders' reports filed in year $t-1$. $X_{i,t-1}$ denotes the set of lagged controls which include the recession dummy, $EU_{i,t-1}$, annual fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), annual fund returns, annual turnover ratio, expense ratio, fund performance measured with the Carhart (1997) four-factor model, the squared of fund performance to account for the convexity of the flow-performance relationship (Chevalier and Ellison 1997), and fund risk as measured by the beta coefficient from the CAPM model. As in the previous sections, I include fund and year fixed effects as well as standard errors double-clustered at the fund and year level.

Table 4.6 on page 89 shows the results of fund flows, business cycles, and economic uncertainty language. The results indicate that economic uncertainty language is more effective in expansion periods. While it is important to keep in mind the lack of power of this test, due to the single period of recession in the present sample shown in grey in Figure 4.2 on page 87, the coefficient on $EU_{i,t-1}$ in column (5) of Table 4.6 on page 89 is negative and statistically insignificant. This indicates that an emphasis on economic uncertainty in recession periods in shareholders' reports does not prevent negative fund flows. In recession periods, the coefficient on lagged flows becomes negative. One possibility is that since flows is lagged, the effect on future flows is reversed as we move from one state of the economy to the other and thus money flows in funds moving from a recession to an expansion period and vice versa. Other controls show similar coefficients in recession and expansion periods with the exception of *beta* which becomes positive and statistically significant. This suggests risky funds suffer more in recession periods. Interestingly, emphasizing on economic uncertainty in expansion periods helps prevent outflows as reported in the previous sections.

4.4.5 Fund Flows, Clienteles, and Economic Uncertainty Language

A potential explanation for investors being influenced by the language of shareholders' report is limited attention. Persson (2018) shows that information overload is optimal for a firm subject to disclosure mandates in order to hide financially relevant information. Motivated by this mechanism, I investigate if the effect of economic uncertainty in mutual fund communication is stronger for investors with limited attention.

For this test, I focus on funds targeted to retail investors. Odean (1999) shows that retail investors are more subject to behavioral biases. I identify funds targeted to retail investors using the Morningstar indicator variable. I merge Morningstar information with the rest of the sample using fund CUSIP and Tickers following Pástor et al. (2015). I estimate the model described in equation (4.6) on page 78 separately for the sample of funds targeted to retail investors and institutional investors.[7] When fund controls are included, I control for annual fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), annual fund returns, annual turnover ratio, expense ratio, fund performance measured with

[7] Mutual funds targeted to institutional investors are funds sold to other financial companies. I assume that these investors devote more resources to the fund products they buy and are less inattentive.

Table 4.6: Document Economic Uncertainty, Recessions, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a recession dummy. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). *Recession* is a dummy for each end-of-year where the U.S. economy was in a recession. All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$					
					Recession	Expansion
	(1)	(2)	(3)	(4)	(5)	(6)
$recession_{t-1}$*$EU_{i,t-1}$	-0.051***	-0.089***	-0.092***	-0.090***		
	(-3.47)	(-5.13)	(-5.26)	(-4.98)		
$EU_{i,t-1}$	0.045***	0.044***	0.044***	0.046***	-0.094	0.043***
	(7.50)	(5.00)	(4.98)	(5.14)	(-1.63)	(4.75)
ln($fund\ age_{i,t-1}$)		-0.022	-0.032**	-0.037**	-0.032	-0.022
		(-1.51)	(-2.19)	(-2.52)	(-0.65)	(-1.20)
ln($TNA_{i,t-1}$)		-0.296***	-0.293***	-0.297***	-1.583***	-0.331***
		(-19.07)	(-18.64)	(-18.59)	(-13.20)	(-17.60)
$flow_{i,t-1}$		0.030***	0.030***	0.029***	-0.074***	0.025***
		(5.57)	(5.54)	(5.18)	(-4.53)	(3.96)
fund return		0.068***	0.075***	0.019	-0.038	0.020
		(8.81)	(9.42)	(1.52)	(-0.52)	(1.57)
$turnover_{i,t-1}$			-0.004	-0.004	-0.018	-0.001
			(-0.57)	(-0.66)	(-1.11)	(-0.13)
$expense_{i,t-1}$			-0.033	-0.118	-1.880	0.286
			(-0.15)	(-0.41)	(-0.95)	(1.01)
$alpha_{i,t-1}$				0.039***	0.073***	0.040***
				(7.87)	(3.14)	(7.61)
$alpha^2_{i,t-1}$				-0.001	-0.009	-0.002
				(-0.34)	(-1.23)	(-0.56)
$beta_{i,t-1}$				0.011	0.041**	0.001
				(1.29)	(2.56)	(0.13)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	32794	27464	26863	26572	1882	23809
Adj R^2	0.275	0.335	0.340	0.344	0.847	0.371

the Carhart (1997) four-factor model, the squared of fund performance to account for the convexity of the flow-performance relationship (Chevalier and Ellison 1997), and fund risk as measured by the beta coefficient from the CAPM model. Fund and year fixed effects as well as double-clustered standard errors are included in all models.

Table 4.7 presents the results. I find that the effect of economic uncertainty is statistically stronger for mutual funds targeted to retail investors. The effect of economic uncertainty language is positive and statistically significant at the 1% significance level for retail investors (column (2) of Table 4.7) and at 5% for institutional investors targeted funds (column (4) of Table 4.7). The coefficient is larger for institutional investors potentially because mutual funds targeted to institutions usually manage large amounts and receive higher flows. These results confirm the hypothesis that the effect of economic uncertainty language is stronger for investors with limited attention.

Table 4.7: Document Economic Uncertainty, Clientele, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty for retail and institutional investors separately. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). We identify retail and institutional investors' mutual funds using Morningstar's classification. All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	Retail		Institutional	
	(1)	(2)	(3)	(4)
$EU_{i,t-1}$	0.012**	0.027***	0.008	0.050**
	(2.10)	(2.81)	(0.89)	(2.14)
Fund Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
# Obs	15247	14973	4138	4028
Adj R^2	0.132	0.358	0.110	0.329

4.4.6 Fund Flows, Expenses, and Economic Uncertainty Language

Barber et al. (2005) find that front-end load are more salient for investors when purchasing funds. Thus, investors are more responsive to higher front-end load funds by flowing less money to these. If economic uncertainty language serves as a tool to obfuscate relevant information, then front-end loads should be less salient for funds with high economic uncertainty language. To test this hypothesis, I investigate how investors respond to front-end loads for funds with high economic uncertainty.

I define a front-end loads dummy for each fund that charges front-end loads. I define funds as *High EU* (economic uncertainty) as funds whose company's shareholders' reports are in the top quartile of the document uncertainty distribution for each year. *Low EU* are all other funds.

Table 4.8 shows the results. I find that investors are not responsive to front-end loads when funds have high economic uncertainty language in their shareholders' reports. For other funds with *Low EU*, front-end loads remain salient for investors, which is consistent with Barber et al. (2005). The results confirm the hypothesis that relevant information is obfuscated when funds communicate more about economic uncertainty.

4.5 Summary

In this chapter, I introduce the study of economic uncertainty in mutual fund communication. Even in the presence of disclosure mandates, information providers have room for strategic communication. This includes an emphasis on uncertainty in mutual fund communication which makes a signal about a fund's products quality less precise.

When measuring economic uncertainty in mutual fund shareholders' reports, I find that uncertainty obfuscates financially relevant information such as upfront costs and helps mutual funds receive more capital. Poorly performing funds benefit more from it.

This chapter shows that mutual fund communication matters for understanding fund flows and investors' behavior. It is an important topic given the size of the industry and the previously documented effects of fund flows on asset prices.

Table 4.8: Document Economic Uncertainty, Expenses, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty for funds with and without front-load charges separately. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). *Front-end loads* is a dummy for each fund that charges front-end loads. *High EU* represents funds in the top quartile of the document uncertainty distribution for each year. All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), (operating) *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$		
	All funds	High EU	Low EU
	(1)	(2)	(3)
$\textit{front-end loads}_{i,t-1}$	-0.052**	-0.029	-0.066***
	(-2.57)	(-0.56)	(-2.76)
Fund Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
# Obs	26572	5384	20465
Adj R^2	0.343	0.403	0.350

Chapter 5

Conclusion

To conclude, this thesis has investigated the behavior of mutual fund managers in terms of investment decisions and its effects on fund performance and asset prices, as well as their behavior when it comes to communicating with their investors.

Regarding the mutual fund performance, the second chapter of this thesis documents that informational advantage is a potential explanation behind the heterogeneity of fund performance. The empirical tests in this chapter build on the hypothesis that fund managers with low holdings similarity with their peers possibly have an informational advantage about the firms they own. I use network analysis to capture holdings similarity at the fund level. Using a change in regulation provides a clean empirical strategy to explore the role of informational advantage in this setting. Indeed, I show that, following the implementation of this new rule by the regulator that forced fund managers to reveal their holdings more frequently, mutual fund managers with low holdings similarity have seen their performance decreased.

To further explore the heterogeneity of mutual fund managers' investment decisions, Dr. Constantinos Antoniou and I build on the behavioral economics literature to investigate if personal experience can help explain this heterogeneity. A growing literature shows that individuals are influenced by their past experiences when making decisions under risk. We hypothesize that mutual fund managers are subject to reinforcement learning, that is, they will invest more in companies where they experienced better returns in the past. We measure experience for each fund manager as an exponentially weighted moving average of past experienced returns and find evidence that fund managers are indeed subject to reinforcement learning. Experiencing good returns affect fund managers' perception of their skills. As they experience positive outcomes, they become overconfident, attributing these good outcomes to their ability. Subsequently, they trade more aggressively and earn lower future returns.

The growth rate of the mutual fund industry has puzzled researchers for many years, given the mixed evidence of positive returns delivered to investors. In the last chapter of this thesis, I explore the role of mutual fund communication in explaining this puzzle. Mutual funds are judged by investors on the basis of their performance. When a fund performs poorly, it experiences outflows and receives inflows following positive fund returns. I hypothesize that mutual funds might emphasize on uncertain economic environment in order to avoid being punished too severely through fund flows. First, I document that risky and poorly performing funds are more likely to emphasize on economic uncertainty in their documents, measured by counting the words related to economic policy uncertainty in their shareholders' reports. Second, I find that increasing the number of words related to economic policy uncertainty has a positive effect on flows, controlling for other fund characteristics such as past performance and past flows. The effect is stronger for funds with lower performance and with retail investors. Moreover, financially relevant information, such as front-end load fees, become less salient when funds communicate more about economic uncertainty.

This thesis sheds light on a number of topics related to the behavior of mutual fund managers. It contributes to a large literature on mutual fund performance and its determinants. It also links the behavioral economics literature on personal experience effects and the behavior of mutual fund managers which helps explaining the heterogeneity of their investment decisions. Finally, using mutual fund communication, which has been little used in the literature, this thesis helps explaining a long-standing puzzle on the growth of the active mutual fund industry.

Appendix A

Additional Tables for Chapter 3

Table A.1: Variable Definitions

Variable	Definition
$Weight$	Dollar amount invested in firm j by the manager of fund i at quarter t obtained from Thomson Reuters, divided by the size of the fund (total net assets obtained from CRSP) at quarter t: $$w_{i,j,t} = \frac{\$holding_{i,j,t}}{TNA_{i,t}}.$$
$Weight^{adj}$	Dollar amount invested in firm j by the manager of fund i at quarter t divided by the size of the fund (total net assets) at quarter t, adjusted for the hypothetical weight that this firm would receive if the manager of fund i was exercising a buy-and-hold strategy using the method in Kacperczyk et al. (2005): $$Weight^{adj}_{i,j,t} = w_{i,j,t} - \tilde{w}_{i,j,t-K:t}$$ where $$\tilde{w}_{i,j,t-K:t} = \frac{w_{i,j,t-k}\prod_{k=0}^{K}(1+R_{j,t-k})}{\sum_j w_{i,j,t-k}\prod_{k=0}^{K}(1+R_{j,t-k})}.$$

(Continued)

Table A1. Continued: Variable Definitions

Variable	Definition
Experience	Exponentially weighted moving average of the returns for firm j experienced by the manager of fund i. The parameter ϕ captures the rate of decay, and reflects the weight on the more recent observation. We use a functional form that implies a recency effect, i.e., the weight on the more recent observation is higher. If the manager of fund i operates with a team, we take a tenure-weighted average of the experiences for stock j by all managers in fund i, where tenure is based on the date that each manager first appears in the Morningstar database: $$Experience_{i,j,t} = \sum_{k=0}^{T}(1-\phi)^k \phi R_{j,t-k} I_{[w_{i,j,t-k}>0]}.$$
TW-Experience	Our alternative experienced returns measure based on Malmendier and Nagel (2011). According to this measure, managers with shorter tenure exhibit a stronger recency effect. The tenure of each manager is based on the date that each manager first appears in the Morningstar database: $$TW-Experience_{i,j,t} = \sum_{k=1}^{tenure_{i,t}-1} \omega_{i,t}(k,\theta) R_{j,t-k} I_{[w_{i,j,t-k}>0]}$$ where $$\omega_{i,t}(k,\theta) = \frac{(tenure_{i,t}-k)^{\theta}}{\sum_{k=1}^{tenure_{i,t}-1}(tenure_{i,t}-k)^{\theta}}.$$
Experience (style)	The experience of the manager of fund i for a specific style. To obtain the style, we first sort stocks in specific categories (3×3 sort based on MV and B/M ratio using using NYSE breakpoints. We then use a $5 \times 5 \times 5$ sort based on MV, B/M ratio using NYSE breakpoints, and momentum using the prior-year average returns following Daniel et al. (1997). Finally, we use two industry-based sorts using Fama-French 12 and 48 industries. We use Compustat SIC codes to assign firms to industry portfolios. If these are not available, we use CRSP SIC codes.

(Continued)

Table A1. Continued: Variable Definitions

Variable	Definition
ExperienceDummy	Equals to 1 if the manager of fund i is in the top 33%, 25%, or 20% in the distribution of experienced returns (*Experience*) for firm j at a given quarter.
$AggExpRet_{Fund}$	A weighted average of $Experience_{i,j,t}$ at the fund level i in a given quarter t, where the weights are proportional to the fund's holdings in stock j.
$AggExpRet_{Firm}$	A weighted average of $Experience_{i,j,t}$ at the firm level j in a given quarter t, where the weights are proportional to the holding by each fund in firm j.
active share	The difference of portfolio holding of firm j by the manager of fund i at period t relative the benchmark index weight (Cremers and Petajisto 2009) obtained from the authors' website (http://www.petajisto.net/data.html). $$AS_{i,t} = \frac{1}{2}\sum_{j=1}^{N} \lvert w_{i,j,t} - w_{index,j,t} \rvert.$$
ChangeShares	The percentage change in shares held by the manager of fund i in stock j from period $t-1$ to t adjusted for stock splits.
flow	The percentage change between quarter t and quarter $t-1$ of total net assets after taking into account the manager of fund i's returns both obtained from CRSP: $$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + Ret_{i,t})}{TNA_{i,t-1}}.$$
fund return	Fund i's quarterly returns computed from monthly returns reported by CRSP.
manager tenure	The number of months since the manager of fund i first appeared in the Morningstar database.

(Continued)

Table A1. Continued: Variable Definitions

Variable	Definition
performance (fund alpha)	The difference between the fund's realized quarterly return in quarter t and the fund's expected return at t, as obtained using the Carhart four-factor model. To obtain factor loadings, we use 24 months returns of past fund return data ending in t-1. Then, using these loadings and factor realization at time t, we estimate the fund's expected return, which we subtract from the realized return.
%Style	The portion of total net assets invested by the manager of fund i in the style category of firm j (along MV and B/M 3×3 dimensions), as in Cohen et al. (2008).
style (fund)	Fund i style category as reported by Morningstar along the a 3×3 MV and B/M classification.
team	A dummy that takes the value 1 if fund i is managed by a team of managers at time t and 0 otherwise.
TNA	The total net assets of fund i in quarter t as reported by CRSP.
tracking error	The standard deviation of the difference between the fund's return and the fund's benchmark index return (Cremers and Petajisto 2009) obtained from the authors' website (http://www.petajisto.net/data.html): $$TE_{i,t} = \sigma(\lvert R_{i,t} - R_{index,t}\rvert).$$
turnover	The minimum of aggregated sales or aggregated purchases of securities obtained from Thomson Reuters divided by the total net assets of the manager of fund i as reported by CRSP: $$turnover_{i,t} = \frac{min(\lvert sales_{i,t}\rvert, \lvert purchases_{i,t}\rvert)}{TNA_{i,t}}.$$

(Continued)

Table A1. Continued: Variable Definitions

Variable	Definition
MV	The total market capitalization of firm j at quarter t as reported by CRSP (number of shares multiplied by the closing price).
B/M	The ratio of the book value of firm j at quarter t to the market capitalization. We compute the book value from Compustat using deferred taxes and investment tax credit added to total shareholders equity and subtract the book value of preferred stock. If the shareholders' equity is not available, we use the sum of common and preferred equity and if these are not available, we use total assets minus total liabilities as shareholders' equity. For market capitalization. we use CRSP outstanding shares multiplied by the closing price and we adjust for stock splits.
illiq (Amihud)	The absolute value of the firm j's daily stock return over the trading volume as reported by CRSP averaged over period t: $$illiq_{j,t} = \frac{1}{T}\sum_{d_t}\frac{\lvert r_{j,d_t}\rvert}{vol_{j,d_t}}.$$
own	The portion that the manager of fund i owns in firm j with respect to the firm's total number of shares outstanding as reported by Thomson Reuters and CRSP.
ret	Quarterly stock returns of firm j computed from monthly returns reported by CRSP.
SUE	The standardized unexpected earnings using the seasonal random walk model following Livnat and Mendenhall (2006), where $SUE_{j,t} = \frac{Ear_{j,t}-Ear_{j,t-4}}{P_{j,t}}$, where $Ear_{j,t}$ is earnings per share before extraordinary items for firm j at quarter t, and $P_{j,t}$ is the stock price for firm j at the end of quarter t.

Table A.2: Correlations of Model Variables

This table presents correlation measures between the performance regression's independent variables: the value-weighted average of the experience measure, which is an exponentially weighted moving average of past stock returns experienced by the manager of fund i on stock j from the time he started investing in it until period $t-1$ with a parameter (rate of decay ϕ) fixed here at 0.31. When funds are team-managed, we average experience weighted by the tenure of the team members. Other variables include *active share*, total net assets (TNA), *fund age*, net fund $flows$, *manager tenure* (we take an equally-weighted average for team-managed funds), *turnover* ratio, a *team* dummy variable, and *fund return* at quarters t-1, t-2, t-3, and t-4.

	AggExpRet	*active share*	*flow*	*age*	*TNA*	*turnover*	*manager tenure*	*team*	*fund return*$_{t-1}$	*fund return*$_{t-2}$	*fund return*$_{t-3}$	*fund return*$_{t-4}$
AggExpRet	1											
active share	0.141	1										
flow	0.105	0.034	1									
age	-0.056	-0.036	-0.171	1								
TNA	-0.043	-0.178	-0.033	0.257	1							
turnover	0.199	0.209	-0.081	-0.053	-0.099	1						
tenure	-0.138	0.023	-0.107	0.238	0.183	-0.023	1					
team	-0.028	-0.004	-0.020	0.039	0.005	0.033	0.101	1				
fund return$_{t-1}$	0.406	0.035	0.140	-0.016	-0.001	0.060	-0.105	-0.025	1			
fund return$_{t-2}$	0.259	0.039	0.127	-0.020	0.004	-0.029	-0.103	-0.021	0.073	1		
fund return$_{t-3}$	0.166	0.042	0.095	-0.019	0.008	-0.023	-0.075	-0.014	0.069	0.066	1	
fund return$_{t-4}$	0.130	0.043	0.066	-0.017	0.010	-0.028	-0.055	-0.009	0.028	0.104	0.019	1

Table A.3: Experienced Returns and Teams

This table presents the results of the effects of managers' experienced stock returns on investment decisions for funds of different team size. We rank funds at each quarter into large (top 50%) and small (bottom 50%) teams after removing all single-managed funds. The dependent variable is the weight invested by the manager of fund i on stock j at quarter t adjusted for changes due to prices increase during buy-and-hold periods. The main independent variable is the experience measure, which is an exponentially weighted moving average of past returns experience by the manager of fund i on stock j from the time he started investing in it until period $t-1$, where the parameter (rate of decay ϕ) represents the weight on the most recent return. We estimate ϕ by selecting the model that minimizes the regressions' sum of squared residuals using a tightly spaced grid for ϕ. We average experience weighted by the tenure of the team members. Fund controls include the previous quarter's natural logarithm of total net assets (TNA) at time, the natural logarithm of the *fund's age* in months, net fund $flows$, *manager tenure* (we take an equally-weighted average for team-managed funds), *turnover* ratio, and the fund Carhart four-factor alpha. Firm controls include the natural logarithm of size (market value of equity; MV), the natural logarithm of book-to-market (B/M) ratio, and stock return (ret) at t-1, t-2, t-3, and t-4. All specifications include an unreported intercept. Standard errors are clustered by firm $\times$ time (quarter). t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

	Small	Large	Diff (L-S)
Avg Team Size	2.31	12.29	
	(1)	(2)	
$Experience_{i,j,t-1}$	0.013***	0.017***	0.004***
	(10.29)	(15.01)	(3.82)
Fund Controls	YES	YES	
Firm Controls	YES	YES	
Fixed Effects	Style x Time	Style x Time	
Parameter	0.22	0.29	
# Obs.	1,824,507	1,784,755	
Adj R^2	0.275	0.219	

Table A.4: Style-Level Experience and Tenure

This table presents the results of the effect of experienced returns on investment decisions at the style level, following the procedures explained in the note to Table 2. The dependent variable is $Weight^{adj}_{i,j,t}$, averaged equally for specific styles for fund i and quarter t. The key independent variable is *TW-Experience*, value-weighted averaged at the style level. *TW-Experience* is our alternative measure for experienced returns, following Malmendier and Nagel (2011), which allows managers with shorter tenures to exhibit a stronger recency effect (*TW-Experience*). We consider four different style categorizations: a split of all stocks according to MV and B/M (3×3 sorts) (column (1)), a categorization based on Daniel et al. (1997), where stocks are sorted in 5 × 5 × 5 portfolios based on MV, B/M and return momentum (column (2)), and industry categorizations using 12 or 48 industries, using Fama/French definitions (columns (3)-(4)). All specifications include a style × time fixed effect, a fund fixed effect and an unreported intercept. For definitions of the variables, see Table A1 in the Appendix. Standard errors are clustered at the style × time level. t-statistics are reported in parentheses. All continuous independent variables are divided by their sample standard deviations. ***, **, and * indicate statistical significance at the 1%, 5% and 10% confidence level respectively.

	Morningstar	DGTW	F-F 12 Industries	F-F 48 Industries
	(1)	(2)	(3)	(4)
$TW\text{-}Experience_{i,s,t-1}$	0.067***	0.059***	0.066***	0.074***
	(16.04)	(65.81)	(35.12)	(62.05)
Controls	YES	YES	YES	YES
Fixed Effects	Style x Time	Style x Time	Industry x Time	Industry x Time
Fixed Effects	Fund	Fund	Fund	Fund
Parameter	4	4	3.9	3.7
#Obs	255,468	2,180,365	659,179	1,452,521
Adj R^2	0.489	0.461	0.467	0.449

Appendix B

Additional Tables for Chapter 4

Example of N-CSR content:

US equity markets rose overall during the period, benefiting from mostly upbeat economic data and better US corporate earnings. Markets were also supported in 2017 by the prospect for reforms in the European Union with Emmanuel Macrons election as Frances president, the Federal Reserve's indication of gradual rate hikes and the passage of the US tax reform bill. However, concerns about political uncertainties in the US, tensions between the US and North Korea, and the progress of the US tax reform bill curbed market sentiment at times. After reaching new all-time highs in January 2018, US stocks declined in February amid concerns that strong economic growth and rising inflation would lead the Federal Reserve to increase its target rate faster than expected. In March, markets were pressured further by a broad sell-off in information technology stocks due to a potential for tighter regulation in the sector arising from concerns about consumer data privacy. The Trump administrations protectionist policies and escalating trade tensions between the US and China also dampened investor sentiment.

Franklin Templeton Fund, 2018 Annual Shareholders' Report

Table B.1: Document Economic Uncertainty, Morningstar Ratings, and Fund Flows
This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty. *EU* (Economic Uncertainty) is measured following Baker et al. (2016). All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely Morningstar ratings, *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$EU_{i,t-1}$	0.017	0.028*	0.028*	0.030**
	(1.08)	(1.92)	(1.96)	(2.07)
$rating_{i,t-1}$	0.045***	0.105***	0.107***	0.111***
	(5.51)	(11.37)	(11.42)	(11.65)
$\ln(fund\ age_{i,t-1})$		0.002	0.004	0.007
		(0.09)	(0.14)	(0.27)
$\ln(TNA_{i,t-1})$		-0.393***	-0.395***	-0.402***
		(-14.89)	(-14.79)	(-14.86)
$flow_{i,t-1}$		0.025***	0.024***	0.025***
		(2.74)	(2.61)	(2.69)
$fund\ return_{i,t-1}$		0.092***	0.092***	0.035*
		(6.33)	(6.25)	(1.82)
$turnover_{i,t-1}$			0.005	0.001
			(0.51)	(0.11)
$expense_{i,t-1}$			0.012	0.004
			(0.38)	(0.14)
$alpha_{i,t-1}$				0.036***
				(5.19)
$alpha^2_{i,t-1}$				-0.003
				(-0.58)
$beta_{i,t-1}$				0.047***
				(5.02)
Year FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
# Obs	9577	9577	9522	9424
Adj R^2	0.288	0.362	0.363	0.366

Table B.2: Relative Document Economic Uncertainty and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their relative document's uncertainty. *Relative EU* (Relative Economic Uncertainty) is measured following Baker et al. (2016) and adjusted by the average document uncertainty within each fund style category as defined by Morningstar style categories. All regressions include fund and year fixed effects. I control for lagged fund-level characteristics, namely *alpha* and squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *expense* ratio, yearly fund *flow*, the natural logarithm of *fund age* , annual fund returns, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund-year. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Relative\ EU_{i,t-1}$	0.024***	0.019**	0.020**	0.021**
	(3.51)	(2.13)	(2.23)	(2.33)
$\ln(fund\ age_{i,t-1})$		-0.028*	-0.026	-0.033*
		(-1.68)	(-1.52)	(-1.93)
$\ln(TNA_{i,t-1})$		-0.298***	-0.301***	-0.306***
		(-18.35)	(-18.02)	(-18.17)
$flow_{i,t-1}$		0.043***	0.044***	0.041***
		(6.88)	(6.88)	(6.52)
$fund\ return_{i,t-1}$		0.139***	0.142***	0.033*
		(10.13)	(10.30)	(1.82)
$turnover_{i,t-1}$			-0.007	-0.007
			(-1.14)	(-1.17)
$expense_{i,t-1}$			-0.014	-0.023
			(-0.64)	(-1.02)
$alpha_{i,t-1}$				0.073***
				(9.97)
$alpha^2_{i,t-1}$				-0.008*
				(-1.70)
$beta_{i,t-1}$				0.004
				(0.49)
Year FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Style-Year FE	Yes	Yes	Yes	Yes
# Obs	22573	19208	19072	18907
Adj R^2	0.283	0.354	0.355	0.362

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