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Essays on Index Funds and Actively Managed Funds

DISSERTATION

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in Management

by

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DEDICATION

To

my parents and friends

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ABSTRACT OF THE DISSERTATION

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Professor Lu Zheng, Chair

Motivated by the increasing importance of passive investment, we first compare index funds with actively managed funds and study the trading performance of index funds. Then we explore the implication of mutual fund trading on stock price efficiency. Finally, we investigate the risk disclosure of mutual funds. We document the overlap and differences between actively managed funds and index funds and show that index funds could be active. Index fund trades lose money in general, specifically, stocks bought by index funds on average underperform stocks sold by index funds in subsequent periods. We also find that stocks traded by both actively managed funds and index funds experience efficiency improvement in the subsequent quarter, but in different ways. Stocks traded by actively managed funds exhibit more random walk patterns than those traded by index funds, while trades by index funds improve liquidity and the incorporation of market information. Finally, we show that most disclosed risks by mutual funds in their summary prospectus can be linked to meaningful and well-known academic risk factors. Our findings suggest that disclosed risks in general reflect a large proportion of funds' investment risks but with substantial cross-fund heterogeneity.

Keywords: index funds, actively managed funds, risk, efficiency, disclosure, trading motivation

CHAPTER 1

Introduction

Mutual funds are one of the most popular investment vehicles in the U.S. At the end of the year 2019, U.S. domestic equity mutual funds accounted for 30% of U.S. stock market capitalization. Approximately 50 percent of U.S. households invest in mutual funds as a way to save for retirement, education, and other purposes. [1] As a result, individuals' fund investment decisions have large implications for individual and public welfare.

Within the universe of equity mutual funds, index funds were offered later than actively managed funds. The first index fund was formed in 1976 by the Vanguard Group. In recent decades, investors have switched their interest from actively managed funds to index funds dramatically. Morningstar reported on August 31, 2019 that for the first time ever, index funds were managing more money than actively managed funds. Passively managed U.S. equity funds had assets under management of $4.271 trillion, while actively managed funds had $4.246 trillion.[2] Therefore, it is important for investors' welfare to understand the performance and investment behavior of index funds, as well as the difference and similarity between actively managed funds and index funds.

We study three main questions in this dissertation. We first compare index funds and actively managed funds and examine the trading performance of index funds. Then we continue to explore the implication of mutual fund trading on price discovery in the financial market. Lastly, we switch the gear from return to risk and investigate mutual fund risk disclosure in their summary prospectus.

[1] In 2019, 46.4 percent of the households in the United States owned mutual funds. Jennifer Rudden, "Share of households owning mutual funds in the U.S. 1980-2019," May 7, 2020, https://www.statista.com/statistics/246224/mutual-funds-owned-by-american-households/

[2] As of Aug 31, 2019

Motivated by the different investment goals of index funds and actively managed funds, we start with the comparison between the two types of funds and then study the trading performance of index funds. Index funds try to match the performance of a specific market benchmark. In contrast, active funds try to beat their benchmark. Given these different investment goals, the two types of funds naturally have different trading strategies and investment behaviors. Index funds buy all (or most) stocks in the index they are tracking while active funds pick stocks. Presumably, active funds trade on information and they are able to improve price discovery; index funds do not. The literature on active fund performance and investment behavior is extensive, but our understanding of the investment behavior of index funds is still limited. Given this background, we first document the differences and overlap between index funds and actively managed funds, and then examine the trading performance of index funds.

Surprisingly, we find that index funds are not always less active than actively managed funds, measured by active share (the deviation in fund holdings from the fund's benchmark), and turnover ratio (how fast a fund replaces its entire portfolio). Nevertheless, the holdings of index funds and active funds have different characteristics. Performance is heterogeneous and persistent among index funds, and their performance can be negatively predicted by their expense and turnover ratios. Finally, we show a novel finding that trading by index funds loses money in general. Specifically, stocks bought by index funds on average underperform stocks sold by index funds.

After understanding the performance and trading behavior of index funds, we want to study the implication of mutual fund trading on stock price discovery in the financial market. In Chapter 3, we study how trading by mutual funds affects the efficiency of stock prices. More importantly, we compare the trading effects of actively managed funds with those of passively managed (index) funds.

We find that both actively managed fund trading and index fund trading are positively correlated with the price efficiency of the stocks they trade, but in different ways. Actively managed fund trading is associated with stock price efficiency improvement, in terms of random walk pattern, but index fund trading improves the incorporation of market and industry information more than actively managed fund trading.

Risk and return are the two most important factors in making investment decisions, and we study actively managed funds and index funds from the perspective of return in Chapter 2 and Chapter 3. In Chapter 4, we switch our focus to the other important topic, which is less discussed in the literature: risk. In order to invest wisely, investors need access to accurate and adequate fund information to make their decisions. So far, required disclosures, fund ratings, and academic research have focused more on fund returns (or risk-adjusted returns) than on risk. However, asset allocation, which builds on appropriate risk assessment, is most important in determining the long-term outcome of an investment portfolio.[3] Investors rely primarily on a fund's prospectus to provide information about the fund's risks. They need to know how much risk and what types of risk they are assuming when investing in a mutual fund. Do funds' risk disclosure statements accurately reflect their actual investment risks? Chapter 4 aims to answer the question by analyzing the text of the summary prospectus. The answer to this question has significant implications for investors and regulators.

In Chapter 4, we first try to understand the meaning of the disclosed risks in an academic context. Our evidence suggests a good correspondence between the industry and academic perspectives on risk. In our main test, we examine the quality of fund disclosure and show that risk disclosures by mutual funds in general explain a large proportion of the risks in funds' actual

[3] For example, see Ibbotson and Kaplan (2000). The substantial noise in asset returns and limited empirical evidence on the investment skills of fund managers further strengthen the importance of asset allocation decisions.

investment strategies. At the same time, we observe cross-sectional heterogeneity across funds in the risk coverage. As a result, we then test the correlation between risk coverage with fund characteristic and future performance and risk level. We document that younger funds, larger funds, riskier funds, funds with higher expense ratios, and funds with inferior performance tend to make more comprehensive disclosures. Investors' flow does not respond to our risk coverage measure, but funds that disclose uncommon risks tend to attract less flow in the subsequent quarter.

In the three main research chapters, we study index fund trading performance, implication of mutual fund trading on price discovery in the financial market, and mutual fund risk disclosure. The rest of this chapter discusses about the introductions in more details for the three main research chapters.

1.1 Trading to Lose—An Analysis of Index Fund

This chapter starts with a bird's-eye view of the differences and overlap between index funds and actively managed funds. In this chapter we study U.S. open-ended domestic diversified equity mutual funds and compare the activeness, performance, and holdings characteristics of the two types of funds. We find that some index funds are even more active than some actively managed funds, measured by both active share and turnover ratio. A closer examination shows that, more than 80% of index funds have an active share that overlaps with that in actively managed funds and 26.45% of index funds have a turnover ratio higher than the median active fund. The active share has evolved differently over time for the two types of funds. It was quite stable for active funds from 2000 to 2017; among index funds, however, the average active share increased from around 0.2 to almost 0.4.[4] As index funds have become more popular in recent years, their holdings have deviated more from the benchmark as well. Also, index funds have replaced their

[4] Active share data are from 2000 because one of the benchmark index constituents are available since 2000.

holdings more quickly in recent years. The average turnover ratio of index funds surpassed that of active funds around the year 2001.

Then we compare the performance of actively managed funds and index funds, including raw returns, CAPM alpha, 3-factor alpha (Fama and French (1993)), and 4-factor alpha (Carhart (1997)). Both actively managed funds and index funds earn positive raw returns, but the magnitude is higher for index funds. Moreover, actively managed funds earn significantly negative alpha, while index funds earn insignificant alpha. The findings are consistent with those in the existing literature.

The last part of the bird's-eye view is a comparison of the holdings' characteristics. We document novel findings that the aggregated holdings of index funds are different from those of actively managed funds. Index funds in aggregation tilt toward large stocks and value stocks and are more likely to buy losers and sell winners. However, actively managed funds are more likely to hold small stocks and to buy winners and sell losers. The aggregated index portfolio earns zero alpha, while the aggregated active portfolio earns significantly negative alpha, consistent with the cross-sectional average.

We then zoom in to a fund-level analysis to examine performance heterogeneity and performance predictors among index funds. We restrict the sample to S&P 500 index funds in order to rule out heterogeneity due to different benchmarks, and therefore the tests are more conservative regarding fund heterogeneity. As is similarly documented in (Carhart (1997)) for actively managed funds, better performers among S&P 500 index funds generate higher CAPM alpha, 3-factor alpha, and 4-factor alpha in the next year. However, unlike in actively managed funds, the spread between the top performers and the bottom performers is similar in magnitude measured by CAPM alpha and measured by 4-factor alpha, consistent with the finding that index funds do not follow a momentum strategy. Across the S&P 500 index funds, surprisingly, larger funds tend to generate higher 4-factor alpha in the following year, which is different from the decreasing returns to scale documented for actively managed funds. This finding is consistent with the hypothesis that when the fund is larger, the management fee per dollar under management is smaller. Besides size, expense ratio and turnover ratio negatively predict future performance. Turnover ratio also has a U-shape relation to future performance. The best performers and the worst performers have a higher turnover ratio, and the median performers have a lower turnover ratio.

The negative predictability of the turnover ratio naturally leads to the study of S&P 500 index fund trades. We then further zoom in to study the performance of fund trades. We examine the performance of a buy-minus-sell portfolio subsequent to each trade measured by 4-factor alpha and DGTW return (Daniel et al. (1997)). In general, S&P 500 index fund trades lose money. A buy-minus-sell portfolio on average earns -1.39% 4-factor alpha and -1.12% DGTW return in the subsequent quarter for each trade, -2.47% 4-factor alpha and -2.31% DGTW return in the subsequent year for each trade. All of these trading subsequent performances are significant at the 5% level. It is well documented that index funds in general perform better than actively managed funds, and that stocks bought by active funds outperform stocks sold by active funds (Chen, Jegadeesh and Wermers (2000)). However, it is surprising to find that stocks bought by index funds underperform stocks sold by index funds. Even though index funds in general perform better, their trading activities harm the performance.

We further test the performance of trades with different motivations. We assign the trades to three categories by motivation: index reconstitution-motivated trades, flow-driven trades, and managers' discretionary trades. When the S&P 500 index rebalances quarterly, S&P 500 index funds must trade accordingly to minimize tracking errors. We divide the rest of the trades into flow-driven trades and managers' discretionary trades. Flow-driven trades refer to buys when the manager has excess cash in hand and sells when the manager faces a sudden redemption. Discretionary trades are manager's voluntary trades. For each motivation type, we examine the performance of buy-minus-sell portfolios. We find that flow-driven trades lose money. Reconstitution-motivated trades lose money over the one-month and one-quarter horizons but recover over the one-year horizon. Among the different motivations, the magnitude of loss is the highest for reconstitution-motivated trades in the short run.

1.2 Mutual fund trading and stock price efficiency

As index funds become more popular in recent decades, there are concerns about the price efficiency of stock market when passive funds become larger and larger. Figure 1.1 presents the time series of mutual fund dollar flows from 1993 to 2016.[5]

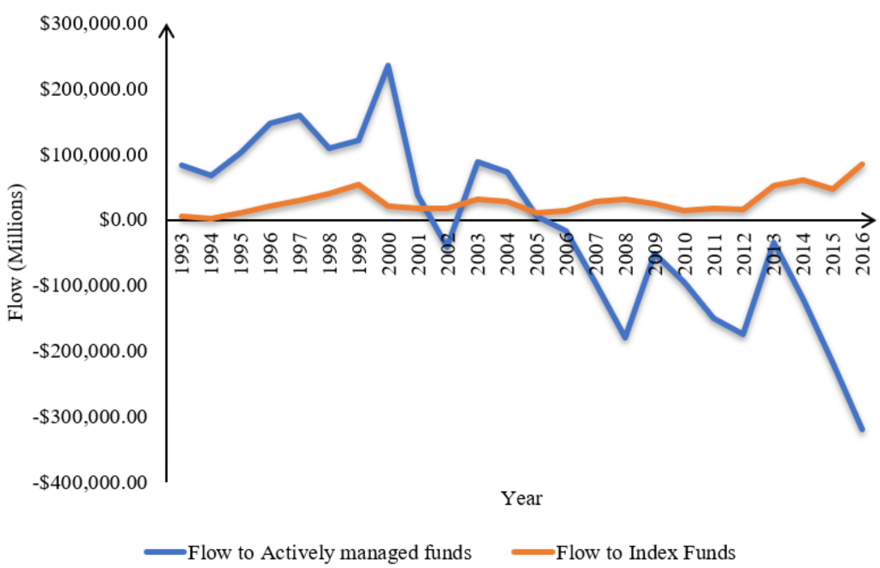

Figure 1.1 Flow to Actively Managed Funds and Index Funds

[5] Data source is Investment Company Institute.

Figure 1.2a and Figure 1.2b present the time series of efficiency measures from 1992 to 2016. A natural question is that when more money is passively invested what happens to the efficiency of asset prices.

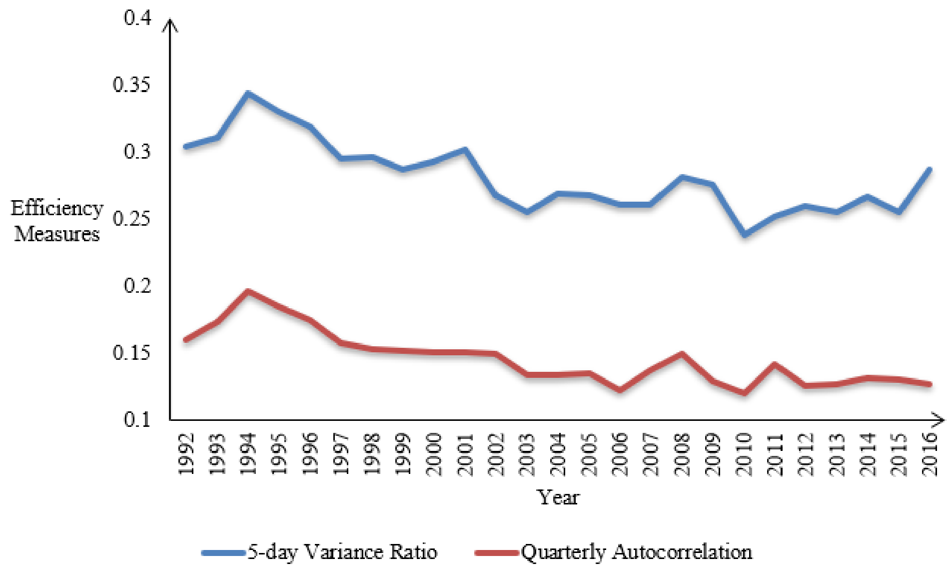

Figure 1.2a Time Series of Stock Efficiency Measures (VR and AR)

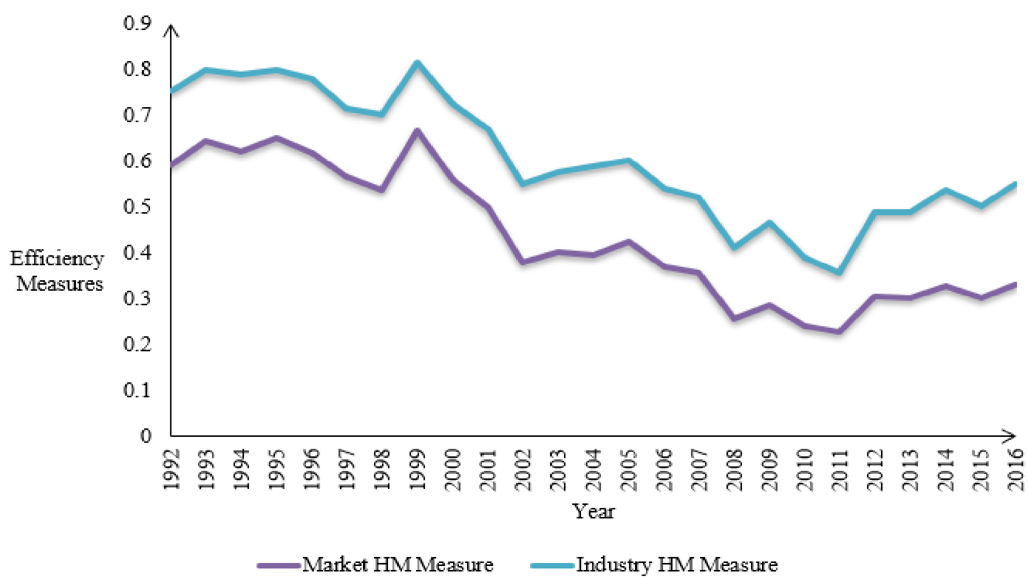

Figure 1.2b Time Series of Stock Efficiency Measures (HM measures)

The measures capture stock price inefficiency, therefore, the smaller the value, the more efficient the stock price. Overall, the stock price efficiency is improving over time, but after about 2006, the improvements in 5-day variance ratio (VR_5) and quarterly autocorrelation (AR_q) are much less obvious. Figure 1.1 and 1.2 combined seem to suggest that when more money is invested in passively managed funds, stock market may behave less like a random walk, but improvements in price delay to market and industry information do not slow down.

To empirically test the relation between stock price efficiency and the mutual fund trading, we derive three main measures for stock price efficiency, variance ratio (VR) (Campbell and Mankiw (1987), Lo and MacKinlay (1988), Campbell, Lo, and MacKinlay (1997)), return autocorrelation (AR) and HM measures (Hou and Moskowitz (2005) and Hou (2007)). All the measures are derived from weak form efficiency.

We find that both actively managed fund trading and index fund trading are positively correlated with efficiency measures. Active trading improves VR and AR more, however, index fund trading improves HM measures more. The positive association with stock price efficiency is not due to holding effect. Holding effect means that stocks that have experienced efficiency improvement just because they are included in a mutual fund holding portfolio. Investors and analysts may pay more attention to stocks in a mutual fund portfolio and such stocks have more information production and therefore their prices are more efficient. If this is the case, stock price efficiency improvement should be only associated with mutual fund buy activities instead of sell activities. To rule out such holding effect, we further look at buy and sell separately and find that both buy and sell activities are positively correlated with stock price efficiency improvement.

In the tests of random walk (VR and AR), the index fund trading effects become insignificant when adding illiquidity measure (Amihud (2002)), however the effects of actively managed fund trading survive. It implies that index fund trading improves stock price efficiency by providing liquidity. A further test using illiquidity measure as a dependent variable confirms this hypothesis.

Knowing that mutual fund trading is associated with stock price efficiency improvement, a natural question to ask is what kind of stocks are more likely to enjoy such improvement. We use analyst coverage to proxy information asymmetry and conduct regressions including an interaction term between mutual fund trading and analyst coverage. The result demonstrates that efficiency improvement effect is stronger for stocks with lower analyst coverage, or the stocks with higher information asymmetry. Another surprising finding is that even index fund trading does not show significant effect on variance ratio and return autocorrelation, the coefficient of the interaction term is significant, implying that index fund trading may incorporate some information (not just market and industry information in the HM test) as well.

Trading motivation also matters. For actively managed funds, information-driven trades are associated with more efficiency improvement than flow-driven trades. For index funds, the liquidity trades due to change in index constituents are negatively associated with efficiency improvement.

Finally, we test whether index fund trading incorporates information. We find that trades by index funds with higher active share improve efficiency more. However, trades by active funds with high active share have little effect, probably due to the fact that actively managed funds with high active share could be both skilled and unskilled.

1.3 Do Mutual Funds Walk the Talk?

This part examines risk disclosures in funds' summary prospectuses to determine whether funds accurately disclose their risks. What risk factors do funds disclose? While a large academic literature has identified numerous risk factors (a phenomenon dubbed “factor zoo” by Cochrane (2011)), there is no systematic study of what risk factors are deemed important by the investment industry. We start our analysis by using textual analysis to document various risks disclosed by mutual funds in their summary prospectuses. We also report their relative disclosure frequency and changes in the disclosures over time. Some disclosed risks are prevalent in disclosures—for example, “active investment risk” and “market risk”. Other disclosed risks are less common and only pertain to specific types of funds—for example, “arbitrage risk” and “micro-cap risk”. The relative frequency of the disclosed risks remains quite stable over our sample period. A few disclosed risks, such as “foreign investment” and “liquidity”, are disclosed by more funds in recent years than in earlier years.

Next, we try to understand the meaning of the disclosed risks in an academic context. For each disclosed risk, we begin by proposing a corresponding risk factor that makes the most economic sense. We then regress the return of the disclosed risk, which is the return of a portfolio of funds that disclosed the specific risk minus the return of a portfolio that did not disclose this risk, on all the proposed academic risk factors. We map each disclosed risk to the three most significant risk factors. The resulting mapping is largely consistent with our economic intuition. For example, “equity risk” is mapped to stock market beta; “growth investing risk” is mapped to the Fama-French HML factor. Thus, our evidence suggests a good correspondence between the industry and academic perspectives on risk.

In our main test, for each fund we examine the quality of fund disclosure. To assess the coverage of the overall risk disclosure, we estimate what proportion of variations in actual fund returns can be explained by a fund’s disclosed risks. We then compare this proportion with the proportion that can be explained by all risks disclosed by all funds. We call the ratio of the two proportions the "risk coverage ratio" (RCR). The higher the explained proportion, the higher the overall risk disclosure coverage is. To proxy for the returns of disclosed risks, for each fund we construct the return of a specific risk as the return of the portfolio of all other funds that disclosed the risk minus the return of the portfolio of funds that did not disclose this risk. We find an overall RCR of 80 percent. In addition, we observe large cross-fund variation in RCR. This finding shows that risk disclosures by mutual funds in general explain a large proportion of the risks in funds' actual investment strategies.

A 2019 SEC proposal emphasizes ordering the risks by importance and providing a concise summary of information. To investigate the ordering of disclosed risks, we examine the explanatory power of each fund's first three disclosed risks.[6] For the top three risks, we find an RCR of 67 percent. The findings suggest that the top risks account for a predominant proportion of the return variations relative to all risks.

To examine the conciseness of the disclosure, we develop a measure of overdisclosure that calculates the number of disclosed risks that are not significantly related to fund returns as a percentage of all disclosed risks. The smaller the percentage, the more concise the overall disclosure is. Our estimate shows an average overdisclosure measure of 48 percent, suggesting room for improvement in streamlining the list of risks in the summary prospectus.

Since we observe substantial cross-fund variation in the risk coverage ratio, we examine what types of funds have a higher risk coverage ratio. Using Fama-Macbeth regression, we show that younger funds, larger funds, riskier funds, and funds with higher expense ratios tend to have a higher risk coverage ratio. Interestingly, funds with worse performance also have a higher risk coverage ratio. The performance result is consistent with the hypothesis that disclosure cost is

[6] SEC ADI 2019-08 - Improving Principal Risks Disclosure: https://www.sec.gov/investment/accounting-and-disclosure-information/principal-risks/adi-2019-08-improving-principal-risks-disclosure

lower for managers with less proprietary information or the hypothesis that funds with worse performance disclose more risks to explain their inferior performance.

How does the risk coverage ratio relate to future fund risk and performance? In further analysis, we find that funds with a higher risk coverage ratio exhibit higher risk in the future. We also find that funds with a higher risk coverage ratio exhibit worse performance in the future. These findings are consistent with our earlier results on the determinants of fund disclosure.

In addition, we study whether investors pay attention to the risk coverage ratio. We find that fund flows are not related to past risk coverage. This is not a surprising result because the risk coverage ratio is not easily observable by investors. This finding does not mean that investors do not pay attention to risk disclosure per se, but that they do not react to measures of risk disclosure quality.

Finally, we test whether funds disclose risks in a timely manner. We find in general that the change in risk disclosure improves overall risk coverage. Furthermore, we find that the improvement is higher for returns after the change in disclosure than for returns before the change. However, the magnitude of the effect is not large. These results suggest that funds disclose some risks in a timely manner.

Our analyses help to inform long-lasting and ongoing policy discussions regarding mutual fund disclosure requirements, especially for risk disclosure. In 1995, the U.S. Securities and Exchange Commission (SEC) issued a Concept Release and Request for Comments on "Improving Descriptions of Risk by Mutual Funds and Other Investment Companies," which received much attention (SEC, 1995).[7] In 2009, the SEC adopted amendments to Form N-1A that "will require every prospectus to include a summary section at the front of the prospectus, consisting of key

[7] SEC S7-10-95: https://www.sec.gov/rules/concept/mfrisk.txt.

information about the fund, including investment objectives and strategies, risks, costs, and performance." These amendments are intended to improve mutual fund disclosure by "providing investors with key information in plain English in a clear and concise format." [8] In 2019, the SEC published Accounting and Disclosure Information recommendations, aiming to improve mutual fund risk disclosures for investors.[9] But despite decades of effort by the SEC and others to improve fund risk disclosure, the basic question of whether fund disclosure is informative remains understudied. Using textual analysis of fund disclosure statements, we provide empirical evidence about the overall risk coverage, the coverage of top risks, tailored risk disclosure, as well as conciseness and timeliness of risk disclosure.

This dissertation documents some novel findings for actively managed funds and index funds. We try to provide new insights about differences and similarities between the two types of funds. In addition, we study mutual funds from both return and risk perspectives. In the risk disclosure study, we provide new method and apply textual data to do the analyses. In the rest of this dissertation, Chapters 2, 3 and 4 discuss each of the main studies mentioned above, including literature review, data source, empirical tests and findings, and conclusions. Chapter 5 concludes the whole dissertation.

[8] SEC S7-28-07: https://www.sec.gov/rules/final/2009/33-8998.pdf

[9] SEC ADI 2019-08 - Improving Principal Risks Disclosure: https://www.sec.gov/investment/accounting-and-disclosure-information/principal-risks/adi-2019-08-improving-principal-risks-disclosure

CHAPTER 2

Trading to Lose—An Analysis of Index Fund

This chapter compares actively managed funds and index funds from activeness, overall performance and holding characteristics, and then studies the trading behavior and performance of index funds. As index funds become more popular in recent decades, it is important for investors to understand index funds deeply. Specifically, Chapter 2 studies the following questions: 1. What are the overlap and differences between index funds and actively managed funds in terms of activeness, performance, and holdings characteristics? 2. What drives performance differences among index funds if there is a substantial cross-sectional difference? 3. How do trades by index funds contribute to their performance?

In the rest of Chapter 2, we first discuss the related literature review and data. Then we start from a bird's-eye view to show the overlap and differences between index funds and actively managed funds, then we zoom in to fund view to investigate the general performance of index funds, and finally, we zoom in further to trade view to explore the trading performance of S&P 500 index funds.

2.1 Literature Review

This chapter fits the literature of index funds in a few fields, such as performance persistence (Crane and Crotty (2018)), trading behaviors around index changes (Dunham and Simpson (2010)) and performance predictors (Elton, Gruber and Busse (2011) and Elton, Gruber, and Souza (2019)). Elton, Gruber and Busse (2011) study S&P 500 index funds and argue that investors are not rational in choosing among index funds. The paper documents that S&P 500 index funds' performance can be predicted by their expense ratio. They address the question from the perspective of investors' rationality; however, we focus on the investment behavior of index funds.

This chapter also contributes to other streams of literature. The first stream is about the comparison of performance between active funds and index funds. It is a well-documented empirical finding that the average risk-adjusted return of active funds is inferior to that of index funds (Malkiel (1995), Gruber (1996) and Fama and French (2010)). We uncover evidence consistent with these findings. In addition to the performance difference, we show that index funds and active funds hold different types of stocks.

Many researchers study performance persistence among actively managed funds (Elton, Gruber and Blake (1996), Bollen and Busse (2005), and Kacperczyk, Nieuwerburgh and Veldkamp (2014)). We document performance persistence among S&P 500 index funds. We also discover that, unlike actively managed funds, the performance persistence among index funds cannot be explained away by the momentum factor.

There is also a rich literature on performance prediction for actively managed funds. Zheng (1999) documents the "smart money" effect—that is, investor flows positively predict future performance over a short horizon. Frazzini and Lamont (2008) however, find that investor flows negatively predict future performance over the longer horizon, which is known as the "dumb money" effect. Ferson (2010) and Wermers (2011) review the factors that can predict fund performance. Some of the factors are based on fund holdings (Cohen, Coval, and Pastor (2005), Kacperczyk, Sialm, and Zheng (2005) (2008), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), Barras, Scaillet, and Wermers (2010), Amihud and Goyenko (2013) and Jiang and Zheng (2018)). Our study finds that both turnover and expense ratio negatively predict future fund performance for index funds.

We also provide novel evidence on the relation between fund size and performance. Chen et al. (2004) document that fund size is negatively related to future performance. Berk and Green provide theoretical background for decreasing returns to scale for active funds. Interestingly, for index funds, we find increasing returns to scale for S&P 500 index funds: larger index funds tend to generate better performance in the following year.

The relation between turnover and performance is in debate for actively manage funds. Chen, Jegadeesh and Wermers (2000), Dahlquist, M., Engström, S. and Söderlind (2000) and Pastor, Stambaugh and Taylor (2017) document a positive relation. Carhart (1997) and Cremers and Pareek (2016) find a negative relation. Here we document novel evidence that turnover negatively predicts performance for index funds. Moreover, we document strong evidence that stocks purchased by index funds earn significantly lower returns than stocks sold by index funds. This pattern contrasts with the finding regarding active fund trades.

Finally, this chapter relates to the literature on mutual fund trading motivation. Alexander, Cici and Gibson (2007) find that, for actively managed funds, information-driven trades perform better than flow-driven trades. Pomorski (2009) documents that trades with "best idea" outperform. We classify and examine the trading motivation for index funds and provide new insight on how various types of trades contribute to index fund performance.

2.2 Data

The sample in Section 2.3 is U.S. domestic diversified equity mutual funds from 1994 to 2017, and we examine actively managed funds and index funds separately. Mutual fund returns and characteristics are from the Center for Research in Security Prices (CRSP). First, we select domestic equity funds following the method in (Kacperczyk, Sialm and Zheng (2008)). The procedure is as follows: if a share class has a Lipper objective code, then it is selected based on the Lipper objective code. If the Lipper objective is missing, then we select share class based on strategic insight object code; if the strategic insight object code is missing, the fund style is selected according to the Wiesenberger objective code. If all these codes are not available, then domestic equity funds are selected based on policy = "CS." If policy is missing, then share class with equity holdings between 80% and 105% is selected.

After eliminating exchange traded funds (ETFs) in the CRSP dataset, index fund share class is identified by the variable "$Index\_fund\_flag$." An $Index\_fund\_flag$ with a value of D or E implies that the share class is a pure index fund or an enhanced index fund. However, this variable is only available since 2003. For those share classes that cannot be identified by this indicator, we identify index funds by manually checking the fund name or looking up the principal investment strategy section in the prospectus. The sample in Section 2.4 and 2.5 is S&P 500 index funds. From the list of index funds, we select the sample based on either the fund name or the Lipper objective code/ Lipper class. If a fund name includes the key words "S&P 500," "SP 500," or the lower case of those, it is identified as an S&P 500 index fund. Or if a fund has a Lipper objective code of "SPSP," which refers to a fund that is passively managed and commits in its prospectus language to replicate the performance of the S&P 500 index, then it is identified as an S&P 500 index fund. For fund characteristics, load fund share class is identified if a share class charges front-end load fee or rear-end load fee. Share class age is calculated as the number of months starting from the first month when return data are available to the current date. Share class flow is calculated as in Equation (2.1) and Equation (2.2):

$$dollar\_flow_t = TNA_t - TNA_{t-1} \times (1 + Return_t) \tag{2.1}$$

$$flow_t = \frac{dollar\_flow_t}{TNA_{t-1}} \tag{2.2}$$

where TNA_t is the total net assets of the share class at the end of period t and $Return_t$ is the return from period $t-1$ to period t. Percentage flow is calculated as dollar flow standardized by the total assets at the beginning of the period. For funds with multiple share classes, the variables are aggregated at the fund level using the MFlink1 table. Fund size and dollar flow are the sum of the corresponding variables for each share class within the fund. Fund return, turnover ratio, and expense ratio are weighted averages across share classes, with the size at the beginning of the period as the weight. If a share class is identified as a load fund, then the fund is identified as a load fund. Fund age is calculated based on the oldest share class. For non-numerical characteristics, such as fund style, fund name, and index indicator, we use the oldest share class's characteristics as the fund's characteristics. To estimate fund alpha, we require a fund to have a return history of 36 months, and within those 36 months at least 30 observations.

Mutual fund holdings data are from Thomson Reuters. Since 2004, the Securities and Exchange Commission (SEC) has required mutual funds to disclose their holdings every quarter. Before 2004 the requirement was semi-annual, but some funds voluntarily disclosed on a quarterly basis. As a result, we carry each holding to the next "rdate" or 6 months, whichever is earlier, where "rdate" is the date when the holdings are effective. Holdings data are then matched with stock return and price data according to the "rdate." Stock return and price data are from the CRSP as well. Trading is calculated as the difference in holdings between two consecutive quarters. Specifically,

$$stock\_trade_{i,j,t} = Holdings_{i,j,t} - Holdings_{i,j,t-1} \tag{2.3}$$

Equation (2.3) calculates the trades of stock j by fund i from quarter $t-1$ to quarter t. $Holdings_{i,j,t}$ is the number of shares if stock j held by fund i in quarter t. If Equation (2.3) is positive then it is a buy, and if it is negative, then it is a sell. If a fund does not have holdings in quarter $t-1$, then the holdings in quarter t constitute a net buy. If a fund has holdings in quarter t but does not have holdings in quarter $t+1$, then the fund has a net sell in quarter $t+1$.

The last part of data is about historical index constituents. In a later section, we calculate the active share measure proposed by (Cremers and Petajisto (2009)). The indexes we use are mainly from the S&P family and the Russell Family. The S&P family includes the S&P 500, S&P MidCap400, S&P SmallCap600, S&P 500 Growth, and S&P 500 Value. The S&P 500 is widely regarded as the best single gauge of large-cap U.S. stocks. It is further divided into growth style and value style. The S&P 400 provides investors with a benchmark for mid-sized companies. The S&P 600 measures the small-cap segment of the U.S. market. S&P family historical constituents are from Compustat. In the Russell family, the indexes are the Russell 1000, Russell 2000, Russell 3000, and Russell MidCap indexes, and the growth and value components of each of the four Russell indexes. That is, we use 12 Russell indexes in total. The Russell index historical constituents are from Bloomberg.

In addition to individual funds, we use the CRSP universe as a benchmark to calculate the active share for the aggregated actively managed fund portfolio and the index fund portfolio. The CRSP universe stocks include all common stocks with a share code of 10 and 11.

2.3 Bird's-Eye View—Overlap and Differences between Index Funds and Actively Managed Funds

As is well known, index funds and actively managed funds have different goals. Index funds minimize tracking errors with a specific market benchmark, while active funds try to outperform their benchmark. So presumably index funds hold stocks in the same weight as in the benchmark, while active funds pick stocks and time the market using managers' information and expertise. Given this background, one would expect an index fund to closely track an index and to be passive, and an actively managed fund to beat its benchmark. However, it is not always easy to tell them apart just by examining their performance and benchmarks. For example, consider two funds and their benchmark performances extracted from Yahoo Finance. Fund A (and its benchmark) has a one-month return of 6.32% (3.79%), a five-year return of 18.99% (12.84%), and a ten-year return of 19.99% (15.12%). Fund B (and its benchmark) has a one-month return of 1.96% (1.60%), a five-year return of 5.61% (5.22%), and a ten-year return of 8.08% (7.88%). Apparently Fund B tracks its benchmark better and Fund A beats its benchmark. However, Fund A is USAA NASDAQ-100 Index Fund, and Fund B is American Century Strategic Allocation (an actively managed fund). To better understand how index funds are different from actively managed funds, we explore the differences in activeness, performance, and holdings between the two types of funds.

2.3.1 Activeness

In this section we compare the activeness of the active funds and index funds by examining the active share measure, proposed by (Cremers and Petajisto (2009)), and the turnover ratio. Active share is calculated as follows:

$$ActiveShare = \frac{1}{2} \times \sum_{i=1}^{N} \left| \omega_{fund,i} - \omega_{index,i} \right| \tag{2.4}$$

Suppose the fund holds N stocks in total, $\omega_{fund,i}$ is the weight of stock i in the fund, and $\omega_{index,i}$ is the weight of stock i in the benchmark index that the fund is tracking. Active share captures how much the holdings of a fund deviate from the benchmark index.

To calculate the active share for individual funds, we select 17 indexes as well as the CRSP universe as potential benchmarks. To select the benchmarks, we regress the daily return of each fund on the contemporaneous daily returns of each of the 17 potential benchmark indexes. The index with the highest R squared of the 17 regressions is selected as the fund's benchmark. In this way, the benchmark is the one whose performance is tracked most closely by the fund. Once the benchmark for each fund has been identified, the active share is calculated according to Equation (2.4).

The active share and turnover ratio of actively managed funds and index funds have evolved differently over time. For each quarter, we calculate the average active share and turnover ratio within active funds and index funds, then plot the time series in Figure 2.1a and Figure 2.1b.

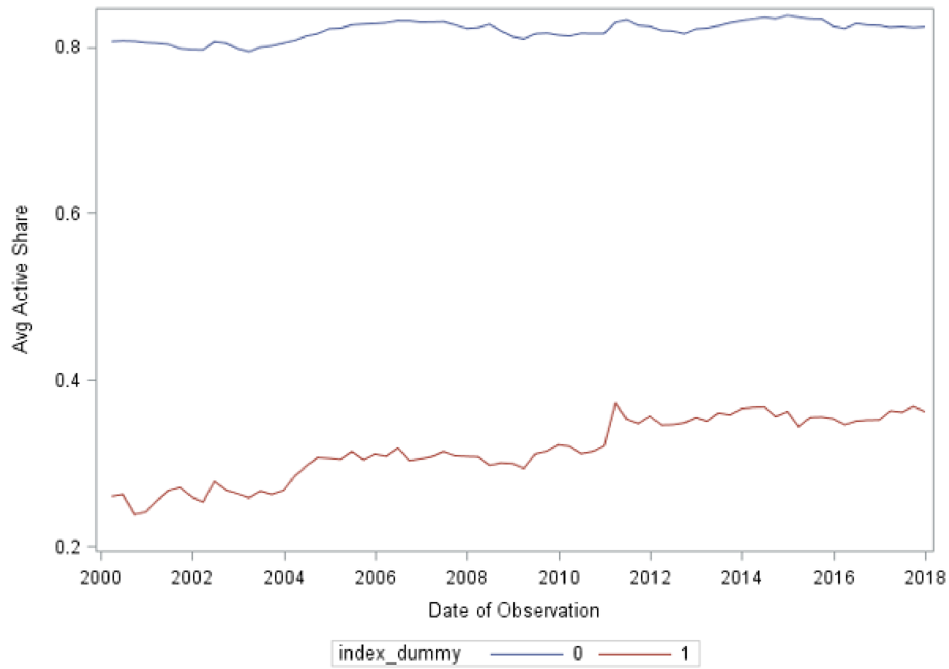

Figure 2.1a Active Share for Actively Managed Funds and Index Funds Over Time

Figure 2.1a plots the average active share. It shows that active funds are quite stable over time, and the active share ranges from 0.7937 to 0.8376. However, index funds' active share increases over time. The average ranges from 0.2382 to 0.3717, and the median ranges from 0.0744 to 0.3645.[10] As index funds have become more popular in recent years, their holdings have deviated more from the benchmark. Turnover ratio is plotted in Figure 2.1b. Early on, index funds' turnover ratio was much lower than that of active funds, but the turnover of index funds has

[10] We calculate the numbers from my sample, but the numbers are not shown in Figure 2.1a.

increased over time and surpassed that of active funds around the year 2011. In more recent years, index funds have replaced their holdings more quickly than they used to.

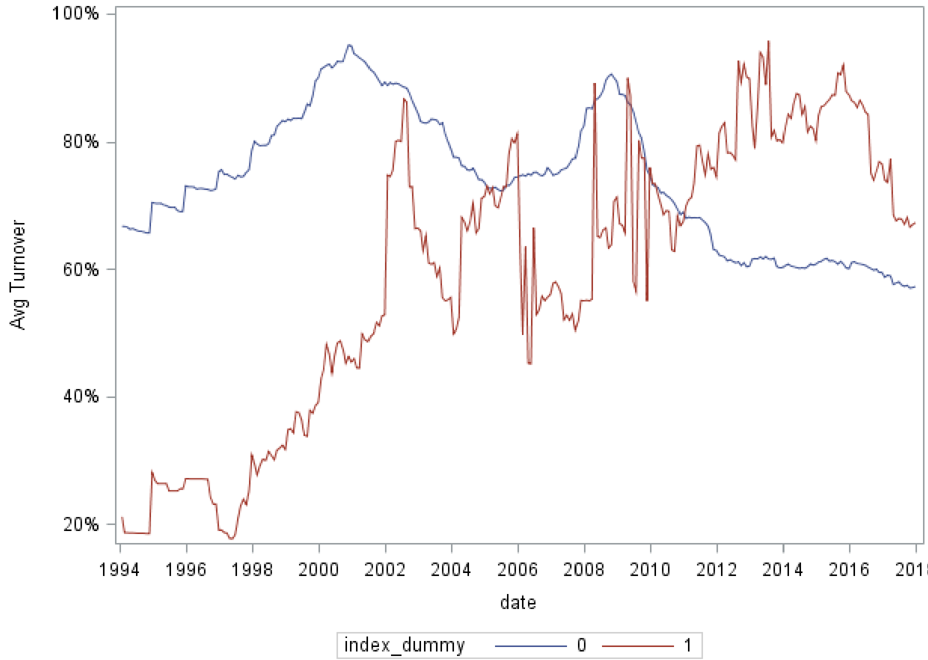

Figure 2.1b Turnover Ratio for Actively Managed Funds and Index Funds Over Time

In addition to the time series evolution, we examine the cross-sectional overlap. A histogram of active share and turnover ratio reveals a clear overlap between the two types of funds. To draw the histogram, we first calculate the average active share and turnover ratio across time for each fund. The histograms are shown in Figure 2.2a and Figure 2.2b. Index funds on average have a lower active share and lower turnover ratio than active funds, but there is large overlap in both figures. Index funds are not necessarily less active than all active funds in the deviations of holdings and holding replacement.

A closer examination of overlap is shown in Table 2.1. The "Median" column in Table 2.1a reports the average cross-sectional median active share and turnover ratio. In addition to examining the individual funds, we calculate the active share for the aggregated actively managed fund portfolio and the index fund portfolio. We first aggregate stock holdings of the individual

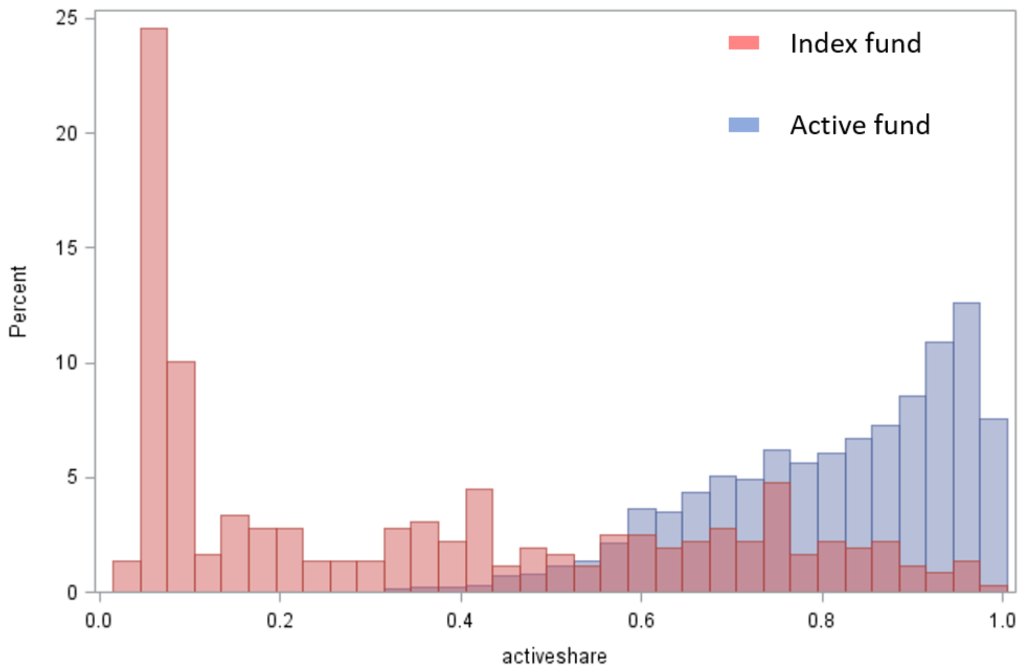

Figure 2.2a Histogram of Active Share for Actively Managed Funds and Index Funds

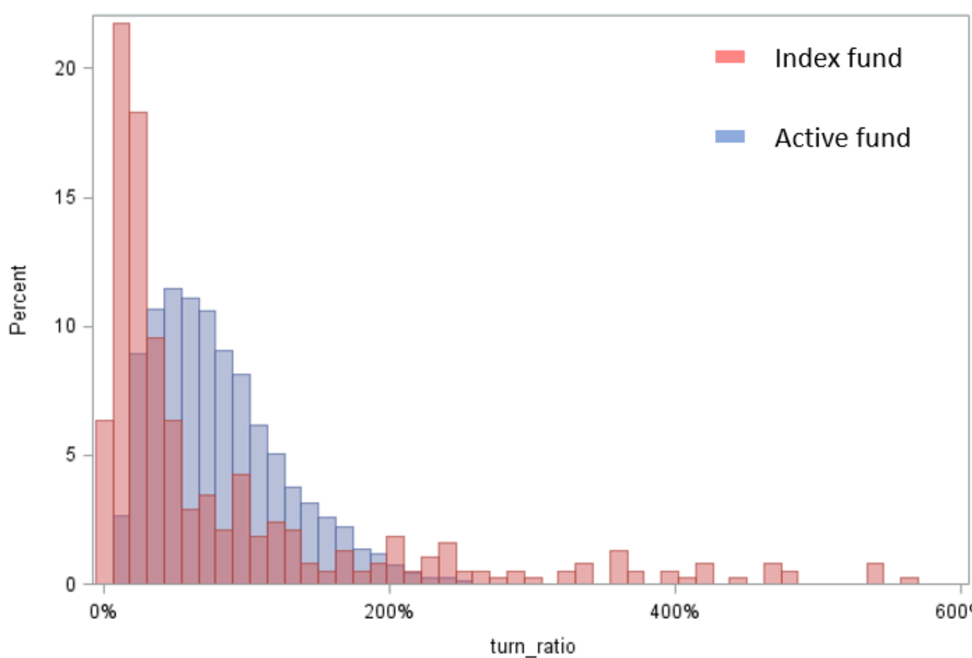

Figure 2.2b Histogram of Turnover Ratio for Actively Managed Funds and Index Funds

funds into an actively managed fund portfolio and an index fund portfolio and treat these two portfolios as super funds; We then calculate the active share for the two portfolios. Since these two portfolios are aggregated from all funds with different benchmarks, the active share is calculated using the CRSP equity universe as the benchmark. The result is shown in Table 2.1a Column "Average of Aggregated Portfolio."

Table 2.1a Active Share and Turnover Ratio Summary Statistics

		Median	Average of aggregated portfolio
Active share	Active funds	84.18%***	22.14%***
	Index funds	21.60%***	12.88%***
Turnover ratio	Active funds	62.01%***	
	Index funds	21.88%***	

The column "Median" reports the time series average of median active share and turnover ratio for actively managed funds and index funds. The column "Average of aggregated portfolio" reports the time series average active share of the two aggregated portfolios. Active share of the aggregated portfolio is calculated using the CRSP equity universe as the benchmark. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

On average, actively managed funds have a median active share of 84.18% and index funds have a median active share of 21.6%. As for the aggregated portfolio, actively managed funds' active share is 22.14% and index funds' active share is 12.88%. Both columns show that, on average, actively managed funds are more active than index funds in terms of holding deviations from their benchmark. The second column shows a smaller number because there is cancelling out in the aggregation. Also, the magnitude of decrease is greater for actively managed funds, meaning that the activeness is more widely dispersed among actively managed funds.

The results in Table 2.1a are consistent with people's prior, but a further examination of the active share and turnover ratios reveals that not all index funds are more passive than actively managed funds. The activeness of the two types of funds overlaps in some respects. We first calculate the minimum, lower quartile, median, upper quartile, and maximum of the active share and turnover ratios in each quarter for actively managed funds and index funds. We compare each individual fund's active share and turnover ratio with these statistics for the other type of funds, and then assign the funds to five groups. Specifically, we compare an index fund's active share and turnover ratio with the statistics for actively managed funds. If the variable is smaller than the minimum, then the index fund is assigned to Group 1; if the variable lies between the minimum and the lower quartile, we assign it to Group 2; Group 3 covers the lower quartile to the median; Group 4 covers the median to the upper quartile; and Group 5 covers the upper quartile to 1. By definition, if an active fund is in Group 1, then this fund is more passive than all index funds. If an index fund is in Group 4 or 5, then this fund is more active than the median active fund. The time series average of the percentage in each group is shown in Table 2.1b and Table 2.1c.

Table 2.1b Matrix of Active Share

	Active funds	Active funds	Active funds	Index funds	Index funds	Index funds
Group	No. of each group	% of each group	Median active share	No. of each group	% of each group	Median active share
[0, min)	1.00	0.05%	5%	22.94	12.16%	6%
[min, P25)	2.75	0.14%	7%	137.13	70.45%	18%
[P25, median)	7.49	0.39%	14%	22.71	11.71%	77%
[median, P75)	200.43	10.46%	53%	8.15	4.23%	89%
[P75,1]	1740.92	89.03%	87%	3.47	1.78%	96%

This table compares the active share for actively managed funds and index funds. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Only 12.16% of index funds' active share is lower than all actively managed funds, meaning that the active share of the remaining 87.84% of index funds overlaps with that of the active funds. Within the overlapping range, 11.71% of index funds lie between the first quartile and the median of active funds, and 6.01% (Groups 4 and 5) of index funds are even more active than the median active fund. In 17.72% of the index funds (those in Groups 3, 4, and 5), the median active share is higher than 0.77, implying that for those funds at least 77% of holdings are different from their benchmark. In terms of turnover ratio, 26.45% of index funds are more active than the median active fund. To sum up, Table 2.1b and Table 2.1c demonstrate that the activeness of index funds is widely dispersed and overlaps with actively managed funds in both holdings deviation from the benchmark and portfolio turnover.

Table 2.1c Matrix of Turnover Ratio

	Active funds	Active funds	Active funds	Index funds	Index funds	Index funds
Group	No. of each group	% of each group	Median turnover	No. of each group	% of each group	Median turnover
[0, min)	39.05	2.21%	2%	13.06	8.96%	2%
[min, P25)	52.44	2.88%	5%	92.14	56.05%	11%
[P25, median)	213.91	11.69%	16%	20.05	12.14%	44%
[median, P75)	737.02	40.33%	44%	14.36	8.35%	79%
[P75, +∞)	757.04	45.08%	120%	33.61	18.10%	251%

This table compares the turnover ratio of actively managed funds and index funds. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

2.3.2 Performance

To examine performance, we first estimate fund CAPM alpha, Fama-French 3-factor alpha, and Carhart 4-factor alpha in rolling regressions. For each month, we estimate factor loadings of the fund using the previous three years' returns, and the alpha is calculated as the difference between the realized return and the expected return implied by the estimated factor loadings. Specifically, the 4-factor alpha is estimated as follows:[11]

$$R_{i,\tau} - rf_\tau = \beta_{01,t} + \beta_{1i,t}\left(R_{m,\tau} - rf_\tau\right) + \beta_{2i,t}SMB_\tau + \beta_{3i,t}HML_\tau + \beta_{4i,t}UMD_\tau + \varepsilon_{i,\tau} \quad (2.5)$$

$$\alpha_{i,t} = \left(R_{i,t} - rf_t\right) - \hat{\beta}_{1i,t}\left(R_{m,t} - rf_t\right) - \hat{\beta}_{2i,t}SMB_t - \hat{\beta}_{3i,t}HML_t - \hat{\beta}_{4i,t}UMD_t \quad (2.6)$$

where $\tau = t - 1$ to $t - 36$. $\hat{\beta}_{1i,t}$, $\hat{\beta}_{2i,t}$, $\hat{\beta}_{3i,t}$ and $\hat{\beta}_{4i,t}$ are estimated from Equation (2.5). We estimate monthly alphas following this procedure. To test the difference in performance

[11] CAPM alpha and 3-factor alpha are estimated similarly.

between actively managed funds and index funds, we calculated the weighted average raw return and three alphas in each month for actively managed funds and index funds, with the fund size at the beginning period as the weight. Then we conduct a *t*-test for the two time series and adjust for Newey-West standard error for 4 lags. The results are shown in Table 2.2.

Table 2.2 Performances of Actively Managed Funds and Index Funds

	Raw return	CAPM alpha	3-factor alpha	4-factor alpha
Active funds	0.7508%***	-0.0716%**	-0.0837%**	-0.1096%***
	(2.91)	(-2.12)	(-2.47)	(-3.34)
Index funds	0.8696%***	-0.0011%	-0.0042%	0.0003%
	(3.22)	(-0.04)	(-0.19)	(0.01)

This table presents the average performance of actively managed funds and index funds. The table shows the results of a *t*-test for the time series performances for actively managed funds and index funds, adjusted for Newey-West standard error. *t*-statistics are reported in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Both actively managed funds and index funds earn significantly positive raw after-fee returns. And index funds' average return is higher than that of actively managed funds. In terms of alpha, actively managed funds on average have negative CAPM alpha and 3-factor alpha at the 5% significance level and negative 4-factor alpha at the 1% significance level. The magnitude is from -0.0716% to -0.1096% monthly. However, index funds earn insignificant alphas across all models. This finding is consistent with the existing literature documenting that actively managed funds on average underperform and index funds on average earn zero alpha.

2.3.3 Holdings' Characteristics

In this section, we examine the differences in overall holdings between actively managed funds and index funds. We first aggregate individual funds into an active portfolio and an index portfolio. The active and index portfolio returns are weighted averages of the returns to individual funds, and the weight is the size of each fund at the beginning of each month. This procedure creates two time series of raw returns for the aggregated portfolios. Then we estimate CAPM, a 3-factor model, and a 4-factor model for each portfolio to obtain the factor loadings. In addition to estimating the models separately, we test the differences in the following equation:

$$exret_{i,t} = \beta_0 + \beta_1 index\_dummy_{i,t} + \beta_2 mktrf_t + \beta_3\left(mktrf_t \times index\_dummy_{i,t}\right) + \beta_4 smb_t + beta_5\left(smb_t \times index\_dummy_{i,t}\right) + \beta_6 hml_t + \beta_7\left(hml_t \times index\_dummy_{i,t}\right) + \beta_8 umd_t + beta_9 \times \left(umd_t \times ndex\_dummy_{i,t}\right) + \varepsilon_{i,t} \tag{2.7}$$

where i represents either the active portfolio or the index portfolio. $index\_dummy_{i,t}$ takes a value of one if the portfolio is an index portfolio. The estimate of β_1 represents the difference in alpha between the index portfolio and the active portfolio. The estimates of β_3, β_5, β_7 and β_9 represent the differences in factor loadings between the index portfolio and the active portfolio. Each estimation adjusts for Newey-West standard error. The result is shown in Table 2.3.

Table 2.3 Factor Loadings of Two Aggregated Super Portfolios: Active Funds vs. Index Funds

Model		Alpha	Market	SMB	HML	UMD
CAPM	Active funds	-0.001**	0.934***			
	Index funds	0.000	0.985***			
3-factor	Active funds	-0.001**	0.923***	0.060***	-0.009	
	Index funds	0.000	1.004***	-0.082***	0.047***	
4-factor	Active funds	-0.001**	0.927***	0.058***	-0.005	0.011
	Index funds	0.000	0.998***	-0.080***	0.041***	-0.015*
4-factor	Active funds	0.001**	0.071***	-0.139***	0.046**	-0.026**
	Index funds	-0.001**	0.934***			

This table reports the alpha and factor loadings of aggregated active and index portfolios. The alpha and factor loadings of different models are reported in the table. The significance adjusts for Newey West standard errors. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.3 first presents the alpha and factor loadings for the active portfolio and the index portfolio across different models and then presents the difference in the 4-factor loadings in the last row. The aggregated active portfolio earns significant negative monthly alphas, while the aggregated index portfolio earns zero alpha. This is consistent with the cross-sectional results. For market factor loading, the index portfolio has a higher value than the active portfolio; the difference is positive and significant. On average, index funds co-move with the market more than actively managed funds. This is consistent with index fund trading, where stocks within an index are more likely to be traded simultaneously and therefore to co-move more closely with the whole market.

In terms of size, the active portfolio has positive and significant loading, whereas the index portfolio has negative and significant loading, and the difference is negative and significant. This result implies that active funds on average hold small stocks while index funds on average hold large stocks. The value factor loadings indicate that index funds hold more value stocks than active funds do. Lastly, momentum factor loading implies that index funds on average are more likely to buy losers and sell winners.

2.4 Fund View—Who Wins

In the rest of this chapter, all the tests focus on S&P 500 index funds. The S&P 500 index is the most commonly followed equity index. We focus on S&P 500 index funds to rule out any heterogeneity across index funds due to different benchmarks; as a result, it is a more conservative sample. In my sample, the average total size of the S&P 500 index funds accounts for half the size of all index funds; as a result, this sample is representative and relevant. Table 2.4 presents the average statistics over time from 1994 to 2017. Even within S&P 500 index funds, the fund characteristics and performances are diverse. On average, the funds earn -0.01% monthly 4-factor alpha. The average size of S&P 500 index funds is $5.04 billion. S&P 500 index funds on average charge a 0.42% monthly fee, and they have an average active share of 0.08. The average flow from investors is positive, and the average turnover ratio is 0.1371. The average return volatility is 0.0383. My sample consists of 59 S&P 500 index funds in an average quarter.

Table 2.4 Summary Statistics of S&P 500 Index Funds

	Mean	Min	P25	Median	P75	Max	StdDev
Raw return	0.0083	-0.0075	0.0080	0.0083	0.0086	0.0267	0.0043
CAPM alpha	-0.0001	-0.0141	-0.0005	-0.0002	0.0000	0.0182	0.0047
3-factor alpha	-0.0002	-0.0163	-0.0006	-0.0003	-0.0001	0.0206	0.0054
4-factor alpha	-0.0001	-0.0184	-0.0005	-0.0002	0.0001	0.0214	0.0058
Size	5.0363	0.0166	0.1951	0.6907	1.8973	10.9643	17.7169
Expense ratio	0.0042	0.0004	0.0021	0.0036	0.0053	0.0164	0.0032
Active share	0.0799	0.0544	0.0584	0.0590	0.0598	0.7114	0.1073
Flow	0.3001	-0.2008	-0.0069	0.0029	0.0146	13.6665	2.0349
Load fund	0.4503	0.0000	0.0000	0.2743	1.0000	1.0000	0.4976
Turnover	0.1371	0.0116	0.0396	0.0620	0.1117	1.5415	0.2626
Volatility	0.0383	0.0314	0.0375	0.0376	0.0377	0.0796	0.0063
No. of funds	59.2188						

This table presents time series average summary statistics for S&P 500 index funds. All the variables are winsorized at 1% level.

2.4.1 Performance Persistence

To test the performance persistence among index funds, we follow the procedure proposed by (Carhart (1997)). At the end of each year, we sort all the S&P 500 index funds into ten portfolios based on their one-year average after-fee raw returns and then assign that rank to the next year. The decile portfolios are held for one year and rebalanced every year. Each portfolio's return is calculated as a simple average of an individual fund's return within the portfolio. This procedure creates a time series monthly raw return for the ten decile portfolios, where rank 1 includes the best performers and rank 10 includes the worst performers. We then run CAPM, a 3-factor model, and a 4-factor model for each decile portfolio. Table 2.5 shows the results. Across the three models, the portfolios that earn higher raw returns tend to have higher alphas in the following year. The alpha shows an almost monotonic pattern, especially for those funds in lower ranks. The highest decile on average earns -0.002% CAPM alpha, -0.01% 3-factor alpha, and -0.006% 4-factor alpha monthly, and the lowest decile on average earns -0.075% CAPM alpha, -0.082% 3-factor alpha, and -0.063% 4-factor alpha monthly. The spread between the top decile and the bottom decile is

0.0727%, 0.0717%, and 0.0576% monthly in terms of CAPM alpha, 3-factor alpha, and 4-factor alpha. All the spreads are significantly positive at the 1% level.

Table 2.5 Performance Persistence

One year rank	CAPM alpha	3-factor alpha	4-factor alpha
1 (High)	-0.002%	-0.010%	-0.006%
2	0.000%	-0.006%	0.006%
3	0.105%	0.096%	0.097%
4	-0.016%	-0.023%	-0.003%
5	-0.007%	-0.014%	-0.003%
6	-0.053%	-0.058%	-0.037%
7	0.015%	0.010%	0.025%
8	-0.032%	-0.039%	-0.026%
9	-0.045%	-0.051%	-0.037%
10 (Low)	-0.075%	-0.082%	-0.063%
High-Low	0.0727%***	0.0717%***	0.0576%***
t-statistics	3.48	3.45	2.83

This table demonstrates performance persistence for S&P 500 index funds. The ranks are presented in the first column, where 1 includes the best performers, and 10 includes the worst performers. The bottom row also reports the spread between the top decile and the bottom decile. The *t*-statistics and significance level are reported. t-statistics are adjusted for Newey West standard errors. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

The result in Table 2.5 implies that the performance of S&P 500 index funds is heterogeneous. The spread between the top decile and the bottom decile is about 1 percent per year and is statistically significant. Also, the difference in performance across funds is persistent. The funds with higher raw returns are more likely to have higher alpha in the next year. The performance persistence among S&P 500 index funds is consistent with the findings in actively managed funds (Carhart (1997)). However, in (Carhart (1997)), the spread between the top decile and the bottom decile is much smaller when measured by 4-factor alpha than when measured by CAPM alpha, implying that the momentum factor explains away most of the difference. In my findings for S&P 500 index funds, the magnitude of the spread measured by CAPM alpha and 4-factor alpha is similar. This finding is consistent with the previous finding that index funds on average are more likely to buy losers and sell winners.

2.4.2 Performance Predictors

The previous section shows that the performance of S&P 500 index funds is heterogeneous and persistent. In this section, we test whether their performance is related to fund characteristics, and if so, what the relation is. Zheng (1999) documents a "smart money" effect, in which flow can predict performance in the short term. Chen et al. (2004) find that performance in the active money management industry declines with their lagged size. Elton, Gruber and Busse (2011) show that S&P 500 index fund performance can be predicted by fund expenses. Turnover ratio is another characteristic that has been studied for actively managed funds. Both (Chen, Jegadeesh and Wermers (2000)) and (Pastor, Stambaugh and Taylor (2017)) find a positive correlation between turnover ratio and performance. Guercio and Reuter (2014) document that actively managed funds that are directly sold and sold through brokers have different incentives to generate alpha. Inspired by the existing literature on both actively managed funds and index funds, we test the performance predictability of fund flow, size, age, expense ratio, turnover ratio, load, and active share in this section.

Fund flow is calculated in Equation (2.1) and Equation (2.2). Fund size is calculated as the logged value of monthly total net assts in millions of dollars. Fund age is calculated as the logged number of months from the first day when the return is available to the current date. Expense ratio is a percentage of total net assets divided by 12. Load fund is a dummy variable that takes a value of one if the fund charges a front-end load or a rear-end load, and zero otherwise. Active share is calculated in Equation (2.4) using the S&P 500 index as a benchmark.

To test the predictability of these characteristics, we apply both a portfolio sorting method and a regression estimation. In the portfolio sorting method, we first rank all the S&P 500 index funds into ten deciles at the end of each year based on the current year's average 4-factor alpha and assign rankings for the previous one year. Each decile portfolio is held for one year and rebalanced once a year. We calculate the equally weighted average of the above characteristics within each decile portfolio. The procedure creates monthly average characteristics for each decile portfolio. To examine the relation between past characteristics and current performance, we calculate the time series average characteristics for each performance decile portfolio and test the difference between the top performance decile and the bottom performance decile. The results are shown in Table 2.6.

Table 2.6 Performance Predictor: Portfolio Sort

Rank	Flow	Log size	Log age	Expense	Turnover	Load fund	Active share
1(High)	0.001	7.112	4.755	0.003	0.142	0.233	0.154
2	0.007	7.719	4.888	0.002	0.086	0.209	0.064
3	0.005	7.193	4.802	0.002	0.100	0.245	0.059
4	0.008	6.885	4.719	0.003	0.079	0.385	0.058
5	0.005	6.816	4.627	0.003	0.091	0.411	0.059
6	0.003	6.762	4.748	0.004	0.081	0.517	0.064
7	0.000	6.720	4.635	0.004	0.100	0.608	0.058
8	-0.001	6.261	4.645	0.005	0.094	0.668	0.062
9	0.002	5.973	4.686	0.007	0.094	0.775	0.059
10 (Low)	0.002	5.806	4.685	0.008	0.249	0.608	0.194
High-Low	-0.001	1.306***	0.070	-0.006***	-0.123***	-0.375***	-0.018
t-statistics	-0.19	5.02	0.33	-16.12	-3.03	-13.90	-0.60

This table presents the result of performance predictors for S&P 500 index funds. The ranks are presented in the first column, where 1 includes the best performers, and 10 includes the worst performers. The table reports the time series average of each characteristic for each decile. The bottom row also reports the difference in each characteristic between the top performers and the bottom performers. t-statistics are adjusted for Newey West standard errors. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Size, expense ratio, and load fund show a monotonic pattern. Bigger funds in the previous year tend to have higher 4-factor alpha in the current year. Expense ratio and 4-factor alpha have the reverse correlation. Funds that charge loads tend to have lower 4-factor alpha. The difference between the top and the bottom decile is significant at the 1% level. Turnover ratio and active share have a U-shape relation to future performance. Both top performers and bottom performers have a high turnover ratio and a large active share in the past year. The interesting finding from portfolio sorting is that S&P 500 index funds exhibit increasing returns to scale, which is different from what (Berk and Green (2004)) predicts for actively managed funds. Expense ratio negatively predicts performance, which is consistent with the findings in (Elton, Gruber and Busse (2004)).

To further test the predictors of S&P 500 index fund performance, we regress fund annualized 4-factor alpha on the previous one year's characteristics as well as the previous one year's raw returns. Specifically:

$$4f\_alpha_{i,t} = \beta_0 + \beta_1 \log\_size_{i,t-1} + \beta_2 \exp\_ratio_{i,t-1} + \beta_3 \log\_age_{i,t-1} + \beta_4 load\_dummy_{i,t-1} + \beta_5 flow_{i,t-1} + \beta_6 yret_{i,t-1} + \beta_7 turn\_ratio_{i,t-1} + \beta_8 turn\_ratio\_sq_{i,t-1} + \beta_9 activeshare_{i,t-1} + \beta_{10} activeshare\_sq_{i,t-1} + \varepsilon_{i,t} \qquad (2.8)$$

where $turn\_ratio\_sq_{i,t-1}$ and $activeshare\_sq_{i,t-1}$ are the square term of turnover ratio and active share. Since the result in table 2.6 implies that turnover ratio and active share have a U-shape relation to future performance, we include quadratic terms for these two variables. We first estimate a univariate regression for each of the independent variables in Equation (2.8) and then estimate a multivariate regression that includes all the right-hand-side variables in Equation (2.8). These are panel regressions with year fixed effects, and the standard errors are double clustered by year and fund level. Table 2.7 presents the results of the regressions.

Columns (1) to (6) show estimates for the univariate regression on size, expense, age, load, flow, and past performance. Columns (7) and (8) demonstrate the results for turnover ratio and active share, as well as the square term of each. Column (9) presents the results for the multivariate regression. In the univariate regression, expense ratio negatively predicts the next year's 4-factor alpha, annual raw return positively predicts the next year's 4-factor alpha, and the other variables are not significant. Turnover ratio itself negatively predicts the next year's performance, and the significant positive coefficient estimate of the square term confirms the U-shape relation between turnover ratio and future performance. The results of the multivariate regressions are consistent with those of the univariate regression.

Table 2.7 Performance Predictor: Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log size	0.00								0.00
	(0.67)								(0.60)
Expense ratio		-1.06**							-1.20**
		(-2.38)							(-2.38)
Log age			-0.00						-0.00
			(-1.15)						(-0.80)
Load fund				-0.00					0.00
				(-1.51)					(0.95)
Flow					-0.00				-0.01
					(-0.87)				(-0.79)
Yret						0.05**			0.14***
						(2.37)			(4.58)
Turnover							-0.02**		-0.02*
							(-2.50)		(-1.81)
Turnover square							0.01*		0.01*
							(2.07)		(1.86)
Active share								0.00	0.06
								(0.01)	(0.87)
Active Share square								-0.01	-0.09
								(-0.11)	(-0.95)
N	1082	1015	1082	1082	1062	1079	1003	885	810
R-sq	0.055	0.057	0.055	0.056	0.055	0.058	0.055	0.064	0.071
adj. R-sq	0.035	0.035	0.035	0.036	0.035	0.037	0.032	0.038	0.034

This table reports the regression result of 4-factor alpha on lag one-year fund characteristics for S&P 500 index funds. Column (1) to (6) present the results of univariate regression. Columns (7) and (8) present the results for turnover ratio and active share as well as the square term of each. Column (9) reports the results of multivariate regression that includes all variables. This is a panel regression with year fixed effects, and standard errors are double clustered at fund and year level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To save space, Table 2.7 only reports the results for 4-factor alpha. When performance is measured by CAPM alpha or 3-factor alpha, the results are qualitatively the same. The negative predictability of the turnover ratio implies that the trading behavior of S&P 500 index funds may play a role in their performance.

2.5 Trade View

2.5.1 General Trading Performance

The results discussed in the previous section show that the S&P 500 index fund turnover ratio negatively predicts future performance, leading to my focus on the trading performance of these index funds. This section explores the general trading performance of S&P 500 index funds.

We first obtain holdings data for each S&P 500 index fund in my sample and then calculate trading data for each quarter. Trading is calculated following Equation (2.3). Then we examine the trading subsequent performance of the stocks over different time horizons. Specifically, we calculate the monthly, quarterly, and annualized performance of each stock subsequent to each trade, measured by 4-factor alpha and DGTW benchmark adjusted returns. For each fund in each quarter, we form a buy portfolio, a sell portfolio, and a buy-minus-sell portfolio. A buy (sell) portfolio includes all stocks bought (sold) by the fund in the quarter. For each fund in each quarter, we calculate the performance of the buy and sell portfolios as an equally weighted average of individual stocks; the performance of a buy-minus-sell portfolio is the difference in performance between the two. Then, for each quarter, we average the performance across funds. This procedure yields the time series performance of buy, sell, and buy-minus-sell portfolios. Finally, we conduct a t test for the three portfolios and adjust for Newey West standard error. The results are shown in Table 2.8. For the buy portfolio, all the six performance measures are insignificant and four of them are negative. For the sell portfolio, all six performance measures are positive. Quarterly 4-factor alpha and DGTW return are significant at the 5% level, and annual 4-factor alpha is significant at the 10% level. For the buy-minus-sell portfolio, all performance measures are negative; except for monthly 4-factor alpha, the other five are all significant at the 5% level. On average, the buy-minus-sell portfolio loses 0.42% monthly and 2.31% annually in DGTW return. Table 8 shows that, on average, S&P 500 index fund trades lose money.

Table 2.8 Trades and Performance

	Buy	Sell	Buy-Sell
4f-alpha_month	0.1160%	0.3083%	-0.1973%
	(0.84)	(1.26)	(-0.86)
4f-alpha_quarter	-0.0026%	1.3050%**	-1.3906%**
	(-0.01)	(2.13)	(-2.34)
4f-alpha_year	0.2400%	2.4312%*	-2.4673%**
	(0.26)	(1.82)	(-2.28)
DGTW_month	-0.1526%	0.2389%	-0.4179%**
	(-1.53)	(1.39)	(-2.05)
DGTW_quarter	-0.1333%	0.9199%**	-1.1198%**
	(-0.58)	(2.21)	(-2.59)
DGTW_year	-0.7248%	1.3616%	-2.3061%**
	(-1.25)	(1.25)	(-2.38)

This table presents general trading performance for S&P 500 index funds and the result of *t*-test for the performance series for each portfolio. *t*-statistics are reported in parentheses and are adjusted for Newey West standard errors. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

It has been well documented that index funds on average perform better than actively managed funds, but Table 2.8 implies that the trading activities of S&P 500 index funds hurt their performance. To find out, we examine whether the trading performance contributes to the heterogeneity and persistence of the performance.

To test this hypothesis, we apply the portfolio sorting method. As before, at the end of each year, we sort all S&P 500 index funds into ten deciles based on their one-year before-fee raw returns. Since the previous results imply that S&P 500 index fund performance is negatively correlated with expense ratio, by sorting on before-fee raw returns, we rule out the heterogeneity in performance due to expenses. As before, the 10 decile portfolios are rebalanced every year. Instead of assigning a rank to the next year, we examine the concurrent year's trading performance. With funds assigned a rank, we calculate the CAPM alpha, 3-factor alpha, and 4-factor alpha after trades over a one-quarter horizon for the buy-minus-sell portfolio for each fund for each quarter.

The trading subsequent performance of each decile portfolio is calculated as an equally weighted average of individual funds in the decile portfolio. This procedure yields a time series of trading subsequent performance for each decile portfolio. We calculate the average over time for each decile portfolio and conduct a *t*-test to test the difference between the top and bottom decile portfolios. Table 2.9 presents the result of this test. We only report quarterly performances because they match the frequency of fund trading. Quarterly performance captures the trading effect better than monthly and annual performance.

Table 2.9 Trading Performance in Decile Portfolios

One year rank	CAPM alpha	3-factor alpha	4-factor alpha
1 (High)	-0.3642%	-0.2271%	-0.3505%
	(-0.60)	(-0.42)	(-0.62)
2	-1.7979%	-1.5326%	-1.9385%
	(-2.11)	(-1.89)	(-2.22)
3	-1.4807%	-1.4713%	-1.6084%
	(-2.01)	(-2.64)	(-2.61)
4	-1.2170%	-1.0424%	-1.1378%
	(-2.06)	(-1.99)	(-2.29)
5	-1.3949%	-1.1446%	-1.3431%
	(-2.11)	(-2.07)	(-2.12)
6	-1.4438%	-1.3725%	-1.1791%
	(-1.59)	(-1.83)	(-1.64)
7	-1.4081%	-1.3173%	-1.4333%
	(-2.22)	(-2.03)	(-2.14)
8	-0.8611%	-0.9425%	-0.8672%
	(-1.45)	(-1.43)	(-1.34)
9	-1.1107%	-1.0911%	-1.1592%
	(-1.38)	(-1.48)	(-1.59)
10 (Low)	-2.4769%	-2.3666%	-2.6911%
	(-2.13)	(-2.45)	(-2.65)
High-Low	2.1098%*	2.0772%**	2.3272%**
t-statistics	1.96	2.18	2.25

This table presents quarterly trading subsequent performance in each decile portfolio for S&P 500 index funds. It reports the time series average of trading subsequent performance for each decile portfolio, as well as the spread between the top decile and the bottom decile. *t*-statistics are adjusted for Newey West standard errors. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

As is shown in Table 2.9, first, all the deciles have negative trading subsequent alpha, which is consistent with the previous finding that S&P 500 index fund trades lose money in general.

Second, even though the performances of buy-minus-sell portfolios does not show a strict monotonic pattern with performance rank, the top and bottom decile portfolios are the most striking. The best performers on average earn the least negative and least insignificant trading subsequent performance. They earn -0.2271% to -0.3642% quarterly alphas. However, the bottom decile portfolio earns significant negative trading subsequent alphas in each quarter, ranging from -2.3666% to -2.6911%. The differences between the top decile and the bottom decile are all significant at the 10% or 5% level. In general, S&P 500 index fund trades lose money. Table 2.9 shows that trading performance contributes to performance heterogeneity and persistence. Funds in each decile earn negative buy-minus-sell performance measured by alpha. More specifically, funds with the best performance lose insignificant money due to their trading; however, funds with the worst performance lose the most money. The trading losses of S&P 500 index funds mainly affects the bad performers.

2.5.2 Trade Motivation and Performance

With an understanding of the general performance of S&P 500 index fund trades, it is interesting to study the different motivations for their trades and how well each type of trade performs. First, when the S&P 500 index rebalances on the second Friday of March, June, September, and December, the corresponding index funds may have to buy stocks newly included by the index and sell the stocks newly excluded from the index to minimize tracking errors. Besides trading due to index reconstitution, index funds face a flow shock from investors. When there is a large cash flow into a fund, the manager must buy stocks to absorb the excess cash; and when there is a large withdrawal by investors, the manager has to liquidate stocks. Therefore, flow shock is another motivation for trading. Previous results imply that some S&P 500 index funds are comparatively active, perhaps because fund managers make discretionary trades. In the following test, we divide all the trades by S&P 500 index funds into three categories: trades due to S&P 500 index reconstitution, flow-driven trades, and managers' discretionary trades.

To identify reconstitution-motivated trades, we first find the historical constituents of the S&P 500 index and identify the stocks included or excluded in each quarter. Since it is not clear exactly when S&P 500 index funds trade in order to rebalance the index, we define a fund's purchase (sale) of a stock from four quarters before to four quarters after its inclusion in (exclusion from) the index as a reconstitution-motivated buy (sell). We divide the rest of the trades into flow-driven and managers' discretionary trades. Applying the method proposed by (Gordor J. Alexander, Gjergji Cici and Scott Gibson 2007), we calculate the following measures at the trade level:

$$BF_t^j = \frac{BUY_t^j - dollar\_flow_t^i}{TNA_{t-1}^i} \quad (2.9)$$

$$SF_t^j = \frac{SELL_t^j + dollar\_flow_t^i}{TNA_{t-1}^i} \quad (2.10)$$

If trade j is a buy, then we calculate BF measure following Equation (2.9). BUY_t^j is the dollar value of stock j bought in quarter t. If trade j is a sell, then we calculate SF measure in Equation (2.10). The BF measure yields a higher value when the fund buys a lot of stocks and at the same time there is a huge outflow; it yields a lower value when the fund buys few stocks and at the same time there is a huge inflow. The logic is that when a manager is facing a large outflow but still buys lots of stocks, the buy is more likely to be at the manager's discretion. Otherwise, such a buy is more likely to be flow driven. When there is huge inflow to a fund and at the same time the manager sells a large number of stocks, then the sale is more likely to be at the manager's discretion. As a result, higher BF and SF measures imply that the trade is more likely to be at the manager's discretion, and a lower value implies that the trade is more likely to be flow driven.

We calculate the BF and SF measures for each trade in each quarter, then sort the measures within each fund for each quarter. A buy (sell) with a BF (SF) measure higher than the median is defined as a manager's discretionary buy (sell), and a buy (sell) with the BF (SF) measure lower than the median is defined as flow-driven buy (sell). At the fund level, we construct flow-driven, reconstitution-motivated, and discretionary buy-minus-sell portfolios. The trades that do not belong to any of the above motivations are identified as "unclassified". Table 2.10 reports the average number of trades by motivation per quarter.

Table 2.10 Summary Statistics for Trade Motivation

Motivation	No. per motivation	Pct per motivation	No. of total trades
Flow-driven buy	3609	23.13%	16342
Flow-driven sell	3454	20.22%	16342
Reconstitution buy	670	4.12%	16342
Reconstitution sell	600	3.59%	16342
Manager buy	3630	23.26%	16342
Manager sell	3473	20.34%	16342
Unclassified	916	5.41%	16342

This table presents summary statistics for the number of trades by motivation for S&P500 index funds. The motivations are identified at trade level. The first column lists the motivations. The second column reports the average number of trades by motivation per quarter. The third column reports the average percentage of trades by motivation per quarter. The last column reports the average number of all trades per quarter.

There are 16,342 trades on average per quarter. 3,609 of them are flow-driven buys and sells, accounting for the highest percentage (roughly 23%). Reconstitution-motivated trades account for about 7.7% of all trades.

To test the performance of trades for each motivation, we first obtain each stock's trading subsequent performance measured by 4-factor alpha and DGTW return over one-month, one-quarter, and one-year horizons. The performance of the buy-minus-sell portfolio for each motivation is calculated as an equally weighted average of stocks' performance in the portfolio. This procedure yields a panel dataset of buy-minus-sell portfolios' performance by motivation.

Then we conduct *t*-test to test the performance for each motivation. The results are presented in Table 2.11.

Table 2.11 Trade Motivation and Performance

	Flow buy-sell	Reconstitution buy-sell	Manager buy-sell
4f-alpha_month	-0.1344%	-0.9440%***	0.1735%*
	(-1.21)	(-4.19)	(1.79)
4f-alpha_quarter	-0.7692%***	-3.6270%***	-0.6435%***
	(-4.70)	(-7.05)	(-4.58)
4f-alpha_year	-1.2590%***	2.7880%***	-1.0997%***
	(-3.71)	(2.83)	(-4.10)
DGTW_month	-0.0843%	-1.9578%***	0.1812%*
	(-0.81)	(-10.26)	(1.90)
DGTW_quarter	-0.5876%***	-3.4637%***	-0.5131%***
	(-3.99)	(-7.64)	(-3.73)
DGTW_year	-1.3195%***	-0.2954%	-0.9407%***
	(-4.38)	(-0.39)	(-3.80)

This table presents trading subsequent performance by motivation for S&P 500 index funds. It reports *t*-test results for the stacked sample for the flow-driven buy-sell portfolio, reconstitution-motivated buy-sell portfolio, and managers' discretionary buy-sell portfolio. The trading motivations are identified at trade level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The flow-driven buy-minus-sell portfolio earns insignificant performance over the one-month horizon, but the performance is significantly negative over the one-quarter and one-year horizons. The reconstitution-motivated buy-minus-sell portfolio loses money over the one-month and one-quarter horizons but recovers over the longer period. Managers' discretionary trades make money over the one-month horizon but lose money over the longer horizons. In magnitude, the reconstitution-motivated buy-minus-sell portfolio loses 3.63% measured by quarterly 4-factor alpha and 3.46% measured by quarterly DGTW return. The magnitude of losses is the highest for reconstitution-motivated trades.

2.5.3 Trade Motivation and Performance—Robustness

We use a different way to differentiate flow driven trades and managers' discretionary trades in this section. The method in Section 2.5.2 sorts BF and SF measures within each fund in each quarter, assuming that all funds must have flow driven trades and managers' discretionary trades at the same time; however, that assumption may not always be correct. The method in this section is the original method used in (Alexander, Cici and Gibson (2007)). Instead of calculating BF and SF measures at the trade level, we calculate those measures at the fund level in this section. Specifically,

$$BF_t^i = \frac{BUYS_t^i - dollar\_flow_t^i}{TNA_{t-1}^i} \tag{2.11}$$

$$SF_t^i = \frac{SELLS_t^i + dollar\_flow_t^i}{TNA_{t-1}^i} \tag{2.12}$$

where $BUYS_t^i(SELLS_t^i)$ is the aggregated dollar value of all stocks bought (sold) by fund i in quarter t. The analysis of BF and SF measures is similar as before. Now funds with higher value of BF (SF) are more likely to buy (sell) stocks discretionarily. Funds with a lower value of BF (SF) are more likely to buy (sell) stocks due to a flow shock from investors. Instead of assuming a fund must have both flow-driven trades and managers' discretionary trades at the same time, this method assumes all trades by one fund are either flow-driven trades or discretionary trades, after ruling out reconstitution trades. The average number of trades per quarter by motivation is shown in Table 2.12. This method yields more flow-driven trades than the first method, but the other numbers are similar. The performance result of this method is presented in Table 2.13.

The identification of reconstitution-motivated trades does not change, so the performance result is the same as in Table 2.11. The performance results for flow-driven trades are qualitatively the same as in previous method. Flow driven trade performance is negative and insignificant over a one-month horizon, but significant over one-quarter and one-year horizons. The flow driven buy-minus-sell portfolio identified in this method on average earns -0.92% 4-factor alpha and -1.04% DGTW return per quarter, -1.37% 4-factor alpha and -1.99% DGTW return per year. Across different motivations, the magnitude of loss is still the greatest for reconstitution-motivated trades. In this method, managers' discretionary trading performances are all insignificant.

Table 2.12 Summary Statistics of Trade Motivation−Robustness

Motivation	No. per motivation	Pct per motivation	No. of total trades
Flow-driven buy	4245	26.27%	16342
Flow-driven sell	4045	23.42%	16342
Reconstitution buy	670	4.12%	16342
Reconstitution sell	600	3.59%	16342
Manager buy	3007	20.23%	16342
Manager sell	2898	17.23%	16342
Unclassified	937	5.50%	16342

This table presents summary statistics for the number of trades by motivation for S&P 500 index funds. The motivations are identified at fund level. The first column lists the motivations. The second column reports the average number of trades by motivation per quarter. The third column reports the average percentage of trades by motivation per quarter. The last column reports the average number of all trades per quarter.

Table 2.13 Trade Motivation and Performance−Robustness

	Flow buy-sell	Reconstitution buy-sell	Manager buy-sell
4f-alpha_month	-0.2560%	-0.9440%***	-0.0267%
	(-1.28)	(-4.19)	(-0.13)
4f-alpha_quarter	-0.9202%***	-3.6270%***	-0.1250%
	(-3.63)	(-7.05)	(-0.42)
4f-alpha_year	-1.3707%***	2.7880%***	-0.3687%
	(-2.71)	(2.83)	(-0.64)
DGTW_month	-0.2397%	-1.9578%***	0.1734%
	(-1.37)	(-10.26)	(0.73)
DGTW_quarter	-1.0375%***	-3.4637%***	-0.2370%
	(-3.78)	(-7.64)	(-0.77)
DGTW_year	-1.9886%***	-0.2954%	-0.6788%
	(-4.10)	(-0.39)	(-1.24)

This table presents trading subsequent performance by motivation for S&P500 index funds. It reports *t*-test results for the stacked sample for the flow-driven buy-sell portfolio, reconstitution-motivated buy-sell portfolio, and managers' discretionary buy-sell portfolio. The trading motivations are identified at fund level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Combining the two methods, over the one-quarter and one-year horizons, flow-driven trades lose money measured by 4-factor alpha and DGTW return. Over the one-month and one-quarter horizons, reconstitution-motivated trades lose money, and the magnitude of loss is highest, but those trades recover over the one-year horizon. Managers' discretionary trades make money over the one-month horizon, but their fortunes reverse over the longer horizon when the motivation is identified at the trade level.

CHAPTER 3

Mutual Fund Trading and Stock Price Efficiency

As index funds become larger and larger, there are concerns and debates on what will happen to stock market efficiency under this trend. Since actively managed fund managers actively pick stocks while index fund managers passively buy and hold. Presumably trades by actively managed funds incorporate information while trades by index funds are not likely to help improve price discovery. This chapter studies the relation between mutual fund trading and stock price efficiency. More specifically, it compares the trading effects of actively managed funds with those of passively managed (index) funds.

The rest of this chapter will be organized as follows: Section 3.1 discusses literature review. Section 3.2 presents the data and summary statistics for the main measures used in this chapter. Section 3.3 documents the tests and results for stock price efficiency and mutual fund trading. Section 3.4 studies liquidity and analyst coverage. Section 3.5 explores trading motivations and Section 3.6 investigates the activeness of index funds.

3.1 Literature Review

This chapter complements the literature on institutional investors' role in stock market efficiency. Boehmer and Kelley (2009) provide evidence that institutional investors as a whole can increase stock price efficiency and variation in liquidity is not the driver of this effect. One of the mechanisms through which prices become more efficient is institutional trading activity. However, even after controlling for institutional trading, holdings still have effects on price efficiency. Another related paper by Cao et al (2018) studies hedge funds' role on stock market. It concludes that hedge funds are arbitrageurs who reduce mispricing in the market. They invest in relatively inefficiently priced stocks and these stocks experience efficiency improvement after hedge funds increase their holdings. This chapter studies the largest institutional investor's role in the stock market and the result that institutional investors overall have a positive role in improving stock market efficiency is consistent with others.

Jeffrey, Heath and Ringgenberg (2018) study index mutual funds' role on stock price efficiency by applying change in Russell index as an instrument variable (IV). The regression discontinuity analysis shows that index investing introduces noise into stock prices but does not impact long-term price efficiency, and these stocks have no difference in turnover, trading volume, or earnings response coefficients. It offers a causal explanation that indexing decreases the price efficiency of the stocks they hold. Our result that trading due to change in index constituents is negatively correlated with the stock price efficiency is consistent with that paper, even we use different indices to do the test. We also complement the role of index funds that trades by index funds improve incorporation of market and industry information more than the trades by actively managed funds.

This chapter focuses on the comparison between actively managed mutual funds and index funds, in terms of the association between stock price efficiency and fund trading, which adds to the literature of comparing actively managed funds and index funds. For example, Gruber (1996) shows that the average risk-adjusted return of actively managed funds is interior to that of index funds. Wermers (2000) argues that actively managed funds' net returns underperform the market, and it is mainly due to expenses and transaction costs. Cremers et al (2016) show that actively management generates higher alpha when there is more explicit indexing, indicating that explicit indexing improves competition in mutual fund industry.

Finally, this chapter investigates the activeness of index funds, adding to the literature of activeness of passive investing. O'Hara et al. (2018) document that many ETFs are active investments in both form and function. This chapter shares the similar finding that index funds vary in activeness. More importantly, the activeness of index funds plays a role in improving stock market efficiency. Trades by index funds with higher active share are associated with larger effect of efficiency improvement. This finding implies that some index funds may have skills as well.

3.2 Data and Summary Statistics

The main efficiency measures used in this chapter are variance ratio based on Lo and Mackinlay (1988), return autocorrelation and HM measures proposed by Hou and Moskowitz (2005) and Hou (2007). The intuition of variance ratio is that if the market in weak-form efficient, then the stock price follows a random walk. As a result, the variance of the change in stock price should be proportional to the time interval in which the prices are sampled. Many empirical studies have exploited this property to construct variance ratio to test weak-form efficiency. Variance ratio is the ratio of long-term return variance to short-term return variance.

Formally, to conduct unbiased estimator of variance ratio, variance ratio is calculated as follows:

$$VR_q = \left|1 - \frac{\sigma_q^2}{q \times \sigma^2}\right| \tag{3.1}$$

where

$$\sigma_q^2 = \frac{k}{(n-q+1)(k-1)} \sum_{t=q}^{n} \left(p_t - p_{t-q} - qu\right)^2 \tag{3.2}$$

$$\sigma^2 = \frac{1}{n-1} \sum_{t=1}^{n} (p_t - p_{t-1} - \mu)^2 \tag{3.3}$$

$$\mu = \frac{1}{n} \sum_{t=1}^{n} (p_t - p_{t-1}) \tag{3.4}$$

q is the time horizon of the long-term return, in this chapter $q = 5$ or 10. The data consists of $(kq + 1)$ observations and $n = kq$. p_t is logarithm of closing daily price at day t. We calculate VR_q for each stock in each quarter using overlapping observations within one quarter. For example, for the variance of 5-day return, if there are 40 trading days in one quarter, then there would be 36 5-day returns in total.[12] If the market is weak-form efficient, then σ_q^2 should be q times of σ^2, and therefore VR_q in Equation (3.1) should be zero. A higher value of VR_q implies more deviation from weak-form efficiency, so this measure captures how much the stock price deviates from what an efficiency market implies.

The second type of efficiency measure is autocorrelation of change in logarithm of closing daily price (AR measure). This measure shares the same intuition with variance ratio. Since both positive and negative autocorrelation imply deviation from weak-form efficiency, we use the absolute value of the autocorrelation. For each stock, we calculate measures within each quarter (AR_q) and each month (AR_m).

The third type of efficiency measure is HM measures. They capture stock price delay in the sense that it responds to past market information and past industry information. In each quarter, we run a regression of stock's daily return on the contemporaneous and lagged returns on the CRSP value-weighed portfolio. Returns on industry portfolios are added in the second regression:

$$ret_t = \alpha + \beta_0 \times R_{m,t} + \sum_{n=1}^{5} \beta_n \times R_{m,t-n} + \varepsilon_t \tag{3.5}$$

$$ret_t = \alpha + \beta_0 \times R_{m,t} + \sum_{n=1}^{5} \beta_n \times R_{m,t-n} + \sum_{n=1}^{5} \delta_n \times R_{ind,t-n} + \varepsilon_t \tag{3.6}$$

[12] Suppose there are 40 trading days in a quarter. The first price change is the difference between the fifth-day closing price and the first-day closing price. The second price change is the difference between the sixth-day closing price and the second-day closing price. The variance is calculated based on these price changes. VR_{10} is calculated using the similar method.

where ret_t is the daily stock return, $R_{m,t}$ is the return on the CRSP universe value-weighted portfolio on day t, and $R_{ind,t}$ is the return on the portfolio of industry which the stock belongs to. We assign all firms in my sample to one of 12 industries according to their four-digit SIC code, following the industry definition from Ken French's website. They are: (1) consumer nondurables; (2) consumer durables; (3) manufacturing; (4) oil, gas, and coal extraction and products; (5) chemicals and allied products; (6) business equipment; (7) telephone and television transmission; (8) utilities; (9) wholesale, retail, and some services; (10) healthcare, medical equipment, and drugs; (11) finance; and (12) others. We construct two HM measures: HM_mkt and HM_ind based on Equation (3.5) and Equation (3.6). For HM_mkt, if the stock price responds to past market information, then the estimates of β_n would be significantly different from zero. We first run Equation (3.5), and then run a restricted regression of Equation (3.5) by forcing β_n to be zero. HM_mkt is defined as one minus the ratio of R-squared from the restricted regression and R-squared from the unrestricted regression.HM_ind is derived based on Equation (3.6), in the similar method.

Variance ratio and return autocorrelation capture a general deviation from a random walk, without specifying a specific source of information that the stock price delays to; however, HM measures capture a specific delay to market and industry information.

Our main sample is based on domestic common stocks obtained from CRSP from 1992 quarter 4 to 2016 quarter 3. We keep the stocks that can be matched with domestic equity mutual fund holdings data and delete stocks with daily closing price lower than $5 to alleviate the concern that the result may be driven by small illiquid stocks. In my final sample, there are 2,254 stocks on average in each quarter.

Table 3.1a shows the statistics of these efficiency measures.

Table 3.1a Summary Statistics

	Mean	Median	P25	P75	StdDev
VR_5	0.28	0.24	0.12	0.41	0.20
VR_{10}	0.39	0.35	0.18	0.55	0.26
AR_m	0.20	0.18	0.08	0.30	0.15
AR_q	0.15	0.12	0.06	0.21	0.11
HM_mkt	0.43	0.38	0.21	0.62	0.28
HM_ind	0.60	0.59	0.42	0.79	0.24
$Active\_abs\_trade$	4.05%	2.97%	0.96%	5.94%	3.93%
$Index\_abs\_trade$	0.45%	0.32%	0.15%	0.59%	0.47%
$Activebuy$	2.16%	1.37%	0.36%	3.08%	2.43%
$Activesell$	1.86%	1.14%	0.23%	2.68%	2.15%
$Indexbuy$	0.29%	0.20%	0.08%	0.37%	0.34%
$Indexsell$	0.15%	0.08%	0.02%	0.18%	0.22%
$Banktrade$	1.94%	1.46%	0.60%	2.67%	1.87%
$Insurancetrade$	0.75%	0.38%	0.09%	0.98%	1.02%
$Othertrade$	1.40%	0.94%	0.35%	1.85%	1.57%
$HFtrade$	1.67%	0.97%	0.32%	2.26%	2.01%
$BidAskSpread$	0.54	0.13	0.01	0.57	1.51
$BooktoMarket$	0.54	0.47	0.28	0.73	0.35
$Leverage$	0.19	0.15	0.03	0.31	0.19
$LoggedTotalAssets$	-0.33	-0.47	-1.67	0.84	1.84
$ShortInterestRatio$	0.03	0.02	0.01	0.04	0.04
$Turnover$	1.85	1.14	0.54	2.14	2.54
$Volatility$	0.03	0.03	0.02	0.03	0.01
$Illiquidity$	0.57	0.02	0.00	0.14	2.3
Avg No. of stocks	2,254				
No. of observations	216,404				

This table presents the summary statistics of efficiency measures, mutual fund trading and holdings, other institutional trading, control variable. The columns show the time series averages of the cross-sectional mean, median, 25th percentile, 75th percentile and standard deviation. All variables are winsorized at 1% level.

Table 3.1b and the correlation between each two measures. All the efficiency measures are positively correlated. Within variance ratio and return autocorrelation, each pair has a correlation higher than 0.4 except AR_m. AR_m has a lower correlation with other measures due to the different frequency in which it is calculated. HM measures have lower correlation with VR and AR, because HM measures capture a more specific price delay, but HM_mkt and HM_ind have a high correlation of 0.88 with each other.

hedge funds and others are calculated based on the holding data extracted from Thomson Reuters S34 files. The trading by mutual funds and other institutional investors are defined as follows:

$$trade_{i,t} = \frac{\sum_j \left| Holdings_{i,j,t} - Holdings_{i,j,t-1} \right|}{TSO_{i,t-1}} \tag{3.7}$$

where $trade_{i,t}$ is the trading of stock i by a certain type of institutional investors in quarter t, $Holdings_{i,j,t}$ is the number of shares of stock held by institution j in quarter t, and $TSO_{i,t-1}$ is the total shares outstanding of stock at the beginning of quarter t. We calculate $trade_{i,t}$ within actively managed mutual funds, index mutual funds, banks, insurance companies, hedge funds, and other institutional investors. This procedure gives the main independent variables $Active\_abs\_trade$ and $Index\_abs\_trade$, and the variables of other institution trading, including $Banktrade, Insurancetrade, HFtrade$ and $Othertrade$. For mutual funds, we further investigate buy and sell. If the change in holdings is positive then the trade is defined as a buy, and if the change in holdings is negative, then the absolute value of trade is defined as a sell.

Table 3.1b Correlation Between Efficiency Measures

	VR_5	VR_{10}	AR_m	AR_q	HM_mkt	HM_ind
VR_5	1.00					
VR_{10}	0.73	1.00				
AR_m	0.28	0.17	1.00			
AR_q	0.62	0.40	0.48	1.00		
HM_mkt	0.23	0.17	0.16	0.25	1.00	
HM_ind	0.20	0.15	0.14	0.22	0.88	1.00

To rule out the concern that actively managed funds and index funds trade different stocks, we restrict the sample to the stocks traded by both type of funds. Table 3.1a report the summary statistics for the main variables in this chapter. The columns show the time series averages of the cross-sectional mean, median, 25th percentile, 75th percentile and standard deviation. In our final sample, actively managed fund trading has an average of 4.05% of the stocks they cover and a standard deviation of 3.93%. It has large variation from 0.96% as the 25th percentile to 5.94% as the 75th percentile. At the same time, index fund trading has a 25th percentile of 0.15% and 75th percentile of 0.59%. Given index funds' low average trading, the variation is still considerable.

We control for the variables that may affect stock price efficiency, including firm characteristics, liquidity of stocks and short interest ratio. These control variables are borrowed from Cao et al (2018) except stock return volatility in the regression of HM measures. Since variance ratio and return autocorrelation are derived from variance of change in prices, the volatility of stock return is not considered as a control variable.

Firm characteristics includes total assets, book to market ratios and leverage. These data are obtained from Compustat quarterly files. $LoggedTotalAssets$ is the natural logarithm of quarterly total assets. $BooktoMarket$ is the book value of shareholders' equity over the market value of equity from CRSP. We allow 4 months lag before dividing the book value by market value to make sure that the fiscal data are available to the public. $Leverage$ is calculated as the sum of current liabilities and long-term debt over total book assets. All these characteristics are quarter-end and matched with trading data.

Liquidity is also related to efficiency. Liquidity or market depth (Kyle (1985)) refers to the market's ability to sustain relatively large market orders without impacting the market price. In an efficiency market, a new public information should be incorporated in the stock price quickly, so that the price follows a random walk. Illiquid stocks have higher transaction costs and therefore are slower to incorporate information. Mutual funds may prefer to trade liquid stocks, and liquid stocks tend to have higher efficiency because they respond to information more quickly. So, we include stock liquidity in the regression to control for this endogeneity. We use three measures to proxy liquidity. The first is $BidAskSpread$. It is computed as two times the absolute value of the difference between the price and the midpoint of bid and ask, divided by the midpoint of bid and ask. The second measure is $Turnover$. It is calculated as the ratio of the annualized trading volume of a stock to the total number of shares outstanding. The last one is $Illiquidity$ proposed by Amihud (2002). In each quarter, it is calculated as the average daily ratio of absolute return over dollar trading volume.

Previous studies (e.g., Nagel (2005), Boehmer and Wu (2012)) show that more shorting flows enhance the incorporation of the public information into stock prices, and stocks held by institutional investors are usually available for short selling borrowers. Therefore, we control for short selling when examining the relation between mutual fund trading and stock price efficiency. The variable we use here is $ShortInterestRatio$, which is computed as monthly short interest divided by total shares outstanding. The data of short interests are obtained from Bloomberg.

Lastly, other institutional trading is controlled, including banks, insurance, hedge funds and other institutions. We also control for the current efficiency measure to deal with momentum in stock price efficiency. Table 3.1a shows the statistics of the control variables. The average firm in my final sample has a logged value of total assets of -0.33, where the total assets are in billions, a book to market ratio of 0.54 and a leverage of 0.19. The mean short interest ratio is 0.03, the effective bid-ask spread is 0.54, the annualized turnover is 1.85, the mean return volatility is 0.03 and the mean Amihud illiquidity is 0.57. There are on average 2,254 stocks in each quarter in the sample and 216,404 observations in total.

3.3 Stock Price Efficiency and Mutual Fund Trading

3.3.1 Absolute Trading

In this section, we investigate the relation between stock price efficiency and actively managed fund trading versus index fund trading. The main regression we estimate is as follows:

$$Efficiency_{i,t} = \beta_0 + \beta_1 Active\_abs\_trade_{i,t-1} + \beta_2 Index\_abs\_trade_{i,t-1} +$$

$$\beta_3 Lag\_efficiency_{i,t} + \sum_j \beta_j Inst.Trade_{i,t-1} + \sum_k \beta_k Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \qquad (3.8)$$

Institutional trades include bank trades, insurance trades, hedge fund trades and other trades. Control variables include short interest ratio, firm size, book to market ratio and leverage and other liquidity measures. The regression includes time fixed effects and standard errors are double clustered at stock and date levels. Table 3.2 presents the results.

$Active\_abs\_trade$ is positively correlated with VR and AR across all the identifications. Since the efficiency measures capture how much the price deviates from what an efficiency market implies, a negative estimated coefficient implies a positive correlation between the trading and stock price efficiency. On average, a stock with a one standard deviation greater in active fund trading would have a 4% to 5% standard deviation lower efficiency measure, and the estimates are significantly different from zero. The statistical significance survives after adding the trading of other institutional investors and control variables. For index fund trading, no significant result shows up in the full identification. The significance of index fund trading goes away when Illiquidity measure is added. This result indicates that index fund trading improves stock price efficiency in terms of random walk pattern by providing liquidity, but after controlling for liquidity, there is no significant effect from index fund trading. The table also reports the *F*-statistics and *p*-value of the *F*-test for the for the difference in the estimated coefficients between active fund trading and index fund trading. Across all the identifications and all the efficiency measures, the

p-values are close to zero. It implies that the magnitude of association between stock price efficiency and actively managed fund trading is significantly greater than that between stock price efficiency and index fund trading.

Table 3.2 Absolute Trade and Efficiency

	(1) VR_5	(2) VR_{10}	(3) AR_m	(4) AR_q	(5) HM_mkt	(6) HM_ind
$Active\_abs\_trade$	-0.05***	-0.04***	-0.04***	-0.05***	-0.04***	-0.03***
	(-13.14)	(-11.78)	(-10.41)	(-11.27)	(-7.87)	(-6.24)
$Index\_abs\_trade$	-0.00	0.00	0.01	-0.00	-0.06***	-0.05***
	(-0.88)	(0.66)	(1.28)	(-0.08)	(-7.85)	(-7.50)
$Lag\_efficiecny$	0.13***	0.07***	0.08***	0.20***	0.34***	0.40***
	(13.80)	(11.51)	(13.31)	(15.40)	(28.97)	(34.95)
$Inst.Trade$	Yes	Yes	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Rsq	0.116	0.056	0.068	0.175	0.494	0.520
adj.Rsq	0.115	0.056	0.067	0.174	0.494	0.519
F_dif_trade	64.40	56.19	61.28	60.01	4.23	4.96
p_dif_trade	0.00	0.00	0.00	0.00	0.04	0.03
N	214,627	214,627	215,221	215,159	183,749	183,749

This table reports the results of relationship between efficiency measures and $Active\_abs\_trade$ and $Index\_abs\_trade$. F_dif_trade and p_dif_trade are the F-statistics and p-value of the F-test for the difference in the estimated coefficients between $Active\_abs\_trade$ and $Index\_abs\_trade$. The regressions include date fixed effect and standard errors are double clustered at date and stock level. t-statistics are in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

For HM measures, both actively managed fund trading and index fund trading are significantly positively correlated with stock price efficiency. A stock with a one standard deviation greater active fund trading would have a 3% to 4% standard deviation lower efficiency measure, and a stock with a one standard deviation greater index fund trading would have a 5% to 6% standard deviation lower efficiency measure. The F-test shows that the difference in magnitudes is significant in 5% level.

This main test demonstrates that stocks traded by actively managed funds are likely to experience an improvement in efficiency in the subsequent quarter, but in different ways. Trades by actively managed funds improve the general weak form efficiency, in the sense that they significantly reduce stock price deviation from random walk. However, trades by index funds do not show such significant effect after controlling for stock liquidity. On the other hand, index fund trading improves stock price efficiency in a more specific way. It reduces stock price delay to market and industry information, with a greater magnitude than actively managed fund trading.

3.3.2 Mutual Funds BUYs and SELLs and Stock Price Efficiency

Besides testing the relation between stock price efficiency and mutual fund absolute trading, we investigate mutual fund buy activities and sell activities separately in this section. The result in Table 3.2 could be that mutual fund trading incorporates information. It also could be the holding effect. As an asset in a mutual fund holding portfolio, a stock bought by mutual funds may attract more attention from analysts and individual investors, therefore, has more information production. If this is the case, one would expect to see that mutual funds' buy activities are positively correlated with stock price efficiency improvement, while sell activities are not or negatively correlated with stock price efficiency improvement. To rule out such possibility, we investigate buy activities and sell activities separately. The regression is in Equation (3.9):

$$\begin{aligned} Efficiency_{i,t} &= \beta_0 + \beta_1 Activebuy_{i,t-1} + \beta_2 Activesell_{i,t-1} + \beta_3 Indexbuy_{i,t-1} \\ &+ \beta_4 Indexsell_{i,t-1} + \beta_5 Lag\_Efficiency_{i,t} + \sum_j \beta_j Inst.Trade_{i,t-1} \\ &+ \sum_k \beta_k Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \qquad (3.9) \end{aligned}$$

We replace the absolute trading with buy and sell and rerun Eq (3.8). The results are shown in table 3.3. The results imply that that both actively managed fund buy activities and sell activities are positively correlated with the price efficiency of the stocks they trade. On average, a stock with a one standard deviation greater active fund purchase would have a 3% to 4% standard deviation smaller efficiency measures. A stock with a one standard deviation greater active fund sale would have a 2% to 3% standard deviation smaller efficiency measures.

Table 3.3 BUYs and SELLs and Efficiency

	(1) VR_5	(2) VR_{10}	(3) AR_m	(4) AR_q	(5) HM_mkt	(6) HM_ind
$Activebuy$	-0.04***	-0.03***	-0.03***	-0.04***	-0.03***	-0.02***
	(-11.24)	(-10.34)	(-10.22)	(-10.58)	(-7.28)	(-5.35)
$Activesell$	-0.03***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(-7.59)	(-5.20)	(-5.58)	(-6.41)	(-4.69)	(-4.19)
$Indexbuy$	-0.01	-0.00	0.00	-0.00	-0.06***	-0.06***
	(-1.50)	(-0.18)	(0.82)	(-1.17)	(-8.49)	(-7.86)
$Indexsell$	-0.00	0.00	0.00	0.00	-0.01**	-0.01**
	(-0.35)	(0.84)	(0.77)	(0.69)	(-2.45)	(-2.33)
$Lag\_efficiecny$	0.13***	0.07***	0.08***	0.20***	0.34***	0.40***
	(13.77)	(11.50)	(13.30)	(15.37)	(28.95)	(34.99)
$Inst.Trade$	Yes	Yes	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Rsq	0.116	0.057	0.068	0.175	0.495	0.520
adj.Rsq	0.115	0.056	0.068	0.174	0.495	0.520
F_dif_buy	29.90	31.82	46.08	33.94	11.92	12.90
p_dif_buy	0.00	0.00	0.00	0.00	0.00	0.00
F_dif_sell	33.86	20.11	19.74	28.85	0.76	0.81
p_dif_sell	0.00	0.00	0.00	0.00	0.38	0.37
N	214,627	214,627	215,221	215,159	183,749	183,749

This table reports the results of linear regressions of efficiency measures on $Activebuy$, $Activesell$, $Indexbuy$ and $Indexsell$. All the variables are standardized to a standard normal distribution. F_dif_buy and p_dif_buy are F-statistics and p-value of the F-test for the difference in the estimated coefficients between Activebuy and Indexbuy. F_dif_sell and p_dif_sell are F-statistics and p-value of the F-test for the difference in the estimated coefficients between $Activesell$ and $Indexsell$. t-statistics are in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Even though the magnitude of active fund sale is slightly smaller than that of active fund purchase, they are still significant, ruling out the possibility that the stocks traded by mutual funds experience efficiency improvement in the next quarter is only due to inclusion in the holding portfolios. The reason that buys have stronger effect than sells could be limits to arbitrage. For index funds, neither buy activities nor sell activities show significant correlation with efficiency measures. This is consistent with the results in Table 3.2. For both buys and sells, all the p-values are close to zero, implying that the magnitude of active fund trading is significantly greater than that of index fund trading.

For HM measures, both buys and sells have significant estimated coefficients. For index funds, buy activities are associated with a larger effect than sell activities. In an unreported regression, we add holdings by actively managed funds and index funds into Eq (3.9) and index holdings explain away a large portion of buy effect, but the estimated coefficient of index fund buys is still significant.

3.4 Liquidity and Analyst Coverage

The result in Table 3.2 shows that when adding liquidity measure to the regression equation, the significant association between index fund trading and stock price efficiency disappears. This result implies that trades by index funds may provide liquidity. In this section, we directly test the relation between mutual fund trading and the liquidity of the stocks they trade. The regression is similar to Equation (3.8) and Equation (3.9) except that we replace the left-hand side variable with $Illiquidity$, and with the corresponding lag measures. $Illiquidity$ is constructed following Amihud (2002). It is defined as the average ratio of the daily absolute return to the dollar trading volume on that day.

$$Illiquidity_{i,t} = \frac{1}{D_{i,t}} \sum_{1}^{D_{i,t}} \frac{|ret_{i,td}|}{VOLD_{i,td}} \tag{3.10}$$

where $D_{i,t}$ is the number of trading days in quarter t for stock i. $ret_{i,td}$ is the daily return in quarter t for stock i, and $VOLD_{i,td}$ is the daily trading volume in dollars in quarter t for stock i. We conduct the test for both absolute trading and buy sell activities separately. The result is shown in Table 3.4.

Since the dependent variable is illiquidity, a negative estimated coefficient implies an increase in liquidity. Both actively managed fund trading and index fund trading are significantly positive correlated with liquidity and F-test shows that the magnitude of the association between liquidity and trading is significantly greater for index funds.

Table 3.4 Liquidity

	(1) $Illiquidity$		(2) $Illiquidity$
$Active\_abs\_trade$	-0.01**	$Activebuy$	-0.00
	(-2.10)		(-0.87)
$Index\_abs\_trade$	-0.04***	$Activesell$	-0.01***
	(-4.72)		(-3.07)
		$Indexbuy$	-0.04***
			(-4.24)
		$Indexsell$	-0.02***
			(-2.99)
$Lag\ Illiquidity$	0.55***	$Lag\ Illiquidity$	0.55***
	(8.76)		(8.75)
$Inst.Trade$	Yes	$Inst.Trade$	Yes
$Controls$	Yes	$Controls$	Yes
Rsq	0.375	Rsq	0.375
adj. Rsq	0.375	adj. Rsq	0.375
F_dif_trade	11.33	F_dif_buy	12.68
p_dif_trade	0.00	p_dif_buy	0.00
N	215,294	F_dif_sell	0.61
		p_dif_sell	0.44
		N	215,294

This table reports the results of relationship between $Illiquidity$ and mutual fund trading. $Illiquidity$ is illiquidity measure proposed by Amihud (2002). F-statistics and p-value have similar meaning as before. t-statistics are in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Next question to ask is that what kind of stocks are more likely to be improved in price efficiency. If the efficiency improvement is due to information incorporated by mutual fund trading, then one would expect that stocks with higher information asymmetry are more likely to experience price efficiency improvement. We use analyst coverage to proxy the information asymmetry. For each stock in our sample in each quarter, the analyst coverage is set to be the number of I/B/E/S analysts who provide fiscal year earnings estimates in that quarter. In the regression, we interact analyst coverage with fund trading on the top of the regression in Equation (3.8). The result is presented in Table 3.5.

Table 3.5 Analyst Coverage

	(1) VR_5	(2) VR_{10}	(3) AR_m	(4) AR_q	(5) HM_mkt	(6) HM_ind
$Active\_abs\_trade$	-0.11***	-0.08***	-0.07***	-0.11***	-0.10***	-0.09***
	(-11.46)	(-8.83)	(-9.56)	(-12.18)	(-8.50)	(-8.36)
$Index\_abs\_trade$	-0.05***	-0.03***	-0.04***	-0.06***	-0.15***	-0.13***
	(-5.82)	(-3.43)	(-5.71)	(-6.30)	(-9.40)	(-7.78)
$Lag\_efficiency$	0.08***	0.04***	0.06***	0.15***	0.34***	0.40***
	(10.62)	(9.28)	(10.69)	(11.85)	(29.99)	(35.31)
Log_numest	0.10***	0.07***	0.07***	0.11***	-0.24***	-0.18***
	(10.15)	(7.57)	(8.16)	(11.52)	(-25.15)	(-16.94)
$Active\_abs\_trade \times Log\_numest$	0.06***	0.04***	0.06***	0.08***	0.11***	0.10***
	(6.52)	(5.01)	(7.01)	(7.03)	(9.17)	(8.37)
$Index\_abs\_trade \times Log\_numest$	0.10***	0.07***	0.07***	0.11***	0.13***	0.10***
	(10.15)	(7.57)	(8.16)	(11.52)	(8.73)	(6.78)
$Inst.Trade$	Yes	Yes	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Rsq	0.079	0.039	0.052	0.127	0.446	0.478
adj. Rsq	0.079	0.039	0.051	0.127	0.445	0.478
F_dif_trade	14.49	17.60	9.14	12.78	5.89	2.07
p_dif_trade	0.00	0.00	0.00	0.00	0.02	0.15
N	187,675	187,675	188,055	188,002	159805	159805

This table reports the results of linear regressions of efficiency measures on $Active\_abs\_trade$, $Index\_abs\_trade$ and the interaction term between fund trading and analyst coverage. log_numest is logged number of analysts who submit earnings forecast in quarter $t-1$. t-statistics are in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

All the estimated coefficients of the interaction terms are significantly positive. Remember that positive coefficients of mutual fund trading mean decrease in efficiency, so a positive coefficient of interaction term implies when analyst coverage is high, efficiency improvement is less. Therefore, the result of interaction terms indicates that stocks with higher information asymmetry are more likely to experience efficiency improvement after they are traded by both actively managed funds and index funds.

3.5 Motivations of Mutual Fund Trading

Previous results show that trades by both actively managed funds and index funds are positively associated with stock price efficiency. If both trades incorporate information, then the motivations of trades matter in improving stock price efficiency. More specifically, trades motivated by information should improve stock price efficiency more than liquidity trades, because the latter incorporate less information.

3.5.1 Liquidity Trading by Index Funds due to Change in Index Constituents

For index funds, one type of liquidity trading is the trades due to change in the constituents of the indices they are tracking. Section 2.5.2 also discusses about this type of trading motivation. Since this type of trades are not due to fund managers' information about the stock, one would not expect to see efficiency improvement after such trades.

In this section, we investigate the association between stock price efficiency and the index fund liquidity trading due to the change in index constituents. Following Cremers and Petajisto (2009), we look at the indices of S&P family, including the S&P 500, S&P 400, S&P 600, S&P 500/Barra Value and S&P 500/Barra Growth. The historical components of these indices are available on Compustat. To achieve this goal, first we create a dummy variable Chg_dummy for stock i in quarter t that takes value of one if it is included or excluded by an index, zero otherwise. Then we include an interaction term between this dummy variable and index fund trading. Since the exact timing of index fund trading due to the change in index constituents is not clear, we do the test for three scenarios. Index funds may trade when the index announces the change, but before the change becomes effective. They may also trade at the same time or after the change becomes effective. So, the dummy variable is defined in three ways in terms of timing. The regression we estimate is as follows:

$$Efficiency_{i,t} = \beta_0 + +\beta_1 Active\_abs\_trade_{i,t-1} + \beta_2 Index\_abs\_trade_{i,t-1}$$
$$+\beta_3 Lag\_efficiency_{i,t} + \beta_4 Chg\_dummy_{i,t-1} + \beta_5 (Index\_abs\_tarde_{i,t-1} \times$$
$$Chg\_dummy_{i,t-1}) + \sum_j \beta_j Inst.Trade_{i,t-1} + \sum_k \beta_k Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \qquad (3.11)$$

The results are shown in Table 3.6. Table 3.6 only reports the scenario that index fund trades one quarter after the announcement of reconstitution. The results for the other two scenarios are qualitatively the same.

Table 3.6 Liquidity Trading by Index Funds due to Change in Index Constituents

	(1) VR_5	(2) VR_{10}	(3) AR_m	(4) AR_q	(5) HM_mkt	(6) HM_ind
$Active\_abs\_trade$	-0.05***	-0.04***	-0.04***	-0.05***	-0.04***	-0.03***
	(-13.14)	(-11.81)	(-10.37)	(-11.26)	(-7.92)	(-6.29)
$Index\_abs\_trade$	-0.01	0.00	0.00	-0.00	-0.06***	-0.06***
	(-1.20)	(0.41)	(0.93)	(-0.42)	(-8.18)	(-7.81)
Chg_dummy	-0.00	-0.00	-0.01**	-0.01	-0.00	0.00
	(-1.30)	(-0.94)	(-2.16)	(-1.51)	(-0.66)	(0.22)
$Index\_abs\_trade$ $\times Chg\_dummy$	0.01***	0.01***	0.01***	0.01***	0.02***	0.02***
	(3.86)	(2.94)	(3.55)	(3.73)	(7.13)	(7.01)
$Lag\_efficiency$	0.13***	0.07***	0.08***	0.20***	0.34***	0.40***
	(13.80)	(11.51)	(13.31)	(15.39)	(28.95)	(34.94)
$Inst.Trade$	Yes	Yes	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Rsq	0.116	0.057	0.068	0.175	0.494	0.520
adj. Rsq	0.115	0.056	0.068	0.174	0.494	0.520
N	214,627	214,627	215,221	215,159	183,749	183,749

This table reports the results for relationship between efficiency measures and the index fund trading due to change in index constituents. *t*-statistics are shown in the parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

All the estimates of the interaction term are significantly positive at 1% level. Even though the timing of trade due to change in index constituents is not known for sure, the overall results imply that this type of trading is negatively correlated with the price efficiency of the stocks they trade. The result in Table 3.6 shows that liquidity trading by index funds due to change in index constituents is negatively correlated with all stock price efficiency. Note that for the efficiency measures related to random walk, index fund trading does not show significant association overall, but a further investigation of trade motivation does pick up this type of liquidity trading by index funds, adversely related to stock price efficiency.

3.5.2 Information-driven Trading and Flow-driven Trading

A fund manager who believes a stock is undervalued will want to buy this stock. But the outside individual investors may withdraw money from the fund and therefore prevent the fund manager from buying the stock shares as many as she wants. At the same time, there might be a situation where outside individual investors invest heavy flows for some irrational reasons, then the heavy inflows drive the fund manager to buy some shares she would not buy otherwise. This section follows the discussion in Section 2.5.3 about trading motivation and divide the trading by mutual fund into flow driven trading and information driven trading after excluding the trading due to index reconstitution. For trades by actively managed funds and index funds, we define a high group to be information driven trades and a low group to be flow driven trades. The goal in this section is to compare the magnitudes of the estimated coefficients of each high group and those of the corresponding low group. A result of high group has greater magnitude than the low group would be consistent with information channel. The results are shown in Table 3.7.

For trades by actively managed funds, results are consistent across all the efficiency measures. Information-driven trades are associated with larger effect of efficiency improvement than flow-driven trades. In addition, F test shows that the differences in magnitude are significant. For index funds, the result is more interesting. In the baseline regression of Equation (3.8), no significant association between index fund trading and stock price efficiency improvement shows up overall for variance ratio and return autocorrelation. But in this table, for VR_5 and AR_q, information-driven trades by index funds are significantly positive correlated with efficiency measure in the subsequent quarter.

Table 3.7 Information-driven Trades and Flow-driven Trades

	(1) VR_5	(2) VR_{10}	(3) AR_m	(4) AR_q	(5) HM_mkt	(6) HM_ind
$Abs\_activetrade\_high$	-0.04***	-0.03***	-0.03***	-0.04***	-0.03***	-0.02***
	(-12.48)	(-10.68)	(-9.27)	(-10.16)	(-6.01)	(-4.69)
$Abs\_activetrade\_low$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-3.35)	(-2.74)	(-3.49)	(-3.76)	(-3.87)	(-4.28)
$Abs\_indextrade\_high$	-0.01**	-0.00	-0.00	-0.01**	-0.06***	-0.05***
	(-2.22)	(-0.42)	(-0.45)	(-2.62)	(-9.22)	(-8.29)
$Abs\_indextrade\_low$	0.00	0.01*	0.01**	0.01***	-0.01*	-0.01*
	(1.19)	(1.88)	(2.52)	(2.83)	(-1.84)	(-1.69)
Chg_dummy	-0.00	-0.00	-0.01*	-0.01	-0.00	0.00
	(-1.01)	(-0.70)	(-1.93)	(-1.31)	(-0.76)	(0.05)
$Intradehigh \times Chg\_dummy$	0.01**	0.01*	0.01*	0.01***	0.02***	0.02***
	(2.18)	(1.70)	(1.71)	(2.76)	(5.34)	(5.28)
$Intradelow \times Chg\_dummy$	0.00	0.00	0.00**	0.00	0.01**	0.01**
	(1.49)	(1.19)	(2.01)	(0.62)	(2.20)	(2.14)
$Lag\_efficiency$	0.11***	0.06***	0.07***	0.18***	0.34***	0.40***
	(13.16)	(10.88)	(12.52)	(14.29)	(29.19)	(34.56)
$Inst.Trade$	Yes	Yes	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Rsq	0.098	0.048	0.059	0.151	0.483	0.510
adj. Rsq	0.098	0.047	0.059	0.150	0.483	0.510
F_dif_activetrade	54.97	32.63	19.38	33.00	9.85	3.18
p_dif_activetrade	0.00	0.00	0.00	0.00	0.00	0.08
F_dif_indextrade	5.90	2.28	2.86	13.71	24.36	17.61
p_dif_indextrade	0.02	0.13	0.09	0.00	0.00	0.00
N	208,293	208,293	208,883	208,821	178,457	178,457

This table reports the results for the linear regressions of efficiency measures on $Abs\_activetrade\_high$, $Abs\_activetrade\_low, Abs\_indexetrade\_high$ and $Abs\_indextrade\_low$. t-statistics are in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

For VR_{10} and AR_m, although information-driven trades do not show significant effect, the flow driven trades show significant effect in decreasing stock price efficiency. For HM measure, information driven trades are associated with larger effect in efficiency improvement than flow driven trades. The analysis of trade motivations reveals that for stock price efficiency that captures deviation from random walk, liquidity trading by index funds due to change in index constituents is negatively associated, information driven trades are positively related, and flow driven trades are negatively correlated. The different effects cancel out with each other and lead to no significant effect of overall trades by index funds. In addition, the asymmetry effects between information-driven trades and flow driven trades imply that trades by index funds may incorporate information as well.

3.6 Activeness of Index Funds

Previous analysis implies that some trades by index funds may incorporate information, then it will be interesting to explore what kind of index funds may have such information. One characteristic of interest is activeness (deviation from benchmark). Given the incentive of index funds to minimize tracking error, the reason that an index fund deviates from its benchmark might be that it has private information. In this section, we first describe some summary statistics of activeness and then investigate the role of activeness in improving stock price efficiency. We use the same measure as discussed in chapter: active share to capture the activeness of mutual funds. In this section we need to calculate active share for both index funds and actively managed funds, so we use CRSP universe as benchmark for all funds. In each quarter, we calculate active share for each fund and then sort all the funds into active share decile portfolios, including both actively managed funds and index funds. Table 3.8 documents the time series average of number of all funds, number of index funds, number of actively managed funds, mean, standard deviation and median of active share in each decile portfolio.

Rank 1 is the portfolio with the lowest active share and Rank 10 has the highest active share. Index funds show up in each of the ten portfolios. The number of index funds is the largest in the most passive rank, however, the standard deviation of active share in Rank 1 is 0.15, much higher than those in other ranks, indicating that even in Rank 1, active share varies across the index funds. This table reveals that activeness of index funds varies and some of index funds are not as passive as we thought.

Table 3.8 Summary Statistics of Activeness

Rank	No. of Funds	No. of Index Funds	No. of Active Funds	Mean	Std.Dev	Median
1(the most passive)	189.54	82.30	107.25	0.40	0.15	0.45
2	190.04	14.61	175.43	0.66	0.03	0.66
3	190.12	11.54	178.57	0.75	0.02	0.75
4	190.03	14.30	175.73	0.81	0.02	0.81
5	189.97	15.65	174.32	0.86	0.02	0.86
6	190.23	26.89	163.34	0.91	0.01	0.91
7	190.14	20.11	170.03	0.95	0.01	0.95
8	189.96	18.74	171.22	0.97	0.01	0.97
9	190.20	7.86	182.34	0.99	0.00	0.99
10 (the most active)	189.64	4.50	185.15	0.99	0.00	0.99

This table presents active share deciles for all the funds in the sample. Rank 1 has the lowest active share and Rank 10 has the highest active share.

To study the role of activeness in improving efficiency, we include an interaction term between activeness and mutual fund trading on the top of baseline regression. Since the regression is run at stock level, for each stock in each quarter, we construct trading value-weighted average active share of the funds that trade this stock. Specifically, suppose that stock i is traded by N actively managed funds and M index funds in quarter t,

$$Activeshare\_active_{i,t} = \frac{\sum_j^N Activeshare_{j,t} \times Dtrade\_active_{j,t}}{\sum_j^N Dtrade\_active_{j,t}} \tag{3.12}$$

$$Activeshare\_index_{i,t} = \frac{\sum_j^N Activeshare_{j,t} \times Dtrade\_index_{j,t}}{\sum_j^N Dtrade\_index_{j,t}} \tag{3.13}$$

where $Activeshare\_active_{i,t}$ ($Activeshare\_index_{i,t}$) is the active share for stock i in quarter t, aggregated from actively managed funds (index funds) that trade stock i in quarter t. $Activeshare_{j,t}$ is the active share of fund j in quarter t. $Dtrade\_active_{j,t}$ ($trade\_index_{j,t}$) is the dollar trading value by fund j. Such procedure generates two active share measures for one stock. In the regression, we include two interaction terms: one between active fund trading and active share aggregated from active funds, the other is between index fund trading and active share aggregated from index fund. The results are shown in Table 3.9.

Table 3.9 Interaction between Trading and Active Share

	(1) VR_5	(2) VR_{10}	(3) AR_m	(4) AR_q	(5) HM_mkt	(6) HM_ind
$Active\_abs\_trade$	-0.01	-0.01	-0.04	0.01	0.02	-0.02
	(-0.46)	(-0.32)	(-1.43)	(0.30)	(0.58)	(-0.50)
$Index\_abs\_trade$	0.03**	0.02**	0.02*	0.04***	0.05***	0.03**
	(2.56)	(2.05)	(1.80)	(3.21)	(3.34)	(2.00)
$Lag\_efficiency$	0.07***	0.04***	0.05***	0.13***	0.32***	0.38***
	(11.82)	(9.16)	(11.68)	(12.71)	(32.85)	(36.78)
$Activeshare\_active$	0.02**	0.02**	0.03***	0.03***	-0.01	-0.03***
	(2.55)	(2.48)	(3.84)	(3.68)	(-1.35)	(-3.75)
$Activeshare\_index$	0.01	0.01*	0.00	0.00	-0.06***	-0.06***
	(0.90)	(1.95)	(0.35)	(0.63)	(-6.56)	(-6.91)
$Index\_abs\_trade$ $\times$ $Activeshare\_index$	-0.04***	-0.02*	-0.02	-0.05***	-0.09***	-0.06***
	(-2.77)	(-1.79)	(-1.61)	(-3.33)	(-4.63)	(-3.39)
$Active\_abs\_trade$ $\times$ $Activeshare\_active$	-0.03	-0.03	0.01	-0.05*	-0.05	-0.01
	(-1.00)	(-0.95)	(0.21)	(-1.70)	(-1.37)	(-0.15)
$Inst.Trade$	Yes	Yes	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Rsq	0.056	0.029	0.041	0.087	0.434	0.468
adj. Rsq	0.056	0.028	0.040	0.087	0.433	0.467
F_dif_trade	1.73	0.98	3.78	1.04	0.50	1.38
p_dff_trade	0.19	0.32	0.05	0.31	0.48	0.24
N	181,817	181,817	182,224	182,173	158,403	158,403

This table reports the results of regression that includes interaction term between trading and active share. *t*-statistics are in parentheses. The superscripts*, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

For the interaction term between index fund trading and active share aggregated from index fund trading, the estimated coefficient is significantly negative except for AR_m. A negative estimate implies that for higher active share, index fund trading improves stock price efficiency more. For actively managed funds, except that the estimated coefficient of AR_q is significantly negative at 10% level, all the others are not significant. The result indicates that trades by index funds with high active share improve efficiency more, while trades by actively managed funds with high active share has little effect. It is probably due to the fact that actively managed funds with high active shares could be both unskilled and skilled. But index funds with high active share are more likely to be skilled. Information incorporated in trades by index funds provides a variety of implications confirmed by the data, such as trades with different motivations have different effects, and activeness of index funds plays a positive role in improving stock price efficiency. it is not obvious what alternative hypothesis would explain these findings.

CHAPTER 4

Do Mutual Funds Walk the Talk?

In this chapter, we switch the gear from return to risk. Return and risk are two main blocks in finance, however return is usually studied more by researchers. In this chapter, we investigate risk disclosure by mutual fund industry. Applying textual analysis on mutual fund summary prospectus, we first document what type of risks are disclosed by mutual fund. Then we study the academic meaning of the disclosure, specifically, we want to test whether there will be a bridge between industrial disclosed risk and academic risk factors. Finally, we study the risk disclosure and fund characteristics.

The rest of this chapter will be organized as follows: Section 4.1 discusses literature review. Section 4.2 talks about the data and background in this chapter. Section 4.3 documents the risks disclosed by mutual funds. Section 4.4 investigates how informative the risk disclosures are. Section 4.5 studies the relation between risk disclosure and fund characteristics. Section 4.6 tests timeliness of risk disclosure.

4.1 Literature Review

This chapter contributes to several strands of the academic literature. First, it contributes to the broad mutual fund literature by evaluating an important and understudied topic, the quality of mutual fund disclosure. Unlike most of the academic literature on mutual funds, the variables of interest in this chapter are qualitative rather than quantitative in nature. Moreover, the main variables reflect the perspective of investors rather than that of the researcher. Note that measuring risk using return data is straightforward for researchers but could be difficult for unsophisticated investors, who rely on information disclosed by funds. As a result, this chapter yields novel evidence and unique insights on an important question: how well does mutual fund disclosure serve the needs of investors? In a study of the readability of S&P 500 index fund prospectuses, Haan et al. (2020) find that statutory prospectuses are complex and not easy for investors to understand. SEC had the same concern and required funds to provide summary prospectus, which aims to provide a concise summary of the statutory prospectus to mitigate the lack of readability problem mentioned above. This chapter examines this new form of required disclosure. While textual analysis of corporate disclosure is a large literature, its application in mutual fund literature is still limited. Existing literature studies strategy description of statutory prospectus (Abis and Line, 2020), the text of letters to shareholders (Hillert et al., 2014; Du et al., 2020) and media coverage of mutual funds (Kaniel and Parham, 2017). This chapter complements to these studies by examining whether funds' risk disclosure accurately reflects their actual investment risks.

This chapter also contributes to the literature on predicting fund performance. A large literature is devoted to uncovering factors that can forecast fund performance.[13] Many of the predictors are based on signals extracted from fund holdings information.[14] Our finding that informativeness of fund disclosures predicts fund performance is a novel finding based on a stable fund characteristic. This chapter also contributes to the literature on understanding mutual funds' risk-taking behavior. Prior researchers have studied how funds shift risk as a way to attract cashflow and win performance tournaments.[15]

This chapter provides new evidence on the benefits and costs of disclosure. Consistent with the hypothesis that disclosure is more costly for entities with more proprietary information, our

[13] See, for example, Brown and Goetzmann (1995); Gruber (1996); Chevalier and Ellison (1999); and Zheng (1999). See Ferson (2010) and Wermers (2011) for a review.
[14] See, for example, Cohen, Coval, and Pastor (2005); Kacperczyk, Sialm, and Zheng (2005) (2008); Kacperczyk and Seru (2007); Cremers and Petajisto (2009); Barras, Scaillet, and Wermers (2010); Amihud and Goyenko (2013); and Jiang and Zheng (2018).
[15] See, for example, Brown, Harlow, and Starks (1996), Brown and Goetzmann (1997), Chevalier and Ellison (1997), Koski and Pontiff (1999), Goetzmann, Ingersoll, Spiegel, and Welch (2007), Kempf and Ruenzi (2007), Huang, Sialm, and Zhang (2011); and Schwarz (2011).

empirical findings suggest that low-skill funds tend to offer more informative risk disclosure. Ge and Zheng (1996) examine the costs and benefits of frequent mutual fund portfolio disclosure by looking at both the determinants and the potential effects of portfolio disclosure frequency. Wermers (2001) discusses in detail the potential costs of frequent portfolio disclosure, including dissemination of private information and the possibility of being “front-run.” In another study, Frank, Poterba, Shackelford, and Shoven (2004) document that the cost of revealing private information can be substantial since the after-expense returns of “copycat” funds are statistically indistinguishable from those of the underlying actively managed funds. Agarwal, Mullally, Tang, and Yang (2015) find that mandatory disclosure improves stock liquidity but imposes costs on informed investors. Brown, Goetzmann, Liang, and Schwarz (2008) examine the value of hedge fund disclosure through the SEC Form ADV requirement. Schwarz and Potter (2016) finds that mutual funds’ voluntary disclosure of portfolio holdings is likely motivated by convenience and advertising. Evans and Sun (2018) show how mandatory benchmark disclosure affects aggregate risk adjustment by retail investors. Dyakov, Harford, and Qiu (2020) find that increased disclosure requirements could be costly to investors due to agency implications.

This chapter also contributes to a general understanding of the economic interpretations of risk factors and how risk perceptions differ in industry and academia (Chinco et al., 2020). Analyzing fund summary prospectuses, we provide novel evidence on the risk perspectives of the investment industry. There is a large academic literature on what risk factors help explain fund performance. In this chapter, we examine the connection between industry risk perspectives and risk factors documented in the academic literature. In addition, this chapter fits into the literature on textual analysis in finance. Prior literature has focused on studying corporate disclosures such as annual reports (e.g., Li, 2008; Loughran and McDonald, 2011) and news articles (e.g., Tetlock, 2007; Manela and Moreira, 2017). Fisher, Martineau, and Sheng (2020) examine how news coverage of macroeconomic risks (e.g., unemployment) affects the stock market. Several recent papers also examine the disclosures of mutual funds. Unlike these earlier studies, we focus on the content and economic meaning of text disclosure in depth and bridge the gap between textual variables and quantitative variables. This approach allows a better understanding of the economic implications of textual disclosure beyond general readability and sentiment.

4.2 Data and Background

4.2.1 Mutual Fund Data

For mutual fund data, we link the CRSP Survivor-Bias-Free U.S. Mutual Fund Database with the Thomson Reuters Mutual Fund Holdings Database using the MFLINKS table (Wermers, 2000). Following Kacperczyk, Sialm, and Zheng (2008), we apply several filters to form our sample. We first examine fund names and index fund indicators in order to identify active index funds and remove passive funds from the sample. We then use the Lipper objective and classification codes, Wiesenberger objective codes, Strategic insight objective codes, Policy codes, and Thomson Reuters style code to identify U.S. domestic equity funds and remove others from the sample. We eliminate balanced funds and highly leveraged funds, which hold less than 80 percent or more than 105 percent of their assets in equity. We remove funds with a time-series average size smaller than $10 million. To estimate factor-adjusted performance for each fund, we require at least three years of return history.

For funds with multiple share classes, we aggregate information from the different classes. Fund-level returns, and expense ratios are the class size-weighted averages. Fund size is the aggregate of all share classes. We define fund age as the age of its oldest share class in our sample. Fund flow is calculated as a percentage of beginning total net assets. Finally, we use funds' management company name to identify funds that are in the same fund family and calculate fund family size as the sum of total assets of its affiliated funds.

4.2.2 Background on Fund Summary Prospectus

The SEC requires funds to provide proper disclosure to investors under the Investment Company Act of 1940. Specifically, each fund must provide this information in its prospectus. There are two kinds of prospectuses: (1) the statutory prospectus and (2) the summary prospectus. The statutory prospectus is the traditional, long-form prospectus with which most mutual fund investors are familiar. Starting from March 31, 2009, the SEC requires funds to also provide a summary prospectus, which is only a few pages long and contains key information about a fund. This new requirement is motivated by the concern of investor advocates, representatives of the fund industry, and others that the statutory fund prospectus is too long and complicated, thus difficult for investors to understand. The purpose of this regulation is "to improve mutual fund disclosure by providing investors with key information in plain English in a clear and concise format, while enhancing the means of delivering more detailed information to investors."[16]

To implement the new disclosure framework, the SEC adopted amendments to Form N-1A that require every prospectus to include a summary section at the front of the prospectus consisting of key information about the fund, including investment objectives and strategies, risks, costs, and performance. In this study, we focus on the disclosure of risks in the summary prospectus.

[16] The full text of this rule can be found here: https://www.sec.gov/rules/final/2009/33-8998.pdf.

4.2.3 Extracting Disclosed Risks from the Summary Prospectus

To get information about a fund's risk disclosure, we use the summary prospectuses available from the SEC EDGAR website.[17] Funds talk about their risk exposure in various ways. Some funds disclose many risks with detailed explanations, while other funds list only a few risks and offer a brief explanation for each one. In short, risk disclosure shows substantial variations, which we will explore in the rest of this chapter.

To capture funds' disclosures about their risk exposure, we extract the phrases that contain the key word "risk" or "risks." Since funds may choose different wording to express the same meaning, we manually check the extracted phrases and combine those that we believe have the same meaning. For example, "small cap risk" encompasses 33 similar phrases, including "smaller company risk," "small company risk," "small capitalization risk," and so on. For funds that make adjustments to their summary prospectus, we combine such disclosures with the main one. Finally, we use the Central Index Key (CIK) of the SEC to match the textual data with the CRSP fund data.

After merging the data on SEC Edgar and the CRSP, we are able to download the summary prospectuses for 1,782 unique funds. Funds with no disclosures after the data cleaning are excluded. Our final sample contains 1,620 funds and spans the period from 2009 to 2016. Table 4.1a reports fund-level summary statistics for our final sample, which is comparable to the summary statistics in the literature. Table 4.1b reports the average correlation between the variables.

4.3 What Risks Do Mutual Munds Disclose?

The academic literature has identified hundreds of return/risk factors, leading to a so-called "zoo" of equity factors (Cochrane, 2011). Which factors are deemed important by the investment industry? Which factors appear in funds' disclosure to investors? In this section, we report the disclosed

[17] The risk disclosure section title may differ from fund to fund. Using various titles to locate fund's risk disclosures, we are able to capture the information for almost all funds.

risks by mutual funds, their relative frequency, and the time trend. Once we identify the disclosed risk in the summary prospectus for each fund in each period, we rank the risks based on the average number of funds that disclose the corresponding risk. The cleaning of textual data leaves a total of 70 risks disclosed by the funds in our sample.

Table 4.1a Summary Statistics of Fund Characteristics

	Mean	Min	P25	Median	P75	Max	StdDev
Alpha	-0.0034	-0.0356	-0.0097	-0.0031	0.0029	0.0263	0.0109
Expense ratio	0.0109	0.0013	0.0089	0.0109	0.0130	0.0216	0.0038
Flow	0.0022	-0.3415	-0.0440	-0.0168	0.0191	0.7578	0.1340
Age	183.3613	2.6207	88.3966	160.9483	237.4828	618.0000	134.2695
Family size	80564.22	7.96	3604.99	20926.43	58368.02	1000182	162422
Size	1867.50	0.68	119.02	442.56	1418.99	88164.19	5565.76
Activeshare	0.7983	0.2453	0.7162	0.8275	0.9143	0.9932	0.1484
Turnover	0.7771	0.0317	0.2946	0.5370	0.9153	5.6640	0.8756
ICI	0.0421	0.0012	0.0185	0.0326	0.0506	0.2932	0.0433
Volatility	0.0099	0.0017	0.0089	0.0098	0.0111	0.0188	0.0025

This table reports the summary statistics for the fund characteristics used in this chapter. The numbers are time-series averages of the cross-sectional statistics. The sample includes open-end diversified domestic equity funds from 2009 to 2016. The funds are selected using methods in the literature. This table reports the statistics for individual variables. Alpha is average quarterly 4-factor alpha within a year. family size is total net assets of a family, in millions of dollars. Size is quarter-end total net assets. Active share measures the deviation in holdings from a fund's benchmark. ICI captures the concentration of holdings within industries. Volatility is the standard deviation of a fund's daily return within a quarter.

Table 4.1b Correlation among Fund Characteristics

	Alpha	Active share	Turnover	ICI	Size	Family size	Flow	Exp. ratio	Volatility
Alpha	1.00								
Active share	0.00	1.00							
Turnover	-0.05	-0.01	1.00						
ICI	-0.01	0.34	0.00	1.00					
Size	0.04	-0.09	-0.11	0.00	1.00				
Family size	0.05	-0.16	-0.07	-0.05	0.30	1.00			
Flow	0.21	0.01	0.03	0.04	-0.01	0.01	1.00		
Exp. ratio	-0.07	0.32	0.29	0.12	-0.26	-0.36	0.00	1.00	
Volatility	-0.01	-0.07	-0.17	-0.04	0.29	0.00	-0.15	-0.12	1.00

This table reports the correlation between each of the two variables.

Table 4.2 reports the top 20 frequently disclosed risks. The most frequently disclosed fund risk is "active investment risk," which is not surprising given our sample choice of actively managed funds. The second frequently disclosed risk is "market risk," which is also not surprising given that all the funds in our sample are subject to market risk. We also see disclosure of some less common types of risks, such as derivatives risk.

Table 4.2 Top 20 Common Risks

Disclosed Risk	No. of disclosing funds
active investment risk	651.09
market risk	587.16
foreign investment risk	555.88
equity risk	432.56
small cap risk	375.31
mid cap risk	304.75
liquidity risk	302.25
derivatives risk	267.13
value investing risk	233.09
growth investing risk	212.53
currency risk	185.00
credit default risk	184.13
industry sector risk	173.81
interest rate risk	166.66
portfolio turnover risk	164.56
non diversification risk	154.66
stock market risk	152.06
company specific risk	150.69
bond risk	147.41
emerging market risk	147.25

This table reports the top 20 most common risks disclosed by mutual funds in their prospectuses. The column "Disclosed Risk" lists the risks. The column "No. of disclosing funds" reports the average number of funds that disclose the risk per quarter in the sample.

To better visualize the top 20 risks, we plot them as a word cloud in Figure 4.1, where higher-ranked risks are plotted in bigger fonts. In general, we see three broad categories of risk. The first type is portfolio-specific risk, for example, active investment risk, portfolio turnover risk, and non-diversification risk. The second type is systematic risk, such as market risk, interest rate risk, and liquidity risk. The third type, which is the largest category, is asset class risk, including foreign investment risk, small cap risk, value investing risk, and derivatives risk. These frequently disclosed risks are also well-known risk factors in the academic literature.

Figure 4.1 Word Cloud of the Top 20 Risks Disclosed by Actively Managed Mutual Funds

Next, we study the correspondence between fund-disclosed risks and academic risk factors. For each disclosed risk, we propose a corresponding risk factor that makes the most economic sense to the best of our knowledge. Among the 70 risks, we were able to map 50 of them, as reported in Table 4.3.

Table 4.3 Subjective Factors for Each Risk

	Text-based risks	Holdings
1	active investment risk	Active share
2	asset-backed securities risk	Beta of ABS index
3	bank loan risk	Beta of loan outstanding (flow of fund data)
4	bond risk	Beta of bond index
5	business risk	Market beta
6	commodity investments risk	Beta of commodity index-CBOE
7	company specific risk	Idiosyncratic risk
8	country/regional risk	Betas of Asia, emerging, and Euro markets
9	credit/default/counterparty risk	Bond factors (FF 1993)
10	currency risk	Beta of Indices of currencies
11	cyber security risk	Beta of Cyber security risk ETF

12	deflation/inflation risk	Beta of inflation
13	derivatives risk	Beta of COBE index
14	economic risk	Market beta
15	emerging market risk	Beta of emerging market
16	equity risk	Market beta
17	event risk	Market beta
18	expropriation and nationalization risk	EPU from Nick Bloom
19	foreign investment risk	Betas of Asia, emerging, and Euro markets
20	globalization risk	Betas of Asia, emerging, and Euro markets
21	governmental risk	EPU from Nick Bloom
22	growth investing risk	Beta of Value factor
23	index/passive investing risk	Active share
24	industry/sector risk	Industry concentration
25	interest rate risk	Beta of interest rate
26	ipo/seo risk	Beta of Jay Ritter IPO index
27	large cap risk	Beta of Size factor
28	leverage risk	Beta of loan outstanding (flow of fund data)
29	liquidity risk	Beta of Liquidity factor
30	manager/advisor risk	Fund turnover
31	market capitalization risk	Beta of Size factor
32	market risk	Market beta
33	market timing risk	Beta of squared excess market return
34	market trading risk	Beta of Trading volume of S&P500
35	micro cap risk	Size factor
36	momentum style risk	Momentum factor
37	political/regulatory risk	EPU from Nick Bloom
38	portfolio turnover risk	Fund turnover
39	prepayment/extension/call/redemption risk	Beta of bond index
40	real estate investing risk	Beta of Case-Shiller index
41	refinancing/reinvestment risk	Beta of bond index
42	repurchase agreement risk	Beta of interest rates
43	security risk	Market beta
44	small cap risk	Beta of Size factor
45	stock market risk	Market beta
46	strategy/style risk	R squared of 4 factor model
47	tax risk	Beta of tax rate
48	temporary defensive investment risk	Beta of Investment factor
49	value investing risk	Beta of Value factor
50	volatility risk	STD of fund return

We use these subjectively mapped risk factors as proxies for the returns of the disclosed risk in one of our specifications to estimate risk coverage. Although we call this “subjective” mapping, it is based on common knowledge in the finance literature. For example, we match market risk with market beta.

To understand the meaning of disclosed risks, we use empirical estimation to identify the most relevant risk factors among all the subjective factors in Table 4.3. Before the estimation, we further narrow the risk universe by excluding the risks disclosed by fewer than 30 funds per quarter. The most common risk, active investment risk, is disclosed by 651.09 funds on average per quarter. Mapping entails matching the disclosed risks with the most closely related academic risk factors. Specifically, we regress the return difference of the disclosed risk, which is the difference between the return of a portfolio of all funds that disclosed this specific risk and the return of a portfolio of all funds that did not disclose this risk, on the subjective risk factors. For fund-specific risk factors, such as turnover, return volatility, Index Concentration Index (ICI) (Kacperczyk, Sialm, and Zheng, 2005), active share, and idiosyncratic risk, we construct the factor returns as the equally weighted average return of the top 30% of funds minus the equally weighted average return of the bottom 30% of funds, sorted on each of these variables. We then map each disclosed risk to the most significant risk factors. Table 4.4 reports the resulting mapping with the top three significant factors (if any). The outcomes are reasonably consistent with our economic intuition. For example, equity risk is mapped to stock market beta; growth-investing-risk is mapped to the Fama-French HML factor. We see that some of the fund-level factors—for example, active share and industry concentration index—are mapped to a number of disclosed risks, indicating that these fund-level factors serve as a proxy for different types of risks. Size beta is also mapped to a number of different disclosed risks, suggesting that it serves as a proxy for different disclosed risks. Overall, our evidence suggests that there is a good correspondence between the industry and academic. perspectives on risk. The heat map in Figure 4.2 allows us to visualize the relative frequencies and the changes over time. We observe that the relative frequencies of the disclosed risks remain quite stable over time. A few disclosed risks, such as foreign investment and liquidity, are disclosed by more funds in recent years. Over time, we see an increase in the number of risks being disclosed.

Table 4.4 Mapping between Risks and Factor Loadings

	Disclosed Risk	beta1	beta2	beta3
1	active investment risk	turnover	profitability beta	beta of loan outstanding (flow of fund data)
2	bond risk	market beta	beta of bond index	size beta
3	company specific risk	market beta	profitability beta	beta of S&P 500 trading volume
4	credit/default/counterparty risk	turnover	active share	investment beta
5	currency risk	market beta	active share	investment beta
6	depositary receipts risk	ICI	turnover	beta of bond index
7	derivatives risk	turnover	market beta	investment beta
8	economic risk	idiosyncratic risk	active share	DEF
9	emerging market risk	market beta	beta of Asia, emerging, and Euro markets	ICI
10	equity risk	turnover	investment beta	market beta
11	event risk	active share	market beta	ICI
12	foreign investment risk	size beta	profitability beta	market beta
13	growth investing risk	value beta	beta of bond index	turnover
14	index/passive investing risk	active share	turnover	beta of loan outstanding (flow of fund data)
15	industry/sector risk	ICI	TERM beta in FF(1993)	profitability beta
16	interest rate risk	market beta	turnover	active share
17	invest vehicle risk	market beta	ICI	beta of Indices of currencies
18	investment risk	interest	idiosyncratic risk	active share
19	ipo/seo risk	size beta	ICI	turnover
20	large cap risk	size beta	active share	ICI
21	leverage risk	ICI	idiosyncratic risk	investment beta
22	liquidity risk	turnover	investment beta	
23	manager/advisor risk	volatility		
24	market capitalization risk	beta of Indices of currencies	volatility	ICI
25	market risk	beta of ABS index	beta of loan outstanding (flow of fund data)	
26	market trading risk	active share	beta of loan outstanding (flow of fund data)	turnover
27	mid cap risk	size beta	active share	ICI
28	non diversification risk	active share	beta of Asia, emerging, and Euro markets	turnover

29	political regulatory risk	beta of Indices of currencies	beta of S&P 500 trading volume	beta of VIX
30	portfolio turnover risk	turnover	investment beta	
31	prepayment/extension/call/redemption risk	market beta	active share	investment beta
32	real estate investing risk	beta of bond index	value beta	beta of ABS index
33	securities lending risk	beta of bond index	investment beta	
34	short position risk	market beta	size beta	ICI
35	small cap risk	size beta	active share	investment beta
36	stock market risk	active share	beta of ABS index	DEF
37	strategy style risk	turnover		
38	valuation risk	size beta	ICI	beta of VIX
39	value investing risk	active share	value beta	turnover
40	volatility risk	beta of Indices of currencies	beta of Asia, emerging, and Euro markets	

This table reports the top three factor loadings mapped to 40 risks disclosed by mutual funds. The column "Disclosed Risk" lists all the risks studied in this chapter. Columns "beta1" to "beta3" report the three most significant loadings for these proposed factors, as well as the corresponding t statistics. For the risks with fewer than three significant loadings, only significant ones are reported.

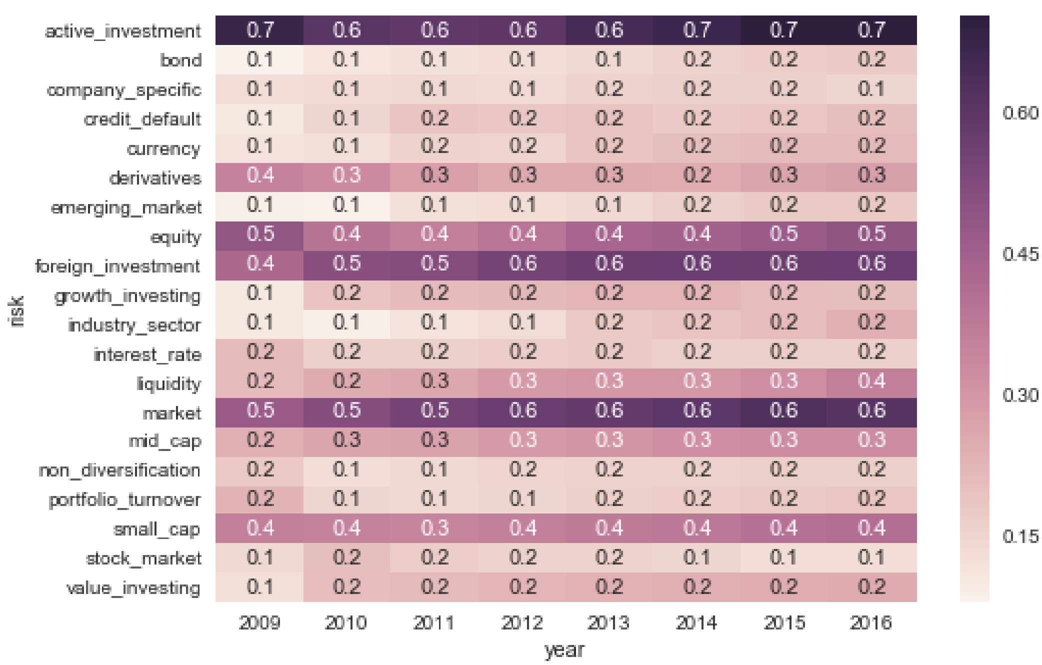

Figure 4.2 Heat Map of the Top 20 Risks Disclosed by Actively Managed Mutual Funds

4.4 How Informative Are Funds' Risk Disclosures?

In this section, we examine several properties of the risks disclosed by mutual funds. Motivated by the guidelines of the SEC, we construct three measures to assess the quality of risk disclosures in a fund's summary prospectus: overall risk coverage ratio (RCR), risk coverage ratio of the top three risks, and conciseness (overdisclosure).

4.4.1 Risk Coverage Ratio

To assess the quality of risk disclosure in a fund's summary prospectus, a natural question is whether the disclosure reflects the fund's actual risk—in other words, whether mutual funds walk the talk. Although all funds are required to disclose risks properly, funds may have various reasons to hide their risk taking. For example, some funds may not want to disclose positions that give them a performance edge. Prior studies also support this argument (e.g., Wermers, 2001; Frank, Poterba, Shackelford, and Shoven, 2004).

We first construct a measure that examines the coverage of all disclosed risks. Because investors need information to assess sources of future risk, we examine how well the disclosed risks explain future fund returns. Specifically, we examine what proportion of variations in actual future fund returns can be explained by disclosed risks. The rationale for this approach is as follows: if a fund discloses its risks properly, its future returns should be largely explained by related risk factors. The higher the explained proportion, the greater the coverage of the overall disclosure. Our general method is to regress future fund returns on the return proxy of disclosed risks and construct our main measures with R-squared from the regression. Specifically, for each fund, we run the following regression:

$$FundReturn_t = \alpha + \beta_1 \times RiskFactor_{1t} + \cdots + \beta_k \times RiskFactor_{kt} + e_t \qquad (4.1)$$

where $RiskFactor_{1t}$ to $RiskFactor_{kt}$ are k risk factors disclosed by the fund at time $t-1$. The R-squared from this regression measures the fraction of future returns that can be explained by the returns of disclosed risks. We call this $R^2\_Disclose_i(r_t, d_{t-1})$. We also run a regression with all risk factors that are disclosed by all funds, not just one fund.

$$FundReturn_t = \alpha + \beta_1 \times RiskFactor_{1t} + \cdots + \beta_n \times RiskFactor_{nt} + e_t \tag{4.2}$$

where $RiskFactor_{1t}$ to $RiskFactor_{nt}$ are n risk factors disclosed by all funds during the whole sample period.

The R-squared from this regression captures the fraction of variations in returns that can be explained by all risk factors that are disclosed in the mutual fund domain. We call this $R^2\_All_i(r_t, d)$. It establishes a base case (upper bound) for the risk coverage since we include all disclosed risks by all funds.

We estimate our main measure, Risk Coverage Ratio (RCR) as follows:

$$RCR_i(r_t, d_{t-1}) = \frac{R^2\_Disclose_i(r_t, d_{t-1})}{R^2\_All_i(r_t, d)} \tag{4.3}$$

RCR captures the comprehensiveness of risk disclosure because it measures the explanatory power of disclosed risks in a fund relative to the explanatory power of all risks by all funds. Benchmarking against $R^2\_All_i(r_t, d)$ allows a comparison across funds with different levels of risk. In general, low-risk funds have low $R^2\_Disclose_i(r_t, d_{t-1})$, but they do not necessarily underdisclose risks. Benchmarking $R^2\_Disclose_i(r_t, d_{t-1})$ against $R^2\_All_i(r_t, d)$ mitigates the problem because $R^2\_All_i(r_t, d)$ is also low for low-risk funds. A high RCR suggests that the risk coverage by the fund's disclosure is higher than the hypothetical risk coverage when we include all disclosed risks by all funds.

One challenge in the above procedure is to estimate the returns of disclosed risks. We construct a proxy for risk returns by using funds' actual returns. Specifically, for each fund in each quarter, the return of disclosed risk is constructed as the return of the portfolio of all other funds that disclose this risk minus the return of the portfolio of all funds that do not disclose this risk. The portfolio return is the equally weighted average return of individual funds in the portfolio. We exclude the observations if the disclosing portfolio contains fewer than five funds. Finally, since our main measures are forward-looking, for the disclosure at time t we estimate the returns of disclosed risks using the fund's daily returns in quarter $t + 1$.

Table 4.5a shows the summary statistics for the risk coverage ratio and other disclosure measures. The average $R^2\_Disclose_i(r_t, d_{t-1})$ is 79 percent. The average RCR is about 80 percent. These numbers suggest that funds' risk disclosure explains a substantial proportion of future return variations. However, we also observe large cross-sectional variations: the cross-sectional standard deviation is 19 percent; the minimum is 11 percent, and the maximum is 99 percent. We further study the determinants and implications of the cross-sectional differences in section 4.5.

As a robustness check, we also estimate RCR using the subjective mapped factors as proxies for returns of disclosed risks. To the extent that the mapping is imperfect and we misrepresent the returns of the disclosed risks, we would likely underestimate the explanatory power of the disclosed risks. The resulting RCR is similar to our earlier estimates, with a mean RCR of 86 percent and a standard deviation of 20 percent.

4.4.2 Top Risks

Not all risks disclosed in the summary prospectus are equally important. The SEC suggests that funds order the risks by importance.[18] In other words, the risks listed first are more important than the risks further down the list. To test whether funds disclose important risks first, we re-estimate RCR by focusing on the first three risks.

Table 4.5a Summary Statistics for Main Measures of Risk Disclosure

	Mean	Min	P25	Median	P75	Max	StdDev
$R^2\_Disclose$	0.7870	0.0915	0.7234	0.8552	0.9214	0.9829	0.1961
RCR	0.8012	0.1053	0.7399	0.8708	0.9328	0.9879	0.1929
Overdisclosure	0.4810	0.0000	0.3207	0.4948	0.6564	0.9951	0.2535
RCR Top	0.6656	0.0645	0.5613	0.7179	0.8182	0.9428	0.2058
No. of risks	6.8386	1.0000	4.0000	6.4310	8.8276	23.6552	3.7935
Change in no. of risks	0.0399	-6.2414	0.0000	0.0000	0.0000	6.6207	0.6285

This table reports the summary statistics for the main measures used in this chapter. The numbers are time-series average of the cross-sectional statistics. All the variables are winsorized at the 1% level.

Table 4.5b Correlations for Main Measures of Risk Disclosure

	$R^2\_Disclose$	RCR	Overdisclosure	RCR Top	No. of risks	Change in no. of risks
$R^2\_Disclose$	1.0000					
RCR	0.9953	1.0000				
Overdisclosure	0.0299	0.0605	1.0000			
RCR Top	0.7259	0.7154	-0.0898	1.0000		
No. of risks	0.5215	0.5506	0.5105	0.2093	1.0000	
Change in no. of risks	0.0487	0.0510	0.0531	0.0135	0.1077	1.0000

This table reports the time-series average correlation between each two variables. All the variables are winsorized at the 1% level.

Specifically, we extract the first three risks disclosed by each fund in its summary prospectus and calculate the RCR measures using the same method as previously. We call this RCR Top. Table 4.5a shows that RCR Top is 67 percent on average, compared to 80 percent for

[18] See the document here https://www.sec.gov/investment/accounting-and-disclosure-information/principal-risks/adi-2019-08-improving-principal-risks-disclosure#_ftn1

all risks. Overall, the top three disclosed risks are indeed important and explain a large fraction of fund returns.

4.4.3 Overdisclosure

While it is important to disclose all risks that funds are exposed to, one question is whether funds may also disclose risks that they are not exposed to. Funds may overdisclose risks for at least two reasons. First, low-skill funds may want to disclose many risks, including some risks that they are not exposed to, to mitigate concerns about potential litigation. Hanley and Hoberg (2012) show that firms use strategic disclosure in IPO prospectuses to hedge against litigation risk. Second, high-skill funds may want to disclose many risks to hide their true exposure. We examine whether funds overdisclose risks in their summary prospectus.

Specifically, we run regression Equation (4.1) with all disclosed risks. We count the number of risks that are statistically significant (with p-value $\leqslant 0.05$). The overdisclosure measure is the number of risks that are not significant divided by the total number of risks disclosed in the fund's summary prospectus. In other words, this measure captures the fraction of disclosed risks that does not significantly affect the fund's returns. Table 4.5a shows that, on average, 48 percent of risks are not statistically significant. This finding suggests that although funds' disclosures appear comprehensive, they also overdisclose, suggesting that the SEC may require funds to disclose relevant information only.

In addition to these measures, we construct two other measures of risk disclosure. First, we count the number of disclosed risks. Table 4.5a shows that an average fund discloses about seven risks. There is large cross-fund dispersion in the number of disclosed risks. While a fund at 25th percentile discloses 4 risks, a fund at 75th percentile discloses about 9 risks. Second, we examine the change in the number of disclosed risks over time for each fund. On average, the number of risks disclosed per fund increases by about 0.04 per quarter. The 25th percentile and the 75th percentile are both zero, implying that most funds do not change the number of disclosed risks over time.

Overall, we find that the risks a fund discloses in its summary prospectus can explain a large proportion of variations in the fund's future returns. Top risks are important as they explain a disproportionally high fraction of fund returns. However, we also find that funds overdisclose risks since half of the disclosed risks are not useful in explaining the variations in fund returns.

4.5 How Does Risk Disclosure Relate to Fund Characteristics, Performance, and Flow?

Once we construct measures to capture the coverage and conciseness of funds' risk disclosures, we examine how these measures relate to fund characteristics, risk taking, and performance.

4.5.1 Determinants of Risk Disclosure

Given that we observe substantial cross-fund variation in the quality of risk disclosure, we now examine how disclosure quality relates to fund characteristics. We use Fama-Macbeth regression where the dependent variables are RCR, RCR Top, log number of risks, overdisclosure, and whether a fund disclosed unique risks. Table 4.6 Column 1 shows that younger funds, larger funds, riskier funds, and funds with higher expense ratios tend to have higher risk coverage ratios. Interestingly, funds with worse performance also have high risk coverage ratios. Why do these funds tend to have higher risk coverage? One possible explanation is that disclosure cost is lower for managers with less proprietary information. Fund managers who possess proprietary information may be reluctant to reveal their edge, which is common in the hedge fund industry. Another possible explanation is that funds with worse performance disclose more risks as a way of explaining their inferior performance.[19] In other words, they blame these risks for their

[19] Barth, Joenvaara, Kauppila, and Wermers (2020) also find that hedge funds with worse performance tend to disclose more.

underperformance. Table 4.6 Column 2 shows that riskier funds tend to have higher risk coverage ratios as constructed by the top three risks.

Table 4.6 Determinants of Risk Disclosure

	(1) RCR	(2) RCR Top	(3) Overdisclosure	(4) Log no. of risks	(5) Unique fund
Log family size	0.001	0.004*	-0.003***	0.008*	-0.002*
	(0.48)	(1.92)	(-3.25)	(1.74)	(-1.92)
Log size	0.006***	0.001	0.003**	0.019***	-0.001
	(6.33)	(0.95)	(2.17)	(5.76)	(-0.24)
Expense ratio	1.902***	-0.313	7.250***	18.585***	2.634***
	(2.81)	(-0.42)	(16.44)	(28.40)	(3.51)
Volatility	21.459***	23.595***	-19.778***	0.697	7.001***
	(11.91)	(9.41)	(-19.91)	(0.38)	(2.82)
Flow	0.036**	0.005	0.017	0.146***	0.013
	(2.67)	(0.33)	(1.25)	(3.59)	(0.51)
Log age	-0.009**	0.008*	-0.032***	-0.100***	-0.014***
	(-2.07)	(2.02)	(-4.80)	(-8.64)	(-4.45)
Alpha	-0.627*	-0.020	-0.225	-3.003**	-0.739***
	(-2.00)	(-0.07)	(-0.64)	(-2.61)	(-3.22)
Constant	0.586***	0.370***	0.758***	1.848***	0.053*
	(15.75)	(8.04)	(16.72)	(15.49)	(1.82)
N	25384	25384	25384	25392	25392
Avg. R-sq	0.0811	0.0875	0.0612	0.0342	0.0353

This table reports the regression results of R-squared measures and other disclosure measures on lagged fund characteristics. The test is a Fama-Macbeth regression and adjusts for Newey-West standard errors for two lags. All the variables are winsorized at the 1% level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We also look at other features of risk disclosures. Table 4.6 Column 3 shows that funds in smaller fund families, larger funds, funds with higher expense ratios, less risky funds, and younger funds tend to overdisclose risks. Table 4.6 Column 4 shows that larger funds, funds with higher expense ratios, younger funds, and funds with worse past performance and higher flow tend to disclose a larger number of risks. We also look at what types of funds are more likely to disclose risks that are unique. We define a risk as unique if it is in the bottom 5% of disclosures in a period across all funds. The dependent variable in Table 4.6 Column 5 is a dummy variable defined at the fund level that takes a value of one if the fund discloses at least one unique risk as defined above, and zero otherwise. The result suggests that funds in smaller families, funds with higher expense ratios, riskier funds, younger funds, and funds with worse past performance are more likely to disclose unique risks in their summary prospectus. This finding is consistent with the economic intuition that smaller and younger funds are more likely to be exposed some unique risks.

4.5.2. Risk Disclosure and Future Risk Taking and Performance

Is the quality of funds' risk disclosure related to their future risk-taking behavior and performance? In this subsection, we look at two important dimensions of mutual funds: risk-taking behavior and performance. We use the standard deviation of a fund's return to proxy its risk. To test this idea, we regress the standard deviation of a fund's return in the next period on the several textual measures we discussed above, controlling for size, fund family size, expense ratios, age, flow, and performance. Table 4.7 Column 1 shows that funds with higher risk coverage ratios exhibit higher risk in the following quarter. Column 3 shows that funds with higher risk coverage ratios estimated using the first three disclosed risks also exhibit higher risk in the future; Column 2 implies that funds with more overdisclosure exhibit lower risk in the future. The results in Column 2 suggest that funds with more comprehensive risk disclosures take on more risk in the future. One possible reason could be that fund manager who overdisclose risks are more conservative and therefore takes fewer risks in the future. The results in Column 4 are consistent with the hypothesis that a fund manager who overdiscloses risks is more conservative and assumes less investment risk. Column 5 shows that funds that disclose unique risks tend to take more risks.

How does risk coverage relate to future fund performance? We examine this question by looking at the association between funds' current disclosures and their performance in the next year, measured by 4-factor alpha (Fama and French, 1992; Carhart, 1996).

Table 4.7 Risk Disclosure and Funds' Future Risk Taking

	(1) Next volatility	(2) Next volatility	(3) Next volatility	(4) Next volatility	(5) Next volatility
RCR	0.279***				
	(4.53)				
Overdisclosure		-0.138***			
		(-8.52)			
RCR Top			0.288***		
			(4.76)		
Log no. of risks				-0.005*	
				(-1.91)	
Unique fund					0.038**
					(2.54)
Log family size	0.011***	0.011***	0.010***	0.012***	0.012***
	(5.97)	(5.82)	(4.99)	(5.97)	(6.12)
Log size	-0.026***	-0.024***	-0.025***	-0.026***	-0.026***
	(-5.84)	(-5.76)	(-5.68)	(-5.68)	(-5.58)
Expense ratio	7.317***	8.624***	7.826***	7.869***	7.593***
	(6.94)	(7.68)	(7.70)	(6.43)	(6.40)
Log age	0.059***	0.054***	0.055***	0.060***	0.060***
	(10.70)	(9.90)	(10.14)	(10.00)	(10.05)
Flow	-0.023	-0.016	-0.022	-0.016	-0.016
	(-0.71)	(-0.47)	(-0.62)	(-0.47)	(-0.47)
Alpha1	0.109	0.087	0.098	0.040	0.069
	(0.44)	(0.31)	(0.37)	(0.16)	(0.27)
Turnover	-0.018**	-0.020***	-0.019**	-0.023***	-0.024***
	(-2.49)	(-2.88)	(-2.58)	(-3.36)	(-3.42)
Constant	0.406***	0.705***	0.450***	0.636***	0.625***
	(11.67)	(8.78)	(12.97)	(8.30)	(8.16)
N	25192	25192	25192	25192	25192
Avg. R-sq	0.1482	0.1281	0.1599	0.1066	0.1098

This table reports the results of regression of fund risks in the next quarter on the current disclosure measures. The test is Fama-Macbeth regression and adjusts for Newey-West standard errors for two lags. All the variables are winsorized at the 1% level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.8 shows that funds with higher risk coverage ratios perform worse in the future (Column 1). Similarly, funds with more overdisclosure tend to underperform in the future (Column 2). Moreover, funds that disclose more risks tend to perform poorly in the subsequent year (Column 5). These findings suggest that risk disclosure quality can predict fund performance. A one standard deviation increase in RCR is associated with a 20-basis point decrease in annualized alpha.

Table 4.8 Risk Disclosure and Fund Future Performance

	(1) Annualized alpha	(2) Annualized alpha	(3) Annualized alpha	(4) Annualized alpha	(5) Annualized alpha
RCR	-0.012***				
	(-4.40)				
RCR Top		-0.001			
		(-0.32)			
Overdisclosure			-0.008***		
			(-4.62)		
Unique fund				-0.007	
				(-1.61)	
Log no. of risks					-0.005***
					(-6.53)
Log family size	0.001	0.001	0.001	0.001	0.001
	(1.68)	(1.66)	(1.51)	(1.56)	(1.70)
Log size	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.20)	(-0.28)	(-0.16)	(-0.20)	(-0.06)
Expense ratio	-0.280	-0.294	-0.229	-0.296	-0.193
	(-1.34)	(-1.44)	(-1.07)	(-1.40)	(-0.89)
Volatility	-0.342	-0.556	-0.781	-0.638	-0.637
	(-0.61)	(-0.98)	(-1.39)	(-1.14)	(-1.17)
Log age	0.000	0.000	0.000	0.000	-0.000
	(0.28)	(0.34)	(0.16)	(0.25)	(-0.08)
Flow	-0.000	-0.000	-0.001	-0.001	-0.001
	(-0.07)	(-0.11)	(-0.24)	(-0.22)	(-0.22)
Turnover	-0.003**	-0.002**	-0.002*	-0.002*	-0.002*
	(-2.17)	(-2.09)	(-1.95)	(-1.99)	(-1.96)
Constant	-0.005	-0.012	-0.007	-0.011	-0.003
	(-0.74)	(-1.68)	(-0.89)	(-1.50)	(-0.39)
N	25067	25067	25067	25067	25067
Avg. R-sq	0.0464	0.0453	0.0448	0.0459	0.0487

This table reports the results of regression of funds' future performance on current R-squared measures and disclosures, controlling for fund characteristics. The test is Fama-Macbeth regression and adjusts for Newey-West standard errors for two lags. All the variables are winsorized at the 1% level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5.3. Do Investors Pay Attention to Funds' Risk Disclosures?

Our findings show that fund risk coverage ratio is generally high and predicts future risks and performance. A natural question is whether investors respond to these measures of disclosure quality. This question is particularly interesting because the SEC's primary goal in requiring funds to provide a summary prospectus is to give investors better access to this type of information. To test whether this goal is achieved, we examine whether funds with a high risk coverage ratio attract more funding from investors, measured by flow.[20] Table 4.9 shows the results of this test. We find that fund flows are not related to a fund's past risk coverage ratio. This is not a surprising result because the informativeness measure is not easily observed by investors. This finding does not mean that investors do not pay attention to risk disclosures per se; rather it suggests that they do not react to the coverage of risk disclosures. Interestingly, the result in Column 5 implies that funds that disclose unique risks attract less flow in the subsequent quarter. When investors notice uncommon risks disclosed in a fund's summary prospectus, they may decide to avoid that fund in order to minimize their risk. This is consistent with the theory in Goldstein and Yang (2019) that disclosure makes decision maker better off only when she already knows well about the variables in the disclosures.

4.6 Do Mutual Funds Disclose Risks in a Timely Manner?

Timeliness is another important measure of the quality of fund disclosures. Although the risk coverage of fund disclosure appears to be high, do they disclose those risks in a timely manner? We examine this question by analyzing changes in risk disclosures. We further test whether changes in disclosure improve the RCR. For each time period, we calculate the RCR using each fund's updated risk disclosure and the previous risk disclosure, respectively. We then calculate the

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[20] Flow is calculated as the new money from investors in each quarter as a percentage of the total net assets at the beginning of that quarter (see Zheng, 1999).

Table 4.9 Risk Disclosure and Fund Flow

	(1) Next flow	(2) Next flow	(3) Next flow	(4) Next flow	(5) Next flow
RCR	0.011				
	(1.48)				
Overdisclosure		-0.003			
		(-1.02)			
RCR Top			0.008		
			(1.37)		
Log no. of risks				0.001	
				(1.02)	
Unique fund					-0.008*
					(-1.99)
Log family size	0.001	0.001	0.001	0.001	0.001
	(0.74)	(0.80)	(0.76)	(0.73)	(0.80)
Log size	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.31)	(-0.15)	(-0.27)	(-0.28)	(-0.19)
Expense ratio	-0.405	-0.404	-0.424	-0.446	-0.404
	(-1.29)	(-1.30)	(-1.34)	(-1.36)	(-1.24)
Log age	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***
	(-8.34)	(-8.74)	(-8.24)	(-8.45)	(-8.47)
Volatility	-0.497	-0.284	-0.381	-0.245	-0.203
	(-0.79)	(-0.51)	(-0.61)	(-0.44)	(-0.35)
Alpha1	0.766***	0.773***	0.772***	0.766***	0.766***
	(11.26)	(12.01)	(11.93)	(11.21)	(11.79)
Turnover	-0.003	-0.003*	-0.003*	-0.003*	-0.003*
	(-1.66)	(-1.79)	(-1.71)	(-1.83)	(-1.76)
Constant	0.067***	0.076***	0.069***	0.073***	0.074***
	(3.85)	(3.98)	(3.77)	(3.73)	(3.72)
N	25183	25183	25183	25183	25183
Avg. R-sq	0.0583	0.0573	0.0580	0.0569	0.0578

This table reports the results of regression of funds' future flow on current R-squared measures and disclosures, controlling for fund characteristics. The test is Fama-Macbeth regression and adjusts for Newey-West standard errors for two lags. All the variables are winsorized at the 1% level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

difference between the two RCRs, which measures the change (hopefully improvement) in RCR due to the change in risk disclosure. Our main variable, DIF_RCR, is defined as follows:

$$DIF\_RCR_{it} = RCR_i(r_t, d_{t-1}) - RCR_i(r_t, d_{t-2}) \quad (4.4)$$

Table 4.10 Column 1 shows the results of this test. We find that an increase in the number of disclosed risks is associated with a significant improvement in RCR. This finding suggests that the change in risk disclosure improves risk coverage, which is good news but not too surprising.

Table 4.10 The Timeliness of Risk Disclosure

	(1) DIF_RCR	(2) DID_RCR
Change in no. of risks	0.010***	0.001**
	(5.61)	(2.36)
Log family size	0.000*	0.000
	(1.88)	(0.92)
Log size	0.000	0.000
	(0.02)	(0.30)
Expense ratio	-0.012	-0.005
	(-0.54)	(-0.34)
Volatility	0.021	-0.066
	(0.63)	(-1.62)
Flow	0.001	0.001
	(0.85)	(1.43)
Log age	-0.000	0.000
	(-1.29)	(0.68)
Alpha	-0.009	0.002
	(-1.15)	(0.24)
Constant	-0.001	-0.000
	(-0.82)	(-0.49)
N	24099	24095
Avg. R-sq	0.3833	0.0571

This table reports the results of regression of DIF_RCR and DID_RCR on the change in number of disclosed risks. The test is Fama-Macbeth regression and adjusts for Newey-West standard errors for two lags. All the variables are winsorized at the 1% level. The superscripts*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The second test focuses on timeliness. Our hypothesis is that if a fund discloses risk change in a timely manner, its RCR improvement should be bigger after time t than before time t because the newly disclosed risks should be relevant to the fund returns only after time t. To further test the timeliness of the risk disclosure, we compare the improvement in the risk coverage ratio for time t versus the improvement for time $t - 1$. The dependent variable in this test is DID_RCR, defined as following:

$$DID\_RCR_{it} = [RCR_i(r_t, d_{t-1}) - RCR_i(r_t, d_{t-2})] - [RCR_i(r_{t-1}, d_{t-1}) - RCR_i(r_{t-1}, d_{t-2})] \quad (4.5)$$

Table 4.10 Column 2 shows the result of this test. We find that improvement in RCR is statistically greater after the change in risk disclosure than before the change, which suggests that funds do disclose risks in a timely manner. However, the magnitude of the coefficient is much smaller than that in Column 1, which suggests that not all disclosure changes are made in a timely manner.

CHAPTER 5

Conclusion

Chapter 2 first documents that index funds are more active than we thought. It offers new insights to understand index funds. Since index funds show different level of activeness, it is meaningful to dig index funds more deeply. It turns out that index funds are also more heterogenous than we thought. Within S&P 500 index funds, even with the same benchmark, their performance is heterogenous. And such heterogeneity is persistent and can be negatively predicted by turnover ratio. It is surprising to discovery cross-funds differences among S&P 500 index funds and their performance differences are statistically and economically significant.

We examine the trading performance of S&P 500 index funds. In general, measured by 4-factor alpha and DGTW returns, S&P 500 index fund trades lose money over one-month, one-quarter, and one-year horizons. Difference from actively managed funds, trading performance hurts their general performance, especially among the worst performers. Flow-driven trades lose money. Reconstitution-motivated trades lose money over the short horizon but recover over the one-year horizon. Also, the magnitude of loss is the highest for reconstitution-motivated trades. Managers' discretionary trades make money in the short term but lose money in the longer term when they are identified at the trade level.

Chapter 2 also raises some possible questions for further study. First, liquidity may play a role in S&P 500 index fund trading. One could test whether trades of illiquid stocks are more likely to lose money. Another question is about managers' discretionary trades. Since index fund managers are not expected to trade on information, then the study of their trading motivation will be interesting.

Chapter 2 provides insights of the overlap and difference between index funds and actively managed funds, especially of the trading performance of index funds. Continually, Chapter 3 studies the implication to stock price efficiency in the financial market. Regression analysis shows that both actively managed fund trading and index fund trading are positively related to the price efficiency of the stocks they trade, but in different ways. Stocks traded by actively managed funds exhibit more random walk patterns than those traded by index funds. While trades by index funds reduce stock price delay to market and industry information more than trades by actively managed funds. Trade motivations matter. For actively managed funds, information-driven trades are associated with stock price efficiency more than flow-driven trades. For index funds, liquidity trading due to change in index constituents is adversely related to stock price efficiency, while information-driven trades are positively correlated with stock price efficiency. Activeness of index funds also plays an important role. Stocks traded by index funds with high active share exhibit more improvement in efficiency. The findings of trade motivations and activeness for index funds are consistent with implications provided by the hypothesis that index fund trading incorporates information. It is not obvious what alternative hypothesis would explain such findings supported by the data.

Then this dissertation switches the focus to risk in Chapter 4. This chapter answers the question whether risk disclosure by mutual funds reflects their actual risk exposure in the investment activities. While the SEC requires mutual funds to disclose risks properly in their summary prospectus, empirical evidence on the quality of the disclosures is limited. One challenge in assessing the disclosure quality is that the disclosure is text based and therefore difficult to analyze. To address this challenge, we use textual analysis to identify the disclosure of risks for a large sample of actively managed domestic equity mutual funds. We examine the content of risk disclosures in detail, documenting the disclosed risks and how they relate to common risks identified in the academic literature. We then assess the quality of fund disclosures by estimating risk coverage, top risk coverage, and the extent of overdisclosure. While we find that, on average, the disclosed risks can explain a large percentage of variations in future fund returns; we also find that. on average, funds overdisclose by about 50 percent.

In addition, we observe large cross-fund variation in the informativeness measure. We find that younger funds, larger funds, riskier funds, and funds with higher expense ratios tend to make more comprehensive risk disclosures. We also find that higher risk coverage in funds' disclosures is associated with higher risk and inferior performance in the future.

Our findings have significant regulatory and legal implications. Whether fund risk disclosure is informative to investors also depends on investors' knowledge and understanding of the common risk factors. Financial education about risk factors would help investors understand risk disclosure and make better-informed investment decisions.

This dissertation starts with the comparison between actively managed funds and index funds in general and provide novel evidence that index funds are more active and heterogenous than we thought. Then we dig deeper into index fund trading performance and show that even with better average return performance, index fund trades lose money. Keeping the activeness of index funds in mind, we continue to investigate the association between mutual fund trading and stock price efficiency. More specifically, we test the difference in such association between actively managed funds and index funds. We show interesting finding that even index funds are believed to be passive, their trading improves stock price efficiency in some way, mainly provides liquidity and reduces price delay to the market and industry information. Finally, we turn to risk and explore mutual fund risk disclosure in their summary prospectus. We demonstrate that overall mutual funds make comprehensive disclosure in the sense that their return performance can be largely explained by the disclosed risks.

This dissertation provides insights and big pictures of actively managed funds and index funds. We find novel evidence that the two types of funds might be different as we thought. We also study these funds from both return and risk perspectives. But our study still has limitations, and some follow-up questions can be done in the future. For example, the relation between stock liquidity and mutual fund trading performance could be a question to further study.

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