ESSAYS ON INSTITUTIONAL INVESTORS AND ASSET PRICING

by

Tianyao Zhang

B.Math, University of Waterloo, 2013
B.B.A., Wilfrid Laurier University, 2013

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in

The Faculty of Graduate and Postdoctoral Studies

(Business Administration)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

July 2019

The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

Essays on Institutional Investors and Asset Pricing

submitted by Tianyao Zhang in partial fulfillment of the requirements for

the degree of Doctor of Philosophy

in Business Administration

Examining Committee:

Ron Giammarino, Business Administration
Co-supervisor

Adlai Fisher, Business Administration
Co-supervisor

Murray Carlson, Business Administration
Supervisory Committee Member

Ralph Winter, Business Administration
University Examiner

Vadim Marmer, Vancouver School of Economics
University Examiner

Additional Supervisory Committee Members:

Russell Lundholm, Business Administration
Supervisory Committee Member

Supervisory Committee Member

Abstract

In this thesis, I study the asset pricing aspect of institutional investors and their ability to provide financial services to households. The thesis consists of three essays.

In the first essay, I theoretically investigate how institutional investors with different holding horizons allocate capital and the related asset pricing implications. I propose a model in which some institutions have shorter holding horizons, defined as short-term institutions, than other institutions, i.e. long-term institutions. The optimal portfolio of short-term institutions tilts towards speculative stocks that experience more volatile future demand shocks, which create transient trading opportunities. The current demand from short-term institutions increases the prices of these speculative stocks and reduces their buy-and-hold returns, making them less desirable for long-term investors. The model provides predictions relating a stock's short-term institutional ownership, trading opportunity, and expected return.

In the second essay, I test the predictions of the first essay. Empirically, short-term institutions, identified as high-turnover institutions, invest more in stocks with higher CAPM beta, higher idiosyncratic volatility, and lower buy-and-hold abnormal returns. The difference in the buy-and-hold abnormal return between stocks with least and most short-term institutional investors is more than 3% per year. Stocks with more short-term institutional investors also provide more trading opportunities, allowing short-term institutions to make more trading profits. Their trading profits increase with market sentiment. This essay demonstrates that the desirability of investing in speculative stocks depends on an institution's holding horizon.

The third essay examines the well-established negative relation between expense ratios and future net-of-fees performance of actively managed equity mutual funds. I show that this relation is an artifact of the failure to adjust a fund's performance for its exposures to the profitability and investment factors. High-fee funds exhibit a strong preference for stocks with low operating profitability and high investment rates, characteristics associated with low expected returns. After controlling for exposures to profitability and investment factors, I find that high-fee funds significantly outperform low-fee funds before fees and perform equally well net of fees. These results support the theoretical prediction that skilled managers extract rents by charging high fees.

Lay Summary

This thesis contains three essays that study institutional investors. In the first and second essays, I theoretically and empirically investigate how institutional investors with different holding horizons allocate capital. I show that short-term institutions allocate more capital to speculative stocks in order to make more trading profits. The demand from short-term institutions reduces the buy-and-hold returns of speculative stocks, making them less desirable to long-term institutions. My second essay confirms the main empirical predictions of the first essay. In the third essay, I examine the fee-performance relationship among actively managed mutual funds. The puzzling negative fee-performance relationship found in the prior literature can be resolved by controlling a mutual fund's exposures to profitability and investment factors in the performance evaluation. After controlling for these two factors, I find that high-fee mutual funds deliver better performance before fees, consistent with the theoretical prediction of an efficient asset management industry.

Preface

The first two essays of this thesis (Chapters 2 and 3) are based solely on my own research. The third essay (Chapter 4) is based on the joint work with Dr. Mikhail Simutin (University of Toronto) and Dr. Jinfei Sheng (University of California, Irvine). In the joint project, all authors worked on every aspect of the project and were in close collaboration in each stage. We contributed equally in the project.

Table of Contents

List of Tables

List of Figures

Acknowledgements

I am greatly indebted to many people during my years in the Ph.D. program at the University of British Columbia. First and foremost, I would like to thank Ron Giammarino (my co-supervisor), Adlai Fisher (my co-supervisor), and Murray Carlson (supervisory committee member) for their teaching, guidance, and support. They have always inspired me to think deeper about the economic forces behind a phenomenon. They have also guided me to the right direction at many critical junctions of my Ph.D. study. Their support and encouragement are instrumental in helping me finish this thesis and advance my career.

Besides my committee members, I also benefited tremendously from faculty members at UBC, who have always kept their doors open. I thank Lorenzo Garlappi, Jack Favilukis, Kai Li, Carolin Pflueger, Ali Lazrak, Jan Bena, Hernan Ortiz-Molina, Elena Simintzi, Will Gornall, Markus Baldauf, Georgios Skoulakis, Alberto Teguia, and Russell Lundholm for their thoughtful feedback about my research and sound advice at various stages of my study. I would also like to thank my co-author Mike Simutin from the University of Toronto for his wisdom and encouragement.

At UBC, I am very fortunate to be surrounded by a group of passionate peers, from whom I have learned so much. A special thanks goes toward Jinfei Sheng, with whom I worked on many interesting projects and traveled to many conferences together. I would also like to thank Ting Xu, Guangli Lu, Kairong Xiao, Charles Martineau, Alex Corhay, and Sheng-Jun Xu for countless times of help.

I cannot complete my Ph.D. journey without the companionship of my friends. I would like to thank Jason Li, a dear friend since high-school, for helping me settle down in Vancouver when I first came to this city. I would also like to thank fellow students in HA 391, who have made my life on campus much more enjoyable.

I would like to acknowledge the financial support provided by UBC and the Social Sciences and Humanities Research Council of Canada.

Finally, I want to say “thank you” to my parents. They have sacrificed so much for me and given me so much. No words can express my gratitude to their unconditional love. I dedicate this thesis to them.

This thesis is dedicated to my mother and father.

Chapter 1

Introduction

This thesis is a collection of three essays that study different aspects of institutional investors. Institutional investors are organizations that pool capital and invest in securities on behalf of households. They play two important functions in the economy. First, institutional investors are dominant players that determine the prices of many assets in the financial market. Second, institutional investors are providers of asset management services to households. Researchers in the field of finance are deeply interested in studying how institutional investors set asset prices and whether they provide valuable services to households. The ensuing chapters contribute to the understanding of these aspects.

Chapter 2 of the thesis theoretically investigates how an institutional investor's ability to trade frequently determines its portfolio choice and the related asset pricing implications. Institutional investors differ significantly in how frequently they trade, which translates into different holding horizons. Some institutions trade in and out of their positions frequently, while others practice long-term buy-and-hold strategies. In terms of portfolio choice decisions, institutions with different holding horizons prefer to invest in different types of stocks. Based on these observations, I develop a theoretical model to understand this phenomenon. My model answers both the portfolio choice question and the asset pricing question in a single framework. On the one hand, the model gives rise to predictions on how an institution's holding horizon affects its portfolio choice given the dynamics of stock returns. On the other hand, the model shows how stock returns are determined in an economy with both long-term and short-term institutions acting optimally. An important result is that stocks that provide more trading opportunities are held by more short-term institutions, whose demand reduces the buy-and-hold returns of these stocks. The model provides testable predictions relating a stock's short-term institutional ownership, trading opportunities, and buy-and-hold returns. The model also gives rise to various other empirical predictions.

Chapter 3 of the thesis empirically tests the predictions of the model developed in Chapter 2. The empirical focus of the chapter is on the cross-section of stocks. I show that in the cross section, short-term institutional investors prefer to invest in younger and more volatile stocks, despite these stocks having lower buy-and-hold alphas, e.g. CAPM and Fama and French (1993) three-factor alphas. I also show that from stocks that short-term institutions overweight, short-term institutions generate more trading profit, which cannot be replicated by long-term institutions. These findings are consistent with the theoretical predictions of Chapter 2. Stocks in the cross section have different amounts of trading opportunities. Short-term institutions overweight stocks that provide more trading opportunities, bidding up their prices. Subsequently, short-term institutions make more trading profits from these stocks by selling them at better prices. Long-term institutions optimally underweight stocks with more trading opportunities, because these stocks have lower buy-and-hold returns. By examining stocks that short-term institutions prefer to hold, I can identify the ones that provide more trading opportunities.

Chapter 4 of the thesis is based on my joint work with Jinfei Sheng and Mikhail Simutin, which focuses on the value of institutional investors to households. It investigates the effectiveness of different benchmark models in evaluating the performance of active mutual funds. A previously documented puzzle in the mutual fund literature is why funds that charge higher fees do not deliver better before-fee performance than funds charging lower fees (see, Carhart, 1997;Wermers, 2000;Fama and French, 2010). This negative fee-performance relationship is in stark contrast with the rational benchmark model of Berk and Green (2004). The puzzle raises serious concerns for the efficiency of the mutual fund industry and has promoted many investors to avoid high-fee mutual funds. In Chapter 4, we show that this puzzle is largely an artifact of the failure of traditional asset pricing models, e.g. CAPM, Fama and French (1993) Three-Factor, and Carhart (1997) Four-Factor, to account for the lower expected return of certain types of stocks, namely stocks with high asset growth rate and low profitability. Using the recently developed Fama and French (2015) Five-Factor model, we demonstrate that high-fee funds perform significantly better than low-fee funds before deducing fees and perform equally well after fees.

All three essays are written to be self-contained. I provide a more detailed exposition of the research question, literature review, and research methodology in the introduction section of each essay separately.

Chapter 2

Institutional Holding Horizon and Portfolio Choice: Theory

2.1 Introduction

After decades of rapid growth, institutional investors currently manage more than 70% of the U.S. equity market (Ben-David et al., 2019). Despite being labeled as a single group, their investment strategies differ significantly along many dimensions. One striking difference is their holding horizon or, equivalently, how frequently they trade. On one end of the spectrum, pension funds and index funds buy and hold each stock for a long period of time. On the other end, active mutual funds and hedge funds have short holding horizons and trade frequently. The holding horizon among institutions of the same legal class also varies substantially.

Financial economists have long been puzzled by the heterogeneity of investment strategies adopted in the real world (Sharpe, 1991; French, 2008). Many asset pricing models imply that investors follow similar strategies, such as buying and holding the market portfolio (Sharpe, 1964). Why would some institutions trade frequently, while others practice long-term investing? Do institutions with higher trading frequencies face a different investment opportunity set from institutions that just buy and hold? What is the market equilibrium when both long-term and short-term institutions co-exist and interact with each other? The answers to these questions are not only relevant to the management of trillions of dollars, but also shed light on the determination of asset prices.

This chapter develops a model to address these questions. I consider long-term institutions as investors that are constrained to buy and hold, such as passive investors, while short-term institutions are ones that can trade frequently, i.e. active investors.[1] My model answers both the portfolio choice question and the asset pricing question in a single framework. On the one hand, the model gives rise to predictions on how an institution's holding horizon affects its portfolio choice given the dynamics of stock returns. On the other hand, the model shows how stock returns are determined in an economy with both long-term and short-term institutions acting optimally. The model is useful in analyzing a series of questions about the relationship between a stock's expected return

[1] Some prior literature assumes that short-term investors are forced to liquidate for exogenous reasons, for example, Amihud and Mendelson (1986), Froot et al. (1992), and Cespa and Vives (2015).

and its institutional ownership structure. The model is also useful in designing benchmark indexes for different types of institutional investors.

One direct application of the model is to provide a rational explanation of a recent empirical puzzle. In particular, Borochin and Yang (2017) and Lan et al. (2015) document that stocks primarily held by short-term institutional investors have lower buy-and-hold abnormal returns than stocks with more long-term institutional investors. Their interpretation is that long-term institutions have better information about the long-run performance of stocks, while short-term institutions lack such information. Hence, long-term institutions are able to consistently pick high-return stocks, whereas short-term institutions end up holding low-return stocks. If this is the case, it is still puzzling why short-term institutions do not tilt their portfolios toward high-return stocks by mimicking the strategy of long-term institutions, given that the holdings of long-term institutions are publicly observable.[2] My model resolves this puzzle. It shows that even if short-term institutional investors understand that long-term institutions overweight high-return stocks, short-term institutions are still willing to overweight low-return stocks. In other words, the empirically observed asset allocation decision of long-term and short-term institutions is a rational equilibrium outcome.

The main elements of the model are the presence of speculative demand shocks that drive stock prices away from their fundamental values and limits to arbitrage that allow mispricing to exist in equilibrium. When a speculative demand shock causes a stock to be mispriced, short-term and long-term institutions respond to the shock differently. Short-term institutions can make trading profits from the shock by rebalancing their portfolios at once, while long-term institutions just buy and hold. When there are limits to arbitrage, especially short-selling constraint, it is optimal for short-term institutions to overweight stocks with greater exposures to speculative demand shocks in advance.

The theoretical literature since Miller (1977) has demonstrated that in the presence of short-selling constraints, when mispricing happens, a stock becomes on average overpriced.[3] As highlighted by Scheinkman and Xiong (2003), the occurrence of mispricing allows the existing owners of a stock to sell it at a favorable price, similar to exercising a resale option. Short-term institutions benefit more from the resale option than long-term institutions. Hence, in equilibrium, short-term institutions are willing to pay a premium for stocks with larger exposure to speculative demand shocks comparing to long-term institutions.

[2] Institutional investors have to disclose their equity positions within 45 days of each calendar quarter end. Private information about a company's long-term performance, if it exists, will become public when long-term institutional investors reveal their holdings.

[3] Studies that explore the implications of short-selling constraint on mispricing include Harrison and Kreps (1978), Abreu and Brunnermeier (2002; 2003), Duffie et al. (2002), Scheinkman and Xiong (2003), Hong et al. (2006), Stambaugh et al. (2015), and Hong and Sraer (2016).

The asset pricing effect of the excess demand from short-term institutions is to raise the prices of speculative stocks, reducing their long-run buy-and-hold returns. It appears that short-term institutions invest more in low-return stocks, when, in fact, they are prepared to sell these stocks in the likely event of a price appreciation driven by future speculative demand. The commonly used method of comparing stock-picking skill based on the covariance of an investor's portfolio weights and the buy-and-hold returns of stocks does not fully capture the investor's trading profit. This is likely to bias against short-term institutions due to the negative correlation between a stock's buy-and-hold return and trading opportunity. Short-term institutions tilt more towards stocks with more trading opportunities and lower buy-and-hold returns.

I build a parsimonious model to illustrate the mechanism and to formulate additional predictions. I model stocks with heterogeneous exposure to the speculative demand from noise traders, who cause stock prices to deviate from their fundamental values. In the model, I assume that long-term institutions construct their portfolios before noise traders arrive and are unable to rebalance in the interim period. Only short-term institutions trade against noise traders, while long-term institutions buy and hold their positions. Short-term institutions' ability to trade comes at the cost of a lump-sum investment in the beginning of the model. A fraction of institutions endogenously choose to pay for such ability.

My model provides several empirical predictions, relating an asset's expected return, ownership structure, volatility, and trading profit. In particular, consistent with the existing evidence, stocks with more short-term institutional investors have lower buy-and-hold abnormal returns. My model shows that these stocks are more likely to become mispriced. When they become mispriced, they are more likely to be overpriced because of the short-selling constraints. Short-term institutions make more abnormal returns through active trading. The model predicts that their trading profits largely come from stocks they ex ante overweight. Thus, in equilibrium, it appears that the more they invest in a stock, the more profit these institutions generate from trading that stock. This prediction does not contradict the intuition that more competition leads to lower profit, because in this setting, more competition is associated with more trading opportunities.

The model also highlights the different impact of long-term and short-term institutional demand on stock returns. When exogenous shocks cause long-term or short-term institutions to invest more in a stock, both types of institutions increase the stock's current price and reduce its future return. However, exogenous increase in long-term demand also increases the stock's future return volatility, while exogenous increase in short-term institutional demand reduces volatility. The opposing effects on return volatility help to distinguish whether certain type of institutions improve or harm market price efficiency. These predictions can be tested with instruments that cause exogenous variations in short-term or long-term ownership of a stock. Finally, my model provides economy-wide predictions. It shows that the dispersion in short-term institutional ownership across stocks is positively associated with the dispersion in the expected stock returns and the level of presence of trading opportunities in the economy. These predictions can be tested over time or in different markets.

2.1.1 Literature review

This chapter builds on the insights developed in the literature on speculation and limits to arbitrage. The central theme of this literature is that rational arbitrageurs face costs, risks, or other constraints that prevent them from immediately trading away any price inefficiencies. Pioneering studies in this area include Miller (1977), Harrison and Kreps (1978), De Long et al. (1990), and Shleifer and Vishny (1997). More recent studies that emphasize the role of short-selling constraints in explaining the dynamics of mispricing include Abreu and Brunnermeier (2002; 2003), Duffie et al. (2002), Scheinkman and Xiong (2003), Brunnermeier and Nagel (2004), Hong et al. (2006), and Nutz and Scheinkman (2018). Nagel (2005), Stambaugh et al. (2012; 2015), and Hong and Sraer (2016) investigate how short-selling constraints are related to well-known asset pricing anomalies. I add to this literature by modeling sophisticated investors with heterogeneous trading capacities and deriving predictions relating their demand to stock returns. My model is useful in connecting the theory of constrained arbitrage with empirical data on the holdings of institutional investors.

This chapter also relates to the theoretical literature on active investing. Sharpe (1991) suggests that in total, active investors must hold the market portfolios, which means that the aggregate of active investors cannot beat the market. Stambaugh (2014) studies the time-series trend of the amount of active investing in the US and highlights the fact that the presence of noise trading is an important determinant of the scale of active institutional investors. Pástor et al. (2017) studies the time series relationship between a mutual fund's turnover ratio and its future performance. They find that the more a fund manager trades, the more abnormal return he or she generates subsequently. This paper contributes to the literature by showing that when noise traders and short-selling constraints are present in the market, neither active nor passive institutions would hold the market portfolio. Active institutions would want to tilt towards stocks with more noise trading.

Finally, this chapter contributes to the growing literature that investigates the heterogeneous preferences among institutional investors. Basak and Pavlova (2013) present a model to illustrate that when institutions care about their performance relative to a certain index, they overweight assets that constitute their benchmark index. Hanson et al. (2015) show that traditional banks prefer to hold illiquid assets with low risk because they qualify for deposit insurance, while shadow banks prefer to own liquid assets because they are subject to runs. Amihud and Mendelson (1986) show that when investors are forced to hold a stock short-term, these short-term investors prefer to hold stocks with lower bid-ask spreads. Pastor et al. (2017) studies how size and investment skill of a mutual fund relate to its portfolio liquidity. My paper contributes to this literature by demonstrating that institutions with different holding horizons prefer to invest in different types of stocks depending on the stock's exposure to speculative demand shocks.

2.2 Model

In this section, I develop a parsimonious model to study the mechanism that drives the asset allocation of short-term and long-term institutions. The model also allows me to investigate the formation of asset prices, which provides several empirical predictions relating a stock's short-term ownership to its expected return, return predictability, and trading opportunities.

2.2.1 Model setup: assets

The economy has three dates: t =0, 1, and 2. There are N risky securities, indexed by $i = 1, 2, ..., N$, with a final pay-off v_{i2} realized at $t = 2$. There is one risk-free security with risk-free rate normalized to 0. The supply of every risky security is fixed to be 1 at $t = 0$, and the supply of the risk-free security is perfectly elastic. The model does not feature any private information. Uncertainties with respect to the risky pay-off are resolved in the last period.

In the baseline model, risky assets in the cross section are ex ante identical in all aspects with one exception. I assume that risky securities differ in their exposure to speculative demand shocks. At $t = 1$, a group of uninformed investors, which I call noise traders, arrive with a random demand u_i for stock i. I refer to u_i as a speculative demand shock, since it is unrelated to the fundamental value of the stock. I assume u_i to be normally distributed with mean zero and variance σ_{ui}^2 [i.e. $u \sim N(0, \sigma_{ui}^2)$]. The volatility σ_{ui} is stock specific and measures the intensity of the potential speculative demand shock to stock i. In the model, the covariance structure of speculative demand shocks does not affect the equilibrium, since institutional investors are assumed to be risk neutral. Investigating the effect of correlated speculative demand shocks in a risk-averse setting is an interesting area of future research.

Noise traders in this model, sometimes also known as liquidity traders, provide a reason for institutions to trade. Without them, the static allocation at $t = 0$ is Pareto optimal and no trade occurs at $t = 1$. The presence of noise trading is a standard modeling technique in studies of mispricing and is a realistic feature of the stock market. Several authors model the behavior of noise traders based on micro-founded behavioral biases, such as overconfidence (Daniel et al., 1998), bounded rationality (Hong and Stein, 1999), style investing (Barberis and Shleifer, 2003), and overextrapolation (Alti and Tetlock, 2014).

My cross-sectional predictions are based on variations in a stock's exposure to speculative demand shocks. It is natural to imagine that different stocks have different degree of noise trading. Empirical evidence indicates that certain types of stocks are more prone to speculation. For example, Barber and Odean (2007) find that stocks more in the news or stocks with more extreme returns attract more trading from retail investors, who are commonly considered as noise traders. Baker and Wurgler (2006) argue that companies whose valuation are highly subjective are more affected by investor sentiment.

2.2.2 Model setup: institutional investors

The economy has a unit mass of ex ante identical and risk neutral institutional investors. At $t = 0$, before trading begins, institutions decide whether they want to be a long-term investor or short-term arbitrageur. Long-term investors can only trade at $t = 0$ and must hold their positions until $t = 2$; short-term arbitrageurs can trade at both $t = 0$ and $t = 1$. By default, every institution starts as a long-term investor. To become a short-term arbitrageur, an institution must incur an up-front cost of c at $t = 0$. I use $\lambda \in [0,1]$ to denote the fraction of institutions that are short-term arbitrageurs. This fraction is endogenous to the model and reflects the trade-off that institutions make between investing in the trading capacity and potential trading profit.

One strand of theoretical literature that studies short-term investors, e.g. Froot et al. (1992), Cespa and Vives (2015), often assumes that short-term investors have to sell, because for exogenous reasons these investors have to exit the market before the asset pays off. My model is different. I assume that long-term institutions cannot change their positions in the interim period due to limited trading capacity. There are several reasons to model long-term institutions this way. First, institutional investors, especially those with a large number of positions under management, might have limited resources to constantly monitor every position. This assumption of limited ability, or lack of attention, is well-rooted in the theoretical literature on rational inattention (e.g. Sims, 2003; Abel et al. 2007; 2013; Kacperczyk et al., 2016). Alternatively, long-term institutions can be interpreted as passive investors that trade infrequently. In practice, many institutions explicitly or implicitly track indexes. These institutions only rebalance their portfolios when the index makes additions or deletions. Popular indexes, such as those of Standard & Poor's and FTSE Russell, only change their underlying composition infrequently. Thus, a short-term arbitrageur in this model has a superior investment technology than a long-term institution, because the short-term arbitrageur can trade in every period. The cost is the up-front investment in the trading capacity. Examples of such up-front investments are hiring traders and developing systems to facilitate trading.

In the model, all institutions also incur a quadratic holding cost when investing in risky securities. If an institution holds x_i shares of stock i, it must pay the following cost per period

$$Q(x_i) = \begin{cases} \frac{q}{2}x_i^2 & x \geq 0 \\ \frac{\theta q}{2}x_i^2 & x < 0 \end{cases} \tag{2.1}$$

This function captures the cost of investing through intermediaries. Similar to idiosyncratic risk in a risk averse setting, this cost function introduces a limit to arbitrage. With this cost function, an institution is unwilling to invest in unlimited number of shares in a stock for a tiny amount of perceived mispricing. Under this assumption, positive abnormal returns could exist in equilibrium. The use of quadratic holding cost is standard in the literature as in Nutz and Scheinkman (2018). Risk neutrality combined with quadratic holding cost allows me to derive many propositions in closed-forms. If I assume institutions to be risk averse, the model's predictions are qualitatively the same, but I lose analytical tractability.

Another important feature of this function is the asymmetry in the cost of maintaining a long position and a short position. This asymmetry is captured by the parameter $\theta > 1$. In practice, shorting a stock is more difficult than purchasing or selling a stock because of the additional cost and complexity, such as, security lending fees, regulatory risk, and operational risk. As documented by Almazan et al. (2004), a large fraction of institutions restrain from selling stocks short. The theoretical literature that models short-selling constraints often assumes that all, or a fraction of, agents cannot sell stocks short. I model short-selling constraints as having a higher cost when institutions carry negative positions. The effect of this assumption on asset prices is mathematically equivalent to assuming a fraction of institutions that cannot sell stocks short.

Under these assumptions, the objective function of a long-term institutions at $t = 0$ can be written as

$$U_L = \max_{x_{i0}^L \geq 0} E\left[\sum_{i=1}^{N} x_{i0}^L (v_{i2} - p_{i0}) - \sum_{i=1}^{N} 2Q(x_{i0}^L)\right] \tag{2.2}$$

where x_{i0}^L is the number of shares that long-term institutions invest at $t = 0$. Similarly, the objective function of short-term arbitrageurs can be written as

$$U_S = \max_{x_{i0}^S, x_{i1}^S(p_{i1})} \sum_{t=0}^{1} E\left[\sum_{i=1}^{N} x_{it}^S (p_{it+1} - p_{it}) - \sum_{i=1}^{N} Q(x_{it}^S)\right] \tag{2.3}$$

where x_{i0}^S is the number of shares that short-term institutions invest at $t = 0$ and $x_{i1}^S(p_{i1})$ is the demand function of short-term institutions at $t = 1$, specifying the number of shares to invest depending on the price of the stock at $t = 1$. I make an additional assumption that long-term institutions cannot sell stocks short at $t = 0$. This assumption is not crucial for the predictions of the model, but it simplifies the proofs. This assumption means that a stock's short-term ownership is bounded at 1 at the beginning of the model, which applies to most stocks empirically. For the majority of analysis in this chapter, I assume that equilibrium short-term ownership at $t = 0$ is less than 1 for all stocks. Thus, both short-term and long-term institutions hold a positive number of shares in each stock at $t = 0$, which is close to empirical observations.

2.2.3 Ex ante short-term ownership

The focus of the model is to explain the initial asset allocation of short-term and long-term institutions. Throughout this chapter, I define a stock's ex ante short-term ownership as the number of shares held by short-term institutions at $t = 0$, which I denote as κ_i for stock i, i.e.

$$\kappa_i \equiv \lambda x_{i0}^S \tag{2.4}$$

where λ is the fraction of short-term institutions and x_{i0}^S is the number shares they invest in stock i at $t = 0$. The market clearing condition at $t = 0$ implies that for each stock i

$$\lambda x_{i0}^S + (1-\lambda)x_{i0}^L = 1 \tag{2.5}$$

since the supply of each stock is assumed to be 1 at $t = 0$. The ex ante long-term ownership in stock i is thus $1 - \kappa_i$. The mechanism that drives the difference in asset allocation between long-term and short-term institutions is short-term institutions' ability to trade in the interim period. The expected return from investing in a stock at $t = 0$ will be different depending on the stock's trading opportunity at $t = 1$, which I formalize in the next section.

2.2.4 Trading and resale option

At $t = 1$, for each stock i, noise traders want to buy u_i shares, where $u_i \sim N(0, \sigma_{ui}^2)$. Note that the supply of shares at $t = 1$ is κ_i, which is the number of shares that short-term arbitrageurs have obtained from $t = 0$. Long-term institutions do not trade at $t = 1$, so the shares that they own are out of the market. When the speculative demand u_i from noise traders is smaller than κ_i, the total number of shares that short-term arbitrageurs have obtained from $t = 0$, short-term arbitrageurs can meet speculative demand by simply selling their stocks. If the noise demand u_i exceeds κ_i, short-term institutions must borrow additional shares to clear the market. The optimal demand from short-term institutions at $t = 1$ is the following

$$x_{i1}^S(p_{i1}) = \begin{cases} \frac{E[v_{i2}]-p_{i1}}{q} & E[v_{i2}] \geq p_{i1} \\ \frac{E[v_{i2}]-p_{i1}}{\theta q} & E[v_{i2}] < p_{i1} \end{cases} \tag{2.6}$$

The demand function for buying is different from short-selling due to the asymmetry in short-selling cost θ. Based on the market clearing condition,

$$u + \lambda x_{i1}^S = \kappa_i \tag{2.7}$$

simple derivation implies the market clearing price for stock i at $t = 1$ is

$$p_{i1} = \begin{cases} E[v_{i2}] + \frac{q}{\lambda}(u_i - \kappa_i) & u_i < \kappa_i \\ E[v_{i2}] + \frac{\theta q}{\lambda}(u_i - \kappa_i) & u_i \geq \kappa_i \end{cases} \tag{2.8}$$

The market price at $t = 1$ is positively related to noise-trader demand. If noise demand is more than κ_i, which is the supply of shares at $t = 1$, the price increases at a faster rate with u_i to compensate for the additional short-selling cost. Equation (2.8) can be re-written as

$$p_{i1} = E[v_{i2}] + \frac{q}{\lambda}(u_i - \kappa_i) + \frac{(\theta-1)q}{\lambda}\max(u_i - \kappa_i, 0) \tag{2.9}$$

Equation (2.9) clearly indicates that p_{i1} contains an option-like pay-off, $\max(u_i - \kappa_i, 0)$, which is referred to as a resale option by Scheinkman and Xiong (2003). I denote the expected value of this resale option as $C(\kappa_i, \sigma_{ui})$. Similar to a call option, $C(\kappa_i, \sigma_{ui})$ decreases in κ_i and increases in σ_{ui}.

2.2.5 Equilibrium asset allocation

This section solves for the equilibrium asset allocation in the model. Holding the fraction of short-term institutions constant at λ, the next proposition specifies the ex ante short-term ownership κ_i for stock i.

Proposition 1. *Let λ be the fraction of institutions that are short-term institutions. When stock i's speculative demand volatility $\sigma_{ui} \leq \sigma_{max}$, stock i's ex ante short-term ownership κ_i, defined as the total number of shares owned by short-term institutions at $t = 0$, solves the following equation*

$$\kappa_i = \lambda + \frac{(1-\lambda)(\theta-1)}{2}C(\kappa_i, \sigma_{ui}) \tag{2.10}$$

where[4]

$$C(\kappa, \sigma) \equiv E[\max(u-\kappa, 0)] = \frac{\sigma^2}{\sqrt{2\pi\sigma^2}}e^{-\frac{\kappa^2}{2\sigma^2}} - \kappa\left(1 - \Phi\left(\frac{\kappa}{\sigma}\right)\right) \tag{2.11}$$

Furthermore, the solution to equation (2.10) *exists and is unique. When $\sigma_{ui} > \sigma_{max}$, stock i's ex ante short-term ownership κ_i is* 1, *where σ_{max} solves the equation*

$$1 = \lambda + \frac{(1-\lambda)(\theta-1)}{2}C(1, \sigma_{max}) \tag{2.12}$$

The proof is in Appendix.

[4]Function Φ denotes the cumulative distribution function of a standard normal random variable.

Proposition 1 states that for any given fraction of short-term institutions, an equilibrium in the asset market always exists and is unique. This proposition also specifies the two components that determine the ex ante short-term ownership. The first component is the fraction of short-term institutions in the economy, denoted as λ. In a frictionless economy where every institution holds the market equally, every stock's short-term ownership should equal to the fraction of short-term institutions in the economy. The equilibrium fraction λ can be considered as a benchmark level of short-term ownership. The second component, the more interesting one, is related to the resale option. Positive value of the resale option gives short-term institutions an additional incentive to buy the stock ex ante. This proposition highlights the role of short-selling cost in determining the ex ante asset allocation among different institutions. The asymmetry in short-selling cost (i.e., $\theta > 1$) is a necessary condition for the ex ante short-term ownership κ to deviate from frictionless level λ. If there is no additional cost, then selling overvalued stocks is as profitable as buying undervalued ones, which removes the incentive for short-term institutions to accumulate positions in advance. Equation (2.10) is important for many analysis in subsequent sections.

2.2.6 Endogenous choice to invest in the ability to trade

This section presents the solution to the equilibrium fraction of short-term institutions. In equilibrium, the additional utility derived from trading at $t = 1$ must at least compensate the up-front cost c for short-term institutions. Hence, institutions choose to become short-term arbitrageurs when $U_S - U_L \geq c$. The utility of each type of institution also changes with the fraction of short-term institutions in the market. The next lemma specifies this result.

Lemma 2. *The utility of every long-term institution increases with the fraction of short-term institutions λ, while the utility of every short-term institution decreases with λ.*

The proof is in Appendix.

As more institutions choose to become short-term investors in the economy, their ability to take advantage of the noise trader demand is reduced by competition with each other. In other words, increases in λ dampens the effect of speculative demand on stock prices and reduces the profit of short-term institutions, which can be easily seen from equation (2.9). Therefore, higher λ lowers the average utility of short-term institutions. The effect of λ on the utility of long-term institutions is interesting. The utility of long-term institutions depends on the average buy-and-hold return of each stock. The long-term buy-and-hold return of each stock can be written as

$$E[v_{i2}] - p_0 = q - \frac{q(\theta - 1)}{2} C(\kappa_i, \sigma_{ui}) \tag{2.13}$$

Since increase in the fraction of short-term institutions λ increases every stock's short-term ownership κ, which reduces the value of their resale options C, more short-term institutions in the market increases the long-term return of all stocks, thus increasing the utility of long-term institutions. The next proposition proves the existence and uniqueness of the equilibrium in the model.

Proposition 3. *An equilibrium in this model is defined as the fraction of short-term institutions, λ, the portfolio weights of long-term and short-term institutions at $t = 0$ and $t = 1$, and the price of each stock at $t = 0$ and $t = 1$. For any up-front cost c, an equilibrium exists and is unique. The equilibrium fraction of short-term institutions is always greater than 0.*

The proof is in Appendix.

From Proposition 1, the equilibrium in holdings and prices in the security market is unique for any fraction of short-term institutions λ. The equilibrium fraction of short-term institutions depends on the difference in utility between the two types of institutions. This difference approaches infinity as the fraction of short-term institutions approaches 0. Therefore, for any up-front cost c, there is always a positive number of institutions that choose to become short-term arbitrageurs. This proposition highlights the incentive for institutions to become a short-term arbitrageurs. When the additional utility from trading exceeds the up-front cost, more institutions will become short-term arbitrageurs, instead of long-term investors. This fraction λ can also be interpreted as the amount of arbitrage capital in the economy.

2.3 Theoretical results and predictions

This section assesses the equilibrium relationship among institutional investors' asset allocation, expected stock return, and trading opportunities from the lens of the model developed in the previous section. The model produces both cross sectional and time series predictions. In addition, I investigate the response of stock return to shocks from speculative demand and to shocks from institutional ownership. These predictions could further substantiate the model's underlying mechanism.

2.3.1 Cross sectional relationship

The main theoretical result is to characterize the cross sectional relationship between short-term ownership and the expected stock return. The next proposition summarizes this prediction.

Proposition 4. *Holding the fraction of short-term institutions λ constant, stock i's ex ante short-term ownership κ_i increases with its speculative demand volatility σ_{ui}. The stock's expected long-term return, $E[v_{i2} - p_{i0}]$, decreases with σ_{ui}.*

Proof is in Appendix.

In essence, this proposition states that everything else equal, stocks with more exposure to speculative demand shocks will be more held by short-term institutions, which also implies that stocks with lower buy-and-hold returns will also be more held by short-term institutions. The intuition of this result is that a stock's exposure to speculative demand reduces its long-term expected return, because the resale option created by the speculative demand shock increases the demand from short-term institutions, who drive up the stock's price at $t = 0$.

A direct implication of this proposition is that short-term institutions invest more in stocks with lower buy-and-hold returns, while long-term institutions overweight stocks with higher buy-and-hold returns. However, short-term institutions are not irrational. In fact, the interpretation is the opposite. Because short-term institutions can trade in the interim, their demand is less sensitive than long-term institutions to the stock's long-run buy-and-hold return. Although short-term institutions invest more in low-return stocks, they make additional returns from trading. The next proposition summarizes this result.

Proposition 5. *Define an institution's trading profit R_i^T from stock i as the difference between its total return with trading and buy-and-hold return*

$$R_i^T \equiv x_{i0}(p_{i1} - p_{i0}) + x_{i1}(v_{i2} - p_{i1}) - x_{i0}(v_{i2} - p_{i0}) = (x_{i1} - x_{i0})(v_{i2} - p_{i1}) \tag{2.14}$$

Long-term institutions' trading profit is zero from each stock. Short-term institutions have positive trading profit in expectation. Their expected trading profit from stock i increases in stock i's speculative demand volatility σ_{ui}.

The proof is in Appendix.

This proposition states that short-term institutions generate additional returns from trading. Their trading skill can be captured by comparing their rebalanced return with the return they would obtain had they practiced a buy-and-hold strategy. Empirically, the literature decomposes a manager's skills into a style-picking component and a stock-picking component (e.g., Daniel et al., 1997; Wermers, 2000). This model provides a theoretical foundation for the empirical distinction between style picking and stock picking. The initial demand x_0 can be interpreted as an institution's choice of style, while subsequent trading is driven by its stock-picking ability within the style. This model helps to explain how institutions pick style. Long-term institutions overweight the style or the type of stocks with higher buy-and-hold returns, whereas short-term institutions choose styles based on whether they can generate trading profit. The style associated with higher exposure to speculative demand offers more trading opportunities to short-term institutions .

Figure 2.1 plots the results of the cross-sectional analysis, where the x-axis is the noise demand volatility σ_u. In panel A, the y-axis is the ratio between initial short-term institution demand x_0^S and long-term institutional demand x_0^L. A ratio of 1 means both short-term institutions and long-term institutions hold the same number of shares. The figure shows that as σ_u increases, short-term institutions start to raise their demand for the stock. The convex shape of the curve indicates that when σ_u becomes large enough, the additional demand by short-term institutions increases drastically. Panel B plots the expected buy-and-hold return, $E[v_2 - p_0]$, as a function of σ_u. It shows that the buy-and-hold return declines with σ_u. The shape of the curve is a reverse image of Panel A. Panel C plots the trading profit of short-term institutions, which increases with σ_u.

2.3.2 Comparative statics analysis

This section performs comparative statics analysis by changing parameters of the model, such as c, θ, and q. These parameter changes can be interpreted as different economic settings. For example, economies with different levels of c corresponds to economies with different cost of becoming short-term arbitrageurs or with different amount of arbitrage capital. Economies with different θ corresponds to economies with different degrees of short-selling constraints. And different levels of q corresponds to economies with different degrees of limit to arbitrage or risk aversion among institutional investors. The predictions of the model can be tested in the US equity market across time. Over the past four decades, the landscape of the investment community has changed dramatically with increasing amount of sophisticated institutional investors entering the market, e.g. hedge funds. Development in trading technologies and market micro-structure could also have shifted the parameters of the model. Alternatively, the predictions can also be tested across different markets. For example, in emerging and less developed markets, both the entry cost and trading parameters are different from more advanced economies. Therefore, these predictions can be tested among different countries (i.e. emerging market vs. developed market) or different asset classes (i.e. equity vs. bond).

Proposition 6. *An increase in the cost of becoming a short-term institution c will reduce the fraction of institutions that are short-term, leading to an increase in the cross-sectional dispersion of ex ante short-term ownership, an increase in the dispersion of expected return across stocks, and an increase in the expected trading profit of short-term institutions.*

The proof is in Appendix.

This proposition specifies the effect of changes in the fraction of short-term arbitrageurs in the economy on various equilibrium quantities. Naturally, increase in the cost of becoming a short-term arbitrageur reduces the fraction of short-term arbitrageurs in the economy. This results in an increase in the cross sectional variations in the stock's short-term ownership and in the cross sectional variation in the stock's expected return. The intuition is that as arbitrageur capital becomes scarce. Short-term arbitrageurs will take on more extreme positions, overweighting more speculative stocks and underweighting less speculative stocks. This results in an increase in the variation in the expected return across stocks. In addition, a decline in the fraction of short-term institutions predicts an increase in their trading profit. Figure 2.2 plots the results of different fractions of short-term institutions in the economy.

Proposition 7. *An increase in the short-selling constraint θ, holding constant the fraction of short-term institutions, will lead to an increase in the cross-sectional dispersion of short-term ownership and an increase in the dispersion of expected return across stocks.*

The proof is in Appendix.

Increasing in the short-selling constraint θ has similar effects as decreasing the fraction of short-term arbitrageurs λ. Short-term institutions take more extreme positions ex ante, which drive up the cross-sectional dispersion in expected returns. Figure 2.3 plots the results for economies with different short-selling constraints. The figure also shows that the trading profit of short-term institutional investors also increases with θ.

Proposition 8. *An increase in the overall holding cost parameter q will leave short-term ownership unaffected, but will increase the dispersion of the expected return and increase the expected trading profit of short-term institutions.*

The proof is in Appendix.

The parameter q, although acting a limit to arbitrage, does not affect the asset allocation between long-term and short-term institutions, which can be seen from the equation (2.10). However, changes in q will change the cross-sectional variation in expected return and in the average trading profit of short-term institutions. As q increases, limit to arbitrage becomes stronger, which magnifies the effect of short-term institutional demand on expect return and the trading profit that short-term institutions are able to generate. Figure 2.4 plots the results for economies with different levels of q.

2.3.3 Dynamic response to shocks in institutional and speculative demand

The previous sections specify equilibrium relationship of the model. To further shed light on the mechanism and to distinguish from alternative hypothesis, this section studies the dynamic response of stock return after an exogenous shock to institutional demand or speculative demand. For reasons outside of the model, institutional investors could exogenous change their demand for a stock. For example, a change of a stock's index membership could result in a sudden increase in demand for the stock by long-term indexers. A shock to the reputation of an institutional investor (e.g. as in the market timing scandal) could lead to a sudden withdraw of funds, which trigger a large selling by affected institutional investors. After these institutional demand shocks, the model provides the following prediction.

Proposition 9. *An exogenous increase to short-term institutional demand at $t = 0$ will increase short-term ownership κ, decrease the stock i's buy-and-hold return $E[v_2 - p_0]$, decrease stock i's non-fundamental volatility $Var(p_1 - p_0)$, and decrease the trading profit that short-term institutions generate from stock i. An exogenous increase in long-term institutional demand at $t = 0$ will decrease short-term ownership κ, decrease the stock i's buy-and-hold return $E[v_2 - p_0]$, increase stock i's non-fundamental volatility $Var(p_1 - p_0)$, and increase the trading profit that short-term institutions generate from stock i.*

The proof is in Appendix A.

Exogenous increase in both long-term or short-term institutional demand would increase the price of the stock, which cause a decrease in the stock's buy-and-hold return. This is the direct price impact from institutional demand. However, long-term and short-term institutional demand have different effect on the stock's volatility. Exogenous increase in long-term holding increases the stock's future volatility due to a reduced number of shares available to meet speculative demand. On the contrary, exogenous increase in short-term holding decreases the stock's future volatility due to increased number of shares available to meet speculative demand. The two type of institutions have opposing effects on the stock's volatility. In addition, increases in long-term demand would also help short-term institutions to make more trading profit by reducing the number of shares available to meet speculative demand, whereas increases in short-term demand reduces the amount of trading profit that short-term institutions will generate.

Conditional on the realization of speculative demand, the model also gives predictions about the stock return from $t = 1$ to $t = 2$. The stock experiencing positive noise demand has lower second-period return than the stock with negative noise demand. As speculative demand volatility σ_{ui} increases, the predictability of noise trader demand on the second period return becomes stronger. This return predictability is asymmetrical: it is stronger for overpriced stocks due to the higher short-selling cost. The next proposition formalizes this result.

Proposition 10. *Realized noise trader demand u_i at $t = 1$ negatively predicts the stock's return in the second period. The expected second-period return, conditional on speculative demand being negative (i.e., underpriced stocks), increases with σ_{ui}, while the expected second-period return, conditional on speculative demand being positive (i.e., overpriced stocks), decreases with σ_{ui}. The rate of change in the conditional expected second-period return with respect to σ_{ui} is greater in absolute terms for overpriced stocks.*

The proof is in Appendix A.

The asymmetrical response to speculative demand shock is a key prediction that verifies the model's mechanism. The model's main cross-sectional result builds on the mechanism that selling overpriced stocks is more profitable than buying underpriced stocks at the time that mispricing, i.e. speculative demand shock, occurs. Due to this asymmetry, short-term arbitrageurs would like to pay a premium for stocks that are more likely to be mispriced even before mispricing occurs. Long-term institutions cannot take advantage of this opportunity. Therefore, the optimal strategy for long-term institutions is to avoid holding stocks that are more likely to experience mispricing in their ex ante asset allocation. Figure 2.5 plots the conditional expected return as a function of σ_{ui}. It displays a clear sign of asymmetry as the return of the overpriced stock declines at an increasingly faster rate.

2.3.4 Determinants of arbitrage capital

Throughout the model, variable λ measures the fraction of institutions that are able to engage in short-term trading or arbitrage. This fraction can be interpreted as the economy's arbitrage capacity or the amount of arbitrage capital. How would λ change with parameters of the model? The next proposition answers this question.

Proposition 11. *Increase in the number of stocks N (holding constant the distribution of σ_i across stocks) will increase the fraction of short-term institutions. Increase in the limit-to-arbitrage parameter q will also increase the fraction of short-term institutions in equilibrium.*

Since short-term institutions obtain higher utility from each stock than long-term institutions, as the number of stocks increases, the difference in utility between short-term and long-term institutions increases. Therefore, more institutions will also choose to be short-term investors. As the trading environment changes due to shifts in parameter q, the fraction of short-term arbitrageurs would also change. The intuition is that when limits to arbitrage become more relaxed, there is fewer institutions to become arbitrageurs. This is because the competition among short-term arbitrageurs becomes more intense, reducing the average trading profit of each short-term institution. These predictions can be tested in the US over time or be tested across different countries or markets. The fraction of short-term versus long-term institutions has changed over time in the US, as illustrated by Stambaugh (2014). My model provides a theoretical framework to understand what drives that change.

2.3.5 Introducing systematic risk

In this section, I introduce the presence of systematic risk, which is important for empirical testing of the model and for asset pricing in general. Suppose each asset i has an exposure to a risk factor. Denote the exposure as β_i. For each stock i, every institution requires a compensation for a unit exposure to the factor. Let d denote the required rate of return for an extra unit exposure to the factor, which means that the utility function of the long-term institutions is

$$U_L = \max_{x_{i0}^L} E_0[\Sigma_{i=1}^N x_{io}^L(v_{i2} - p_{i0}) - 2d\Sigma_{i=1}^N x_{io}^L \beta_i - 2\Sigma_{i=1}^N Q(x_{i0}^L)] \tag{2.15}$$

Similarly, the utility function of short-term arbitrageurs is now

$$U_S = \max_{x_{i0}^S, x_{i1}^S(p_{i1})} \sum_{t=0}^{1} E\left[\sum_{i=1}^{N} x_{it}^S(p_{it+1} - p_{it}) - d\Sigma_{i=1}^N x_{it}^S \beta_i - \sum_{i=1}^{N} Q(x_{it}^S)\right] \tag{2.16}$$

Proposition 12. *The expected return for stock i with exposure to the systematic factor β_i and speculative demand σ_{ui} is*

$$\frac{E[v_2 - p_0]}{2} = d\beta_i + \frac{q}{1-\lambda} - \frac{q}{1-\lambda}\kappa_i \tag{2.17}$$

and short-term ownership κ_i solves

$$\kappa = \lambda + \frac{(\theta - 1)(1-\lambda)}{2} C(\kappa, \sigma_i) \tag{2.18}$$

The proof is in Appendix A.

As shown by the proposition, exposure to the systematic risk does not alter the asset allocation of short-term and long-term institutional investors. The effect of introducing systematic risk is to introduce another determinant of the stock's expected return. In this model, two things determine the stock's expected return, its exposure to systematic risk β and its exposure to speculative demand σ. The two exposures have opposing effects on the stock's expected return. Empirically, when estimating the risk premium of the systematic factor d. Empiricists face an identification challenge if the distribution of σ_{ui} in the cross section is correlated with the distribution of β_i. For a given systematic factor, if stocks with high exposure to such systematic factor also have high exposure to speculative demand. Then, estimates of the factor's risk premium without controlling for the effect of speculative demand would underestimate the price of risk for such a factor. The price of risk would be overestimated if β and σ are negatively correlated. The similar issue would also affect studies that investigate the risk taking behavior of institutional investors. If β and σ are positively correlated, then short-term institutions would invest more in stocks with higher β, appearing to take on more systematic risk.

2.4 Discussion of results

This chapter develops a model that studies a different dimension along which institutional investors allocate their capital. Traditional theories dictate that investors make asset allocation decisions based on the risk-return trade-off or liquidity considerations. Specifically, investors with different levels of risk aversion or background risk make investment decisions along different dimensions of risk. The commonly used investment categories, such as value and size, are often argued as two important dimensions of risk (Fama and French, 1996), along which investors allocate their capital. Similarly, investors with different exogenously short holding horizon would prefer more liquid stocks than other. The model that I present provides a different theory that guides investor asset allocation decision. Rather than making risk-return trade-off or liquidity-return trade-off, investors with different trading frequency trade-off an asset's buy-and-hold return against its trading opportunity. Assets with higher buy-and-hold returns have fewer trading opportunities, thus are more suitable for long-term investors, while assets with lower buy-and-hold returns have more trading opportunities, thus are more suitable for short-term investors. Based on this theory, investment categories should be defined along dimensions that best capture a stock's trading opportunities.

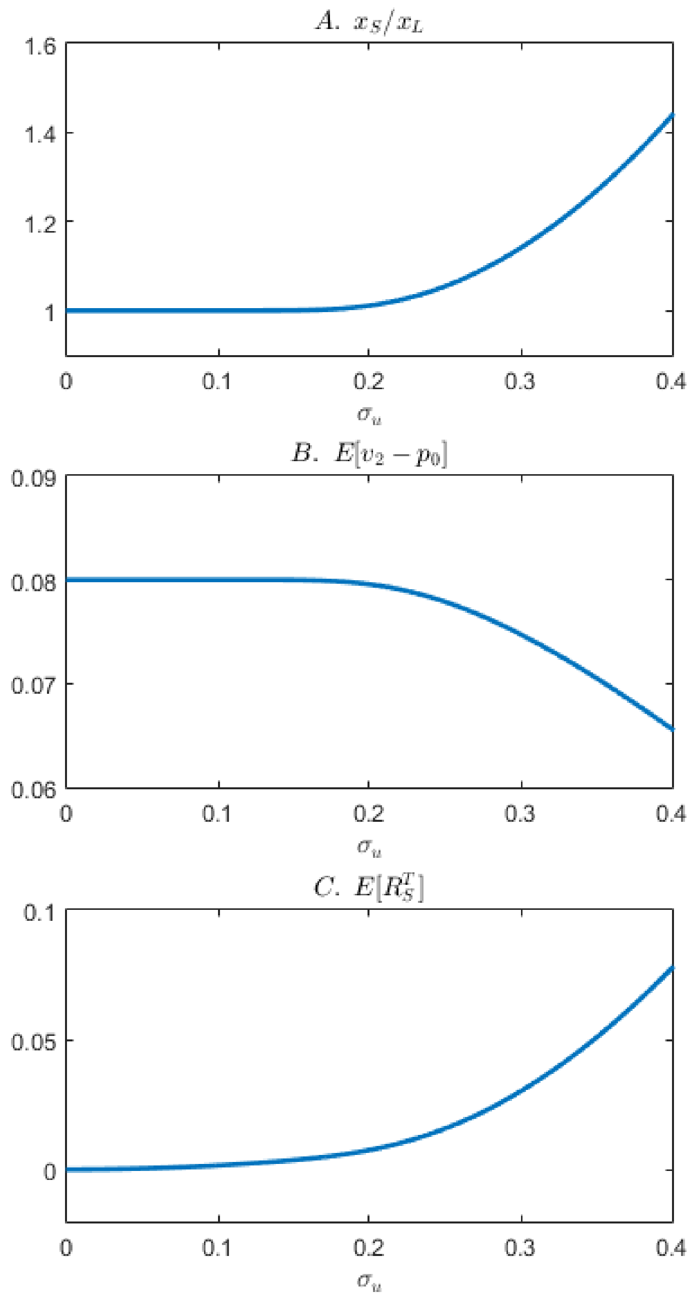
The model has many practical applications. For example, the model can be applied to the design of benchmark indexes that are tracked by passive mutual funds. Passively managed mutual funds only rebalance when their benchmark indexes change composition. The model suggests that a passive benchmark index should take into account a stock's exposure to speculative demand shocks. Instead of weighting each stock according to its market cap weight, the passive benchmark should reduce its exposure to stocks that are more likely to be mispriced.

2.5 Conclusion

This chapter develops a model to analyze the asset allocation decision among institutional investors with different holding horizons. Short-term institutions prefer to invest in stocks with greater exposure to speculative demand shocks, because short-term institutions can make trading profits from these stocks by rebalancing frequently. The excess demand from short-term institutions reduces the buy-and-hold returns of these speculative stocks. The optimal strategy of long-term institutions is to reduce their holdings of speculative stocks. In equilibrium, stocks with more short-term institutional holdings have lower buy-and-hold returns and more trading opportunities.

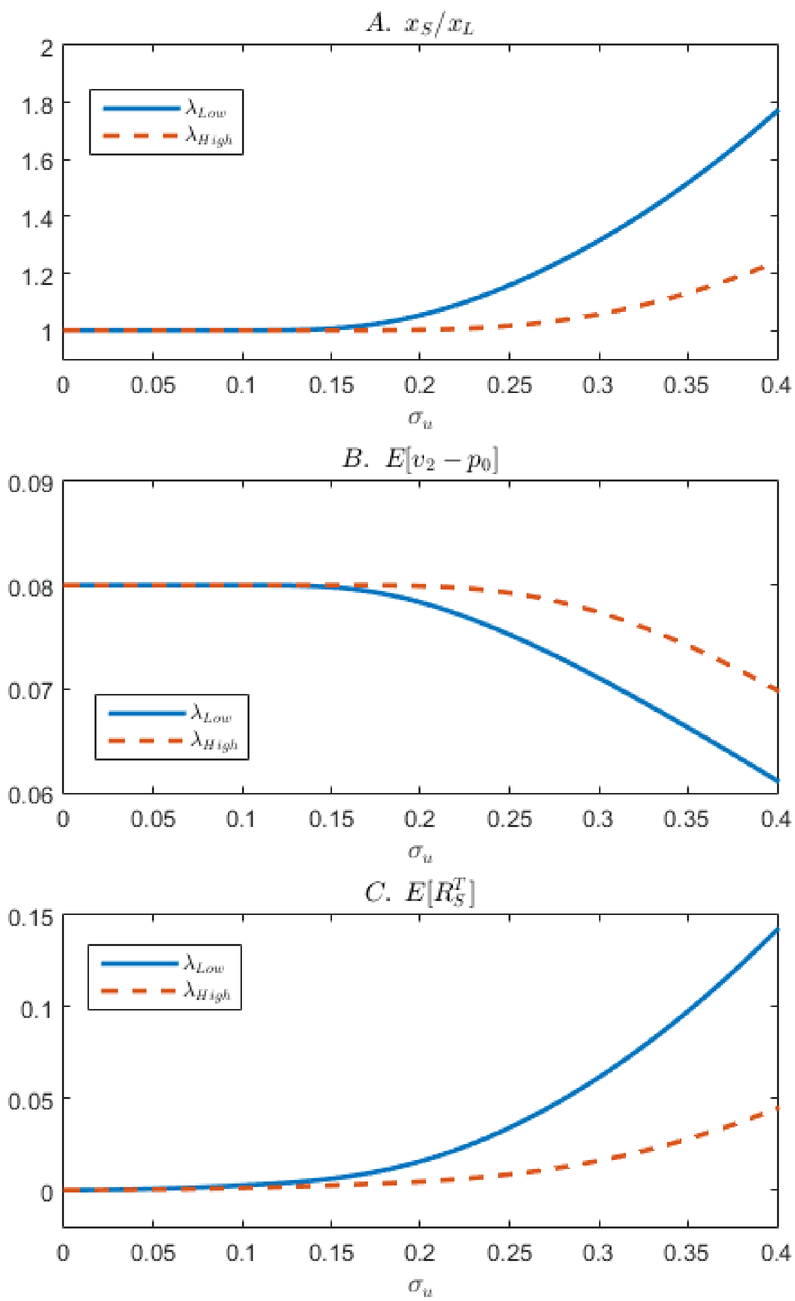
My model rationalizes why short-term institutions overweight low-return stocks and predicts these institutions generate additional returns by trading these stocks actively. Furthermore, stocks primarily held by short-term institutions should have more predictable returns, and their return predictability is stronger when they become overpriced. My results highlight how market frictions determine the equilibrium asset allocation of institutional investors according to their trading ability.

Figure 2.1: Cross-sectional effect of speculative demand



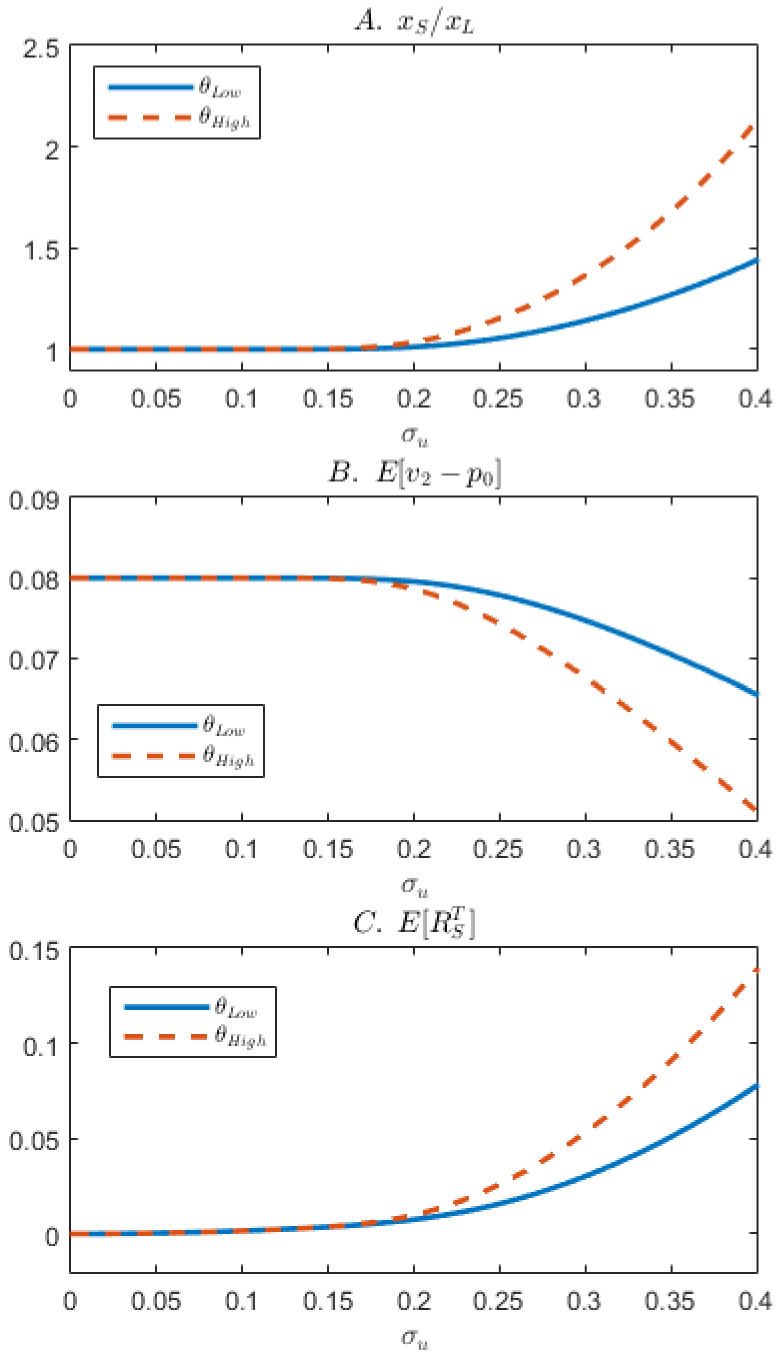
This figure plots numerical quantities of the model. The x-axis in all three panels is the volatility of noise trader demand, σ_u. In Panel A, the quantity on the y-axis is the ratio between short-term demand x_0^S and long-term demand x_0^L at $t = 0$. In Panel B, the y-axis is the expected return of the stock $E[v_2 - p_0]$ from $t = 0$ to $t = 2$. In Panel C, the y-axis is the expected trading profit of short-term institutions from stock i. The parameters for these graphs are $\lambda = 0.5$, $\theta = 30$, and $q = 0.04$.

Figure 2.2: Economies with different fractions of short-term arbitrageur



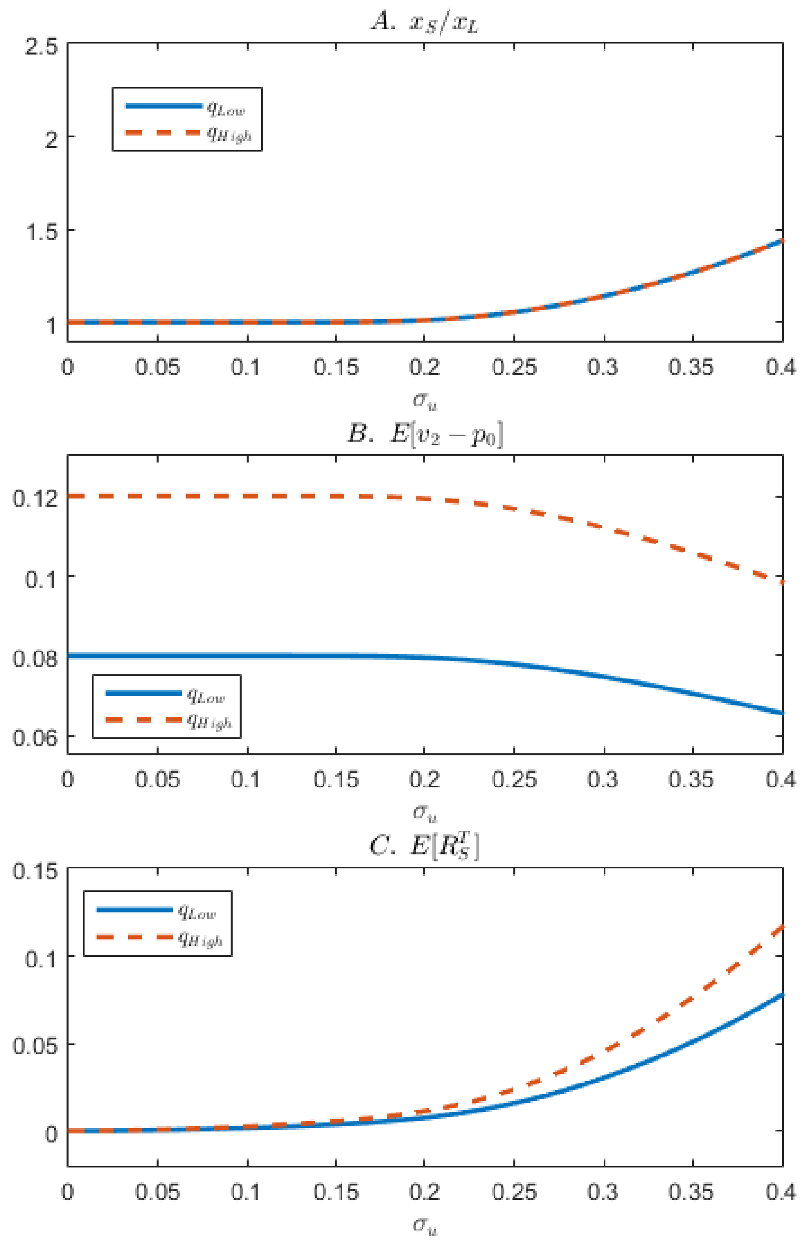
This figure plots numerical quantities of the model with different levels of λ. The solid blue lines corresponds to an economy with $\lambda = 0.4$. The dash orange lines corresponds to an economy with $\lambda = 0.6$. The x-axis in all three panels is the volatility of noise trader demand, σ_u. In Panel A, the quantity on the y-axis is the ratio between short-term demand x_{i0}^S and long-term demand x_{i0}^L at $t = 0$. In Panel B, the y-axis is the expected return of the stock $E[v_{i2} - p_{i0}]$ from $t = 0$ to $t = 2$. In Panel C, the y-axis is the expected trading profit of short-term institutions from stock i. Other parameters for these graphs are $\theta = 30$ and $q = 0.04$.

Figure 2.3: Economies with different degrees of short selling constraint



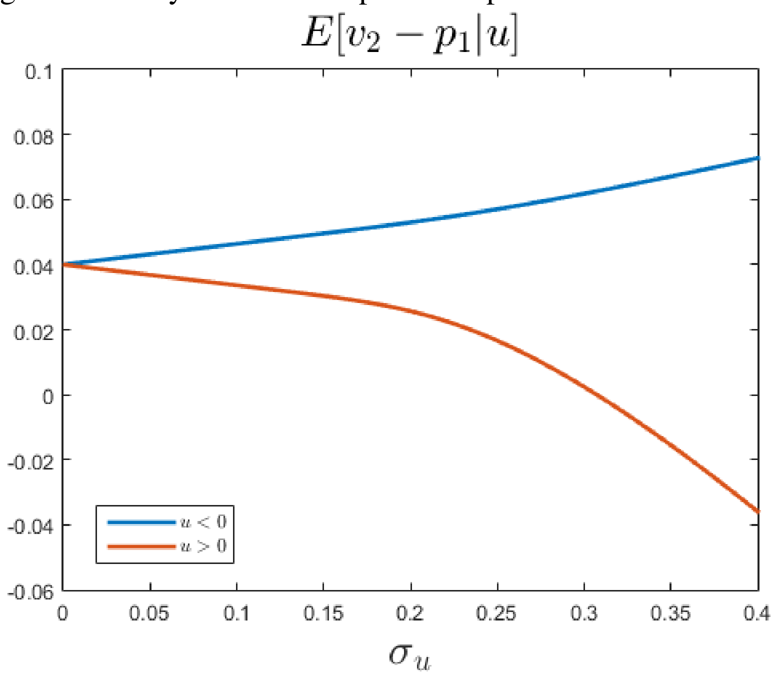
This figure plots numerical quantities of the model with different levels of θ. The solid blue lines corresponds to an economy with $\theta = 30$. The dash orange lines corresponds to an economy with $\theta = 100$. The x-axis in all three panels is the volatility of noise trader demand, σ_u. In Panel A, the quantity on the y-axis is the ratio between short-term demand x_{i0}^S and long-term demand x_{i0}^L at $t = 0$. In Panel B, the y-axis is the expected return of the stock $E[v_{i2} - p_{i0}]$ from $t = 0$ to $t = 2$. In Panel C, the y-axis is the expected trading profit of short-term institutions from stock i. Other parameters for these graphs are $\lambda = 0.5$ and $q = 0.04$.

Figure 2.4: Economies with different degrees of limit to arbitrage.



This figure plots numerical quantities of the model with different levels of q. The solid blue lines corresponds to an economy with $q = 0.04$. The dash orange lines corresponds to an economy with $q = 0.06$. The x-axis in all three panels is the volatility of noise trader demand, σ_u. In Panel A, the quantity on the y-axis is the ratio between short-term demand x_{i0}^S and long-term demand x_{i0}^L at $t = 0$. In Panel B, the y-axis is the expected return of the stock $E[v_{i2} - p_{i0}]$ from $t = 0$ to $t = 2$. In Panel C, the y-axis is the expected trading profit of short-term institutions from stock i. Other parameters for these graphs are $\lambda = 0.5$ and $\theta = 30$.

Figure 2.5: Asymmetrical response to speculative demand shock.



This figure plots the expected stock return after a speculative demand shock occurs. The y-axis is the expected return of the stock i from $t = 1$ to $t = 2$ conditional on the realized speculative demand being greater or smaller than 0. The top (bottom) line is the conditional expected return after negative (positive) speculative demand shock. The parameters for these graphs are $\lambda = 0.5$, $\theta = 30$, and $q = 0.04$.

Chapter 3

Trading Opportunities and the Portfolio Choices of Institutional Investors

3.1 Introduction

Institutional investors have grown tremendously over the past four decades with their asset under management exceeding 70% of the U.S. equity market (Ben-David et al., 2019). Lewellen (2011) shows that institutional investors in aggregate hold the market portfolio, which suggests that institutions on average add little value to households since their portfolio as a whole is merely a reflection of the market. However, this aggregation masks the large degree of heterogeneity across different types of institutions. In particular, institutional investors differ significantly on their holding horizon or equivalently trading frequency. Pension funds and index fund families have low turnover ratio and practice buy-and-hold strategies. The aggregate portfolio holdings of this group of long-term investors is different from the aggregate holdings of active mutual funds and hedge funds, which have short holding horizons and trade frequently. Understanding how an institution's holding horizon relates to its asset allocation can shed light on how financial institutions affect asset prices and add value to the society.

Chapter 2 develops a theory on how institutions with different holding horizons make asset allocation decisions. This chapter tests the main predictions of the model empirically based on institutional investor holdings data in the US. This chapter primarily focuses on testing the equilibrium predictions in the cross-sectional of US stocks. Specifically, stocks with more short-term institutional investors have lower buy-and-hold abnormal returns and offer more trading opportunities that allow short-term institutions to make trading profits. First, I proxy an institutional investor's holding horizon with its turnover ratio, controlling for flow induced trades. Then, for each stock, I compute its short-term ownership as the average turnover ratio of institutions that own the stock, weighted by the stake of each institution. This measure of short-term ownership is persistent, suggesting that long-term and short-term institutions have persistent differences in holdings. For example, short-term institutions invest significantly more than long-term institutions in stocks that are younger, have higher CAPM beta and idiosyncratic volatility. At the industry level, healthcare and information technology industries have the highest amount of short-term ownership, while utilities and real estate industries have the lowest.

To test my model's predictions, I sort stocks into five portfolios each year based on their average short-term ownership in the prior year, which I refer to as *ShortOwn* quintiles. Empirically, the abnormal buy-and-hold returns decline with a stock's short-term ownership, consistent with the existing literature. The difference in the valued-weighted monthly alphas between stocks in the top and bottom *ShortOwn* quintiles are -0.56% (t-statistic: -2.36) under the capital asset pricing model (CAPM), -0.26% (t-statistic: -1.89) under the Fama and French (1993) three-factor model, and -0.31% (t-statistic: -2.12) with the additional control of the Carhart (1997) momentum factor.

I then check if stocks with more short-term institutional investors are more susceptible to mispricing. To do so, I apply a trading strategy based on the mispricing score developed by Stambaugh et al. (2015) to each *ShortOwn* quintile. This trading strategy should generate higher abnormal returns from the quintile with stocks more exposed to mispricing shocks. I find this to be the case. For stocks in each *ShortOwn* quintile, I further assign them into overpriced, fairly priced, and underpriced terciles in the beginning of every month based on their score. Underpriced stocks in the top *ShortOwn* quintile have a monthly three-factor alpha of 0.41% (t-statistic: 2.94), while overpriced stocks in this quintile have a monthly three-factor alpha of -0.97% (t-statistic: -6.15), resulting in a spread of 1.37% per month (t-statistic: 6.77). For stocks in the bottom *ShortOwn* quintile, the three-factor alphas of underpriced and overpriced stocks are 0.25% (t-statistic: 3.36) and -0.29% (t-statistic: -1.99) per month, which have a spread of only 0.53% (t-statistic: 3.17). These results indicate that stocks primarily held by short-term institutions are more likely to become mispriced, evidenced by the fact that their returns are more predictable by their mispricing scores. The substantial negative abnormal return of overpriced stocks in the top *ShortOwn* quintile also confirms the effect of short-selling constraint. The presence of mispricing shocks or return predictability provide trading opportunities for investors with better trading skills.

Finally, I test whether the different exposure to mispricing shocks across stocks translates into variations in the trading profit that institutional investors generate. I compute the return of each quintile portfolio by mimicking the trading activities of long-term and short-term institutions. To mimic their trading activities, I group institutions according to their turnover ratio and use the total dollar value they invest in each stock as weights to compute a portfolio's return. Instead of weighting stock returns according to their market capitalization as buy-and-hold investors would do, holding-weighted return better captures any additional returns that institutional investors obtain from rebalancing their positions.

The portfolio returns weighted by the holdings of short-term institutions are higher than the portfolio returns weighted by the holdings of long-term institutions in all five *ShortOwn* quintiles. Their difference between holding-weighted returns and buy-and-hold returns, i.e. trading profit, monotonically increases from the bottom to the top *ShortOwn* quintile. Collectively, short-term institutions beat long-term institutions in the top *ShortOwn* quintile by 0.28% per month (t-statistic: 4.28) in terms of the three-factor alpha. Their performance in the bottom *ShortOwn* quintile is similar with a difference of only 0.04% per month (t-statistic: 0.86). This result is robust to a variety of other factor models and to excluding micro-cap stocks. The finding that short-term institutions generate more trading profit from stocks they overweight highlights the importance of trading opportunities in their asset allocation decisions.

I perform time series predictability tests to examine if the trading profit of short-term institutions varies over time. Pástor et al. (2017) suggest that the total number of trading opportunities in the market changes with investor sentiment. I find that the trading profit of short-term institutions can be predicted by proxies of market sentiment, such as Baker and Wurgler (2006) sentiment index and the first-day returns of initial public offerings (measured according to Ibbotson et al., 1994). The time series predictability in trading profit is more significant in the top *ShortOwn* quintile, while it is insignificant in the bottom *ShortOwn* quintile. The stronger time-series predictability in the top *ShortOwn* quintile is another evidence that ex ante short-term ownership identifies variations in trading opportunities across stocks. I also rule out an alternative explanation based on the illiquidity risk. Overall, these empirical findings support my theoretical explanation of why short-term institutions overweight low-return stocks. Short-term institutions have a comparative advantage in trading stocks that are more exposed to mispricing shocks and overweight these stocks in advance, despite their lower buy-and-hold returns.

3.1.1 Related literature

My findings contribute to several strands of literature. First, I contribute to the literature that investigates the skill of institutional investors. There is an on-going debate on what kind of institutions have better stock-picking skill. Studies that favor long-term institutions include Cremers and Pareek (2016), Borochin and Yang (2017), and Lan et al. (2015), while studies that support short-term institutions include Yan and Zhang (2007) and Pástor et al. (2017). The main issue lies in how to assess stock-picking skill empirically. My findings add to this debate by demonstrating that short-term institutions have the ability to trade against temporary mispricing, which allows them to generate higher returns than buy-and-hold investors who invest in the same type of stocks. However, short-term institutions allocate more capital toward stocks that are more likely to become mispriced. This type of stocks has lower buy-and-hold returns. The differential trading ability makes institutions hold different types of stocks. When institutions invest in different types of stocks, several papers, including Ferson and Wang (2018), Busse et al. (2017), and Sheng et al. (2019), indicate that the performance evaluation largely depends on the choice of benchmark model, which is still an area of controversy.

Finally, this paper contributes to the growing literature that investigates the heterogeneous preferences among institutional investors. Basak and Pavlova (2013) present a model to illustrate that when institutions care about their performance relative to a certain index, they overweight assets that constitute their benchmark index. Christoffersen and Simutin (2017) find that fund managers tilt more toward high-beta stocks in their benchmark after pension sponsors increase monitoring. Hanson et al. (2015) show that traditional banks prefer to hold illiquid assets with low risk because they qualify for deposit insurance, while shadow banks prefer to own liquid assets because they are subject to runs. Giannetti and Kahraman (2017) find that closed-end funds are more likely to purchase fire-sale stocks than open-end funds because closed-end funds do not face the pressure from fund flow. Koijen and Yogo (2018) develop a methodology to structurally estimate the preference parameters of different asset characteristics for various types of institutional investors. My paper contributes to this literature by demonstrating that asymmetrical arbitrage costs make short-term institutions prefer to own stocks that are more exposed to mispricing shocks.

3.2 Hypothesis development

This section develops the empirical hypotheses to be tested later. Based on the idea that short-term institutions can trade more frequently than long-term institutions, the model built in Chapter 2 predicts that stocks with more volatile speculative demand are more held by short-term institutions than long-term institutions. Empirically, this means that by sorting stocks according to whether they are more or less held by short-term institutions, I should observe variations in the expected buy-and-hold return and trading opportunities of stocks. Specifically, I expect to observe:

- Stocks that short-term institutions overweight ex ante have lower risk adjusted returns than stocks that long-term institutions overweight ex ante, because the additional demand from short-term institutions drives up the prices these stocks.

- Stocks that short-term institutions overweight ex ante experience greater mispricing, either overpricing or underpricing, depending on the realization of speculative demand shocks.

- Short-term institutions are able to make more trading profit from stocks they ex ante overweight than from stocks that long-term institutions ex ante overweight.

Another important mechanism in the model is the presence of short-selling constraint. The presence of short-selling constraint predicts that when mispricing happens, overpricing is more severe than underpricing, especially among stocks that short-term institutions ex ante overweight. Note that these empirical predictions involve sorting stocks based the ex ante short-term ownership, i.e. the demand of short-term institutions at $t = 0$ in the model. The empirical measure that I develop will try to measure the ex ante level of short-term ownership, rather than unexpected short-term ownership due to trading against noise traders.

Finally, the model in the previous chapter has several other economy wide predictions. Testing those predictions are beyond the scope of this chapter because of identification challenges. Testing those predictions is an interesting area of future research.

3.3 Data, measurement, and motivating evidence

This section presents motivating evidence on the asset allocation decision of institutional investors with different holding horizons. Based on 13F institutional holdings data, I construct measures of holding horizon for institutional investors and I compute short-term ownership for each stock. I use these measures to show the persistence of short-term ownership and how it correlates with other stock characteristics in this section. The next section tests my model's main predictions.

3.3.1 Data

I collect data from several sources. First, I construct a dataset containing quarterly institutional holdings. The bulk of holdings data are from Thomson Reuters S34 Database, previously known as CDA/Spectrum, which has collected quarterly positions for institutional investors since 1980. The SEC requires institutions that conduct business in the US and manage more than $100 million in assets to report all their holdings of publicly traded stocks within 45 days after the end of each calendar quarter, except for small positions that are below 10,000 shares and $200,000. The type of institutional investors includes investment advisors (e.g., mutual funds or hedge funds), banks, insurance companies, pension plans, and endowment funds. Because Thomson Reuters reuses the same identifier for different institutions, to track institutional investors over time, I use the permanent institution identifier constructed by Brian Bushee (2001). [5] Following the recommendations of Blume et al. (2014) and Wharton Research Data Services (WRDS), I correct for errors in share splits in the S34 Database.

WRDS finds that after 2013 Thomson Reuters S34 Database removed many institutional investors.[6] To remedy this problem, I use an alternative data source for observations after 2013: Thomson Reuters Global Ownership Database, which also contains holdings data for US institutions. This new database corrects for the omission problems of the S34 database.

For stock return and company characteristics, I use standard datasets from the Center for Research in Security Prices (CRSP) and Compstat. I also download factor returns and the risk-free

[5] Details about how Brian Bushee constructs the permanent ID can be found on his personal website at http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

[6] The details of the issue can be found in this document
https://wrds-www.wharton.upenn.edu/documents/533/Research_Note_-Thomson_S34_Data_Issues.pdf

rate from several authors' websites. The Fama and French (1993; 2015) and Carhart (1997) factor returns are from Ken French's website. [7] Liquidity factor and mispricing factors are from Robert Stambaugh's website.[8] I also use Baker and Wurgler (2006) sentiment index for time series analysis. For return predictability test, I download mispricing score created by Stambaugh et al. (2015) from Jianfeng Yu's website.[9] Appendix B provides more details on the definitions of variables.

3.3.2 Measurement of stock level short-term ownership

A stock's ownership structure is multi-dimensional. The dimension relevant to this paper is the degree to which the stock is held by short-term institutions relative to long-term institutions. Institutional investors do not explicitly state their holding horizons. Therefore, I must compute their holding horizons from the data. One simple and widely adopted approach is to proxy an institution's holding horizon with its portfolio turnover.[10] In the literature, high-turnover institutions are referred to as short-term investors, while low-turnover institutions are considered long-term investors. Following the literature, I proxy an institution's holding horizon based on its portfolio turnover ratio. Specifically, I measure the average turnover ratio of institution j as of quarter t as the sum of quarterly turnover ratios in the four most recent quarters

$$Turn_{jt} = \sum_{\tau=t-3}^{t} \frac{\min(Purchase_{\tau}, Sales_{\tau})}{\frac{1}{2}(Size_{\tau-1} + Size_{\tau})} \tag{3.1}$$

To compute aggregate purchases and sales, I assume institutions rebalance their portfolios at the end of each calendar quarter. I use the minimum of purchases and sales to reduce the influence of fund flow induced trades. I exclude observations where an institution holds fewer than 10 US common stocks, and I winsorize $Turn_{jt}$ at the 1st and 99th percentiles. Table 3.1 Panel A reports summary statistics for institutions in my sample. On average, I have 1309 institutions each year from 1981 to 2017. The average turnover ratio among of institutions is 46% per year, which suggests that the average holding horizon is slightly more than two years.

The turnover ratio of an institution is a persistent variable. Table 3.1 Panel B regresses $Turn_{jt}$ on its lagged values. The coefficients for 1-year, 5-year, 10-year, and 20-year lagged $Turn_{jt}$ are 0.9, 0.79, 0.70, and 0.53, respectively. The persistence in turnover ratio indicates that this ratio captures a fundamental and time-invariant dimension of institutional characteristics; it is unlikely that institutions will frequently change the level of their turnover ratio or holding horizons. A long-term institution (e.g., Vanguard) has low turnover ratio for many years. Similarly, a short-

[7]The link to the website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8]The link to the website is http://finance.wharton.upenn.edu/~stambaug/

[9]The link to the website is https://sites.google.com/site/yujianfengaca/

[10]For example, papers that use turnover ratio, also known as the churn rate, to classify institutions include Bushee (2001), Gaspar et al. (2005), and Yan and Zhang (2007).

term institution (e.g., Renaissance Technologies) maintains high turnover ratio for a long period of time. Table 3.1 Panel C presents summary statistics of $Turn_{jt}$ for institutions with different legal designations. Bank trusts and public pension funds have the lowest turnover ratio, thus longest holding horizon, while investment companies, including mutual funds and hedge funds have the highest turnover ratio or shortest holding horizon. The standard deviations of $Turn_{jt}$ within each class of institutions are large, indicating that even among institutions within the same legal definition, the heterogeneity in holding horizon is still rich.

There are different ways to measure a stock's short-term ownership. One way is to classify institutions into two disjointed types and aggregate a stock's ownership by each type. However, this approach potentially loses a significant amount of information. Having numerically computed each institution's turnover ratio, I compute each stock's short-term ownership as the average turnover ratio of its institutional investors weighted by the stake of each institution. For example, the short-term ownership of stock i in quarter t is measured as

$$ST\ Own_{it} = \frac{\sum_{j=1}^{N} Shares_{ijt} \times Turn_{jt}}{\sum_{j=1}^{N} Shares_{ijt}} \tag{3.2}$$

where $Shares_{ijt}$ is the number of shares of stock i that institution j holds in quarter t. If a stock's institutional investors have high turnover ratio on average, this means the stock is primarily held by short-term institutions. This measure incorporates more information by considering the turnover ratio of all institutions. The denominator of $ST\ Own_{it}$ is the number of shares held by all institutions. This scaling allows me to focus on the difference in asset allocation between short-term and long-term institutions, rather than on the difference between institutional investors and non-institutional investors. For my empirical tests, I require a stock to have more than five different institutional investors in at least one quarter in the prior year. This requirement reduces the measurement error from stocks with very few institutional investors. Table 3.2 Panel A reports summary statistics for $ST\ Own_{it}$ and other stock characteristics. On average, I have 4025 stocks each year in my sample from 1981 to 2017.

3.3.3 Short-term ownership and stock characteristics

This section discusses how short-term ownership correlates with other stock characteristics. Table 3.2 Panel B reports pairwise correlation between quarterly short-term ownership and various other stock characteristics among all stocks in the sample. Short-term ownership is positively associated with a stock's CAPM beta, momentum, and idiosyncratic volatility. It is negatively associated with a stock's size, book-to-market ratio, and age. Table 3.2 Panel C presents the same set of pairwise correlations by excluding micro-cap stocks, which are stocks with prior year-end market caps smaller than the 20th percentile of stocks traded on the New York Stock Exchange (NYSE).

The correlations become stronger in this sample due to reduced noise in short-term ownership from micro-cap stocks.

Figure 3.1 plots average short-term ownership for stocks in characteristic sorted deciles and shows that some of the relationship are not monotonic. In particular, among stocks ranked in the bottom five size deciles, short-term ownership is positively correlated with size, while for stocks in the top three deciles, short-term ownership is negatively correlated with size. This explains why size is weakly correlated with short-term ownership in the full sample. Similarly, among stocks in the bottom five momentum deciles, short-term ownership decreases with momentum, while it increases with momentum in the top five deciles. Stock age appears to be the best characteristic to explain short-term ownership. Stocks listed for shorter periods of time have more short-term investors, while stocks listed for long period of time have more long-term investors. Overall, these plots indicate that short-term institutions prefer to invest more in younger stocks, growth stocks, and stocks with more idiosyncratic volatility. Figure 3.2 plots average short-term ownership by sector. Healthcare and information technology sectors have the highest short-term ownership, while utilities and real estate sectors have the lowest amount.

Table 3.3 presents the result of a regression analysis on short-term ownership in a multivariate setting for the full sample and all-but-micro sample. In Columns 1 and 4, the independent variable is a stock's short-term ownership in the prior year. The coefficients are 0.61 and 0.64, respectively. The R-squared in the two columns are 40% and 48%, respectively, indicating that a stock's short-term ownership is persistent and can be explained by its past realizations. Stocks with more short-term institutional investors on average continue to have more short-term institutional investors. Notably, the persistence in institution turnover ratio does not mechanically imply a stock's short-term ownership is persistent. It is possible that short-term and long-term institutions only have transitory differences in their holdings. However, long-term institutions and short-term institutions persistently tilt towards different types of stocks as shown in this table. Columns 2 and 5 regress short-term ownership on contemporaneous stock characteristics with sector and time fixed effects. The signs of the coefficients are consistent with pairwise correlations. Columns 3 and 6 combine lagged short-term ownership and stock characteristics. The coefficient on lagged short-term ownership only changes slightly, while the magnitude of coefficients on other stock characteristics are reduced. Notably, the sign on the coefficient of book-to-market ratio changed from negative in Column 5 to positive in Column 6, suggesting short-term institutions are not necessarily chasing overpriced companies. This table indicates that short-term ownership is persistent and is correlated with other stock characteristics. The correlations are suggestive that short-term ownership is related to noise traders, since the types of stocks that short-term institutions overweight are often associated with investor sentiment (Baker and Wurgler, 2006). However, correlation does not necessarily imply causation. It is possible that short-term ownership might influence the characteristics of these stocks, for example, idiosyncratic volatility. Future research remains to better identify the causal relationship between short-term institutional ownership and stock characteristics.

3.4 Empirical findings

This section presents empirical tests of my model's cross-sectional predictions. These predictions relate a stock's ex ante short-term ownership with its buy-and-hold return, return predictability, and trading profit generated by short-term institutions. Following the traditions in empirical asset pricing, I test these predictions based on portfolios sorted by ex ante short-term ownership.

3.4.1 Ex ante short-term ownership sorted portfolios

At any point in time, a stock's short-term ownership can be affected by the realized demand of noise traders. According to my model, ex ante short-term ownership and realized short-term ownership predict future stock returns in different directions. Ex ante short-term ownership negatively predicts a stock's future long-term return, but realized short-term ownership positively predicts stock return in the short run, because short-term institutions trade against noise traders. To reduce the effect of realized mispricing shocks, I first take the average of short-term ownership in each year. Then, in the beginning of April in year $t+1$, I sort stocks into five different portfolios based their average short-term ownership in year t. Skipping one quarter between the measurement period and sorting period further reduces the influence of any realized shock to short-term ownership.

Table 3.4 Panel A presents summary statistics on the composition of each quintile portfolio. Quintile 1 contains stocks with the lowest ex ante short-term ownership, while quintile 5 contains stocks with the highest. On average, each quintile portfolio has approximately 790 stocks. The aggregate market weight of quintile 1 is the largest at 33% of the market. Institutions ranked in the bottom turnover decile (i.e. long-term institutions), on average, invest 41% of their total capital in quintile 1, while institutions ranked in the top turnover decile (i.e., short-term institutions) only invest 11% of their capital in quintile 1. The aggregate market weight for quintile 5 is 6%. Low turnover institutions underweight quintile 5, only investing 3% of their capital, while high-turnover institutions devote 21% of their capital to quintile 5, which is more than three times the market allocation. The deviation in asset allocation indicates the sorting is effective in separating stocks primarily held by long-term and short-term institutions.

Table 3.4 Panel B depicts the transition matrix for the five quintile portfolios. This panels confirms the persistence of short-term ownership. Stocks in quintile 1 remain in the same quintile the next year with a probability of 71%. Similarly, for stocks sorted into quintile 5, there is a 57% probability of remaining in the same quintile the next year. The persistence indicates that the difference in holdings between short-term and long-term institutions is not likely to be driven by differences in private information, since private information is often short lived. Even if any group of institutions have long-lived private information, that information is revealed through disclosures of quarterly holdings, which are publicly available.

3.4.2 The cross-section of expected returns

Table 3.5 reports the first set of the main empirical results regarding the relationship between expected return and expected short-term ownership. The portfolios are sorted based on each stock's prior year average short-term ownership and held from the beginning of April until the end of March the next year. For each portfolio, I compute its value-weighted and equal-weighted returns. The sample period is from 1982:04 to 2017:12. I control for risk using the CAPM, the Fama and French (1993) three-factor, and the Carhart (1997) four-factor models. Quintile 1 contains stocks with the lowest short-term ownership or highest long-term ownership. These stocks have the highest risk-adjusted expected return among all five portfolios. The value-weighted CAPM, three-factor, and four-factor alphas of quintile 1 are 0.20%, 0.12%, and 0.12% per month with t-statistics at 2.79, 2.35, and 2.28, respectively. For quintile 5, the portfolio's value-weighted CAPM, three-factor, and four-factor alphas are -0.36%, -0.14%, and -0.19% per month, respectively. The difference in alphas between quintile 5 and 1 are negative and statistically significant across all three risk adjustment models. For example, in terms of the three-factor alpha, the difference in value-weighted return between quintile 5 and 1 is -0.26% per month or -3.12% per year. The magnitude of this difference is economically large considering the average mutual fund expense ratio is about 1% per year.

The comparison in expected return is more pronounced using equal weighting, which means the relationship between expected return and short-term ownership is stronger among small cap stocks than large cap stocks. Under equal weighting, the spread in the CAPM, three-factor, and four-factor alphas between quintile 5 and 1 are -0.74%, -0.50%, and -0.37% per month with t-statistics at -4.64, -4.24, and -2.92, respectively. These findings are consistent with Chapter 2's prediction that a stock's expected return increases in its long-term ownership:

$$E[v_2 - p_0] = 2qx_L \tag{3.3}$$

Based on the data of mutual fund holdings, Lan et al. (2015) also find that stocks largely held by long-term funds have higher alphas than stocks largely held by short-term funds. The magnitude in their study is similar to what I find here.

3.4.3 Return predictability and short-term ownership

This section presents the tests for return predictability of stocks with different levels of ex ante short-term ownership. The model predicts that stocks with higher ex ante short-term ownership have more predictable returns. In addition, the return predictability for overpriced stocks is stronger than the return predictability of underpriced stocks. To test this prediction, I need a signal to proxy for noise trader demand, which predicts stock returns. Stambaugh et al. (2015) constructed such a proxy based on 11 asset pricing anomalies documented in the literature. These 11 anomalies include financial distress, equity issuance, momentum, investment, and profitability anomalies, etc. The authors convert each stock's anomaly characteristic into a percentile rank and average the ranks across all 11 anomalies. Stocks with higher average scores are more overpriced. This mispricing score is effective in separating overpriced stocks from underpriced stocks in each month. In unreported analysis, when I sort all stocks in my sample each month into terciles based on their mispricing score, the monthly spread in the value-weighted three-factor alpha between the underpriced tercile and overpriced tercile is 0.77% per month (t-statistics of 6.47) or 9.24% per year.

To test my model's prediction, I perform a conditional double sort. For each year, I start with the five portfolios sorted by ex ante short-term ownership as described in the previous section. Then, within each quintile portfolio, I further sort stocks into terciles each month based on their mispricing scores. The three terciles represent the overpriced, fairly priced, and underpriced stocks within each quintile portfolio. I compute the value-weighted return for all 15 sub-portfolios and report their three-factor alphas in Table 3.6. The spread in alpha between underpriced and overpriced stocks increases with the stock's ex ante short-term ownership. In quintile 1, the spread in the three-factor alpha is 0.53% per month, while in quintile 5, the spread is 1.37% per month, more than double the spread in the bottom quintile. This increased spread is primarily driven by the overpriced stocks. Overpriced stocks in quintile 1 have a monthly abnormal return of -0.29% and overpriced stocks in quintile 5 have a monthly abnormal return of -0.97%, a striking difference of -0.68% per month. Underpriced stocks in quintile 1 have a monthly abnormal return of 0.25% and underpriced stocks in quintile 5 have a monthly abnormal return of 0.41%, a difference of only 0.16% per month. Figure 3.3 plots the annualized abnormal return of each sub-portfolio. The figure clearly illustrates not only that the spread in return increases with ex ante short-term ownership but also that such a relationship is asymmetrical: more pronounced on the downside.

Both Table 3.6 and Figure 3.3 provide strong evidence that short-term institutions prefer to hold stocks with more predictable returns. The spread in abnormal return between underpriced stocks and overpriced stocks is much higher in quintile 5 than in quintile 1. This indicates that stocks in quintile 5 are much more predictable on a monthly basis than stocks in quintile 1. Any investor who trades on this monthly predictor, the mispricing score, can make much higher abnormal returns from quintile 5 than from quintile 1.

Figure 3.3 also provides strong support for the model's assumption that short-selling is more costly. This can be seen from the fact that overpriced stocks in quintile 5 experience much greater decline in return in the following month than the increase in return of underpriced stocks. The profit of an investor who trades on the mispricing score largely comes from selling overpriced stocks. This asymmetry in trading profit is due to the weaker aggregate selling pressure of overpriced stocks, which allows the degree of overpricing to be greater than underpricing. The selling pressure of overpriced stocks from arbitrageurs is weaker than their buying pressure of underpriced stocks, because selling stocks short is more costly than buying stocks.

3.4.4 Trading profits of short-term and long-term institutions

My model predicts that short-term institutions benefit more than long-term institutions from trading against noise traders. More importantly, my model predicts that among stocks with more ex ante short-term ownership, short-term institutions generate more trading profit, because their ex ante ownership indicates that those stocks are more exposed to noise trader shocks. To test this prediction, I first select institutions ranked in the top decile in terms of turnover ratio as short-term institutions and institutions in the bottom turnover decile as long-term institutions. Then, I aggregate the holdings of these two groups, which allow me to determine the number of dollars invested in each stock in each quarter by those two groups. With this information, I can compute the total return generated by each group of institutions among a given portfolio of stocks. This approach allows me to measure the trading profit conditional on both the type of institutions and the type of stocks.

I start with the same quintile portfolios sorted by ex ante short-term ownership. Instead of computing the buy-and-hold returns using market capitalization as weights, I compute the total return of these quintile portfolios using the actual number of dollars invested in each stock as weights. Table 3.7 Panel A reports the risk-adjusted total return in each quintile by long-term institutions. Similar to the buy-and-hold return, long-term institutions have lower total return in quintile 5 than in quintile 1. The difference between long-term institution's total return and market value weighted return, reported in Table 3.5 , is within only a few basis points. This means that long-term institutions are not rebalancing much within each quintile.

Table 3.7 Panel B reports the total return of short-term institutions from each quintile. Similar to long-term institutions, short-term institutions also generate higher abnormal return from quintile 1 than quintile 5, but the difference is smaller in both magnitude and statistical significance. Panel C shows the difference in total return between long-term and short-term institutions in each quintile. First, short-term institutions deliver higher abnormal return in every quintile portfolio than long-term institutions under the CAPM and the three-factor models. Second, the difference monotonically increases with ex ante short-term ownership. In quintile 1, short-term institutions outperform long-term institutions by a small and statistically insignificant margin across all three models. However, in quintile 5, short-term institutions outperform long-term institutions by 0.25%, 0.28%, and 0.17% per month under the CAPM, the three-factor, and the four-factor models. These results are all statistically significant at the 1% level.

In Panel C, this rising pattern is consistent across all three models. With the addition of the momentum factor, the excess returns of short-term institutions are reduced by about one-third, which indicates that the momentum factor explains part of the trading profit of short-term institutions. Figure 3.4 plots the market, long-term and short-term institutions' total return from each quintile. The graph clearly indicates that long-term institutions and the market have similar returns, and their returns both decrease with short-term ownership, while short-term institutions generate higher returns than long-term institutions. This finding provides evidence that short-term institutions are more sophisticated than long-term institutions at trading against mispricing. Short-term institutions anticipate which stocks are more likely to be mispriced and are willing to pay a premium for holding these stocks in order to sell them at more favorable prices in the future.

Table 3.7 is based on the performance of institutions in the top and bottom turnover deciles. Table 3.8 reports the trading profit of institutions in deciles 2 to 9. Qualitatively, the results presented Table 3.8 are similar to those in Table 3.7 . Institutions in higher turnover deciles outperform long-term institutions among stocks in quintile 5. For example, the aggregate of institutions in decile 8 and 9 outperform long-term institutions among stocks in quintile 5 by 0.12% per month in term of the three-factor alpha. Institutions in deciles 4 to 7 also generate significantly more abnormal return in quintile 5 than institutions in the bottom turnover decile. The findings in this section confirm my prediction that short-term institutions perform better than long-term institutions among stocks with more ex ante short-term ownership.

3.4.5 Exploring the performance of short-term institutions over time

My model so far only predicts where short-term institutions generate more trading profit in the cross section of stocks. It is worthwhile to explore when short-term institutions deliver more trading profit. An intuitive prediction is that during periods when investor sentiment is high, short-term institutions have better performance. This prediction can be easily seen from the model assuming during periods with more investor sentiment, the volatility of noise trader demand σ_u increases for all stocks. I test this prediction using the sentiment index constructed by Baker and Wurgler (2006), which is the first principle component of six proxies of investor sentiment: the first day return of IPOs, number of IPOs in a month, closed-end fund discount, premium on dividend paying stocks, the ratio of equity issuance to debt issuance, and NYSE share turnover. Pástor et al. (2017) show that the BW sentiment index explains the average turnover ratio of active mutual funds. Therefore, it is suggestive that the BW sentiment index also predicts the trading profit of short-term institutions, especially, in quintile 5. To test this prediction, I perform the following time series regression:

$$R_t = a + b\Delta S_{t-1} + cMKT_t + dSMB_t + eHML_t + \varepsilon_t \tag{3.4}$$

where ΔS_{t-1} is change in the BW sentiment index in month $t-1$ andMKT_t, SMB_t, HML_t are the three Fama-French factors. Table 3.9 reports the results. In Columns 1 to 5, the dependent variable is the difference in the total return between short-term and long-term institutions in quintiles 1 to 5. The coefficient b increases from 0.28 (t-statistic: 0.87) in Column 1 to 1.36 (t-statistic: 2.02) in Column 5. In Column 6, the dependent variable is the simple average of the difference in all five quintiles. The coefficient b is 0.70 with a t-statistic of 1.87. Among the six components of the BW sentiment index, I find that the first day return on IPOs is the most robust predictor of short-term institutions' trading profit. Table 3.10 presents the result using the IPO first day return as the predictor.

$$R_t = a + bR^{IPO}_{t-1} + cMKT_t + dSMB_t + eHML_t + \varepsilon_t \tag{3.5}$$

The dependent variables are the same as in 3.9. The coefficient b increase from 0.33 (t-statistic: 1.09) in Columns 1 to 1.41 (t-statistic: 2.34) in Column 5. The coefficient b in Column 6 is 1.18 (t-statistic: 3.07) . This section confirms that the time series variation in investor sentiment affects the time-series performance of short-term institutions.

3.4.6 Robustness

This section checks the robustness of my main empirical findings. First, following the advice of Fama and French (2008) and Hou et al. (2017), I exclude micro-cap stocks from my sample to check whether my results rely on micro-cap stocks. Table 3.11 performs the same test as Table 3.7 by removing micro-cap stocks at the portfolio sorting stage. The results are quantitatively similar to Table 3.7. Stocks primarily held by short-term institutions have negative buy-and-hold alpha measured by all three models, and short-term institutions deliver more trading profit than long-term institutions in all five quintile portfolios. The difference is monotonically increasing from quintile 1 to quintile 5 and statistically significant in quintile 5 across all three models.

I control for additional factors when I evaluate the total return of short-term institutions relative to long-term institutions. The additional factors are the Pástor and Stambaugh (2003) liquidity factor, the Fama and French (2015) five factors, and the Stambaugh and Yuan (2016) mispricing factors. As shown in Table 3.12, the results are qualitatively consistent with previous tables. The trading profit in quintile 5 is the largest under across all four factor models in both all-stock sample and all-but-micro sample. An interesting finding from Table 3.12 is that the model based on Stambaugh and Yuan (2016) mispricing factors produces the smallest average alpha across the five quintile portfolios. This result means that the trading profits of short-term institutions can be best explained by mispricing factors.

The previous section shows that during periods with more investor sentiment, short-term institutions perform better. During the last four decades, the period with the highest level of investor sentiment is arguably the dotcom bubble era. The Nasdaq composite index reached an all-time high in March 2000. Several authors have documented that hedge funds generated more abnormal returns during the dotcom bubble period (Brunnermeier and Nagel, 2004; Griffin and Xu, 2009; Griffin et al., 2011). This section shows that my result is robust when excluding the dotcom bubble period. Table 3.13 reproduces the results of Table 3.7 excluding the period from 1998:04 to 2001:03. The results are qualitatively the same as Table 3.7. Short-term institutions outperform long-term institutions in quintile 5 by 0.19% (t-statistics 2.57), 0.20% (t-statistics 3.30), and 0.12% (t-statistics 2.01) per month in terms of the CAPM, the three-factor, and the four-factor alphas, respectively.

3.4.7 Alternative explanations

This section discusses alternative explanations to why short-term institutions overweight low-return stocks relative to long-term institutions. One alternative explanation is that long-term institutions have private information that short-term institutions do not have. Therefore, long-term institutions can select high-return stocks. This explanation suffers from two drawbacks. First, any private information not incorporated into stock prices within 45 days is revealed through the public disclosure of portfolio holdings. If long-term institutions have private information, rational investors can mimic their strategy after observing their holdings, which eliminates the information advantage of long-term institutions. The private information of long-term institutions should not have long-run return predictability beyond 45 days, which is at odds with the fact that the higher abnormal return of stocks primarily held by long-term institutions lasts beyond one year. The second drawback is that this explanation does not explain why short-term institutions outperform long-term institutions through trading. In all five quintile portfolios, short-term institutions have higher total return than long-term institutions, which indicates that short-term institutions are more skilled than long-term institutions in trading. Overall, the private information channel does not systematically explain my empirical findings.

The second explanation is based on liquidity risk. Long-term institutions could be more tolerant towards liquidity risk than short-term institutions (Kamara et al., 2016). Amihud and Mendelson (1986) and Beber et al. (2018) develop models that predict long-term investors take more liquidity risk, because they are able to hold on to assets for longer period of time than short-term institutions. Therefore, stocks primarily held by long-term institutions could have higher expected return due to compensation for illiquidity. In Table 3.14, I regress the value-weighted return of each quintile on the three Fama-French factors, the Carhart momentum factor, and the Pastor-Stambaugh liquidity factor. The results do not support the liquidity hypothesis. First, the additional liquidity factor does not explain the difference in expected return between quintile 1 and 5. In fact, the loadings on the liquidity factor have the opposite signs as the liquidity based explanation. If long-term institutions are more willing to take illiquidity risk, the loading on the liquidity factor of quintile 1 should be greater than quintile 5's loading. The liquidity based explanation also does not explain why the performance of short-term institutions relative to long-term institutions monotonically increase from quintile 1 to quintile 5 and the asymmetry in return predictability. The fact that larger and older stocks have more long-term institutional investors further weakens the liquidity risk based explanation. Therefore, it is difficult to explain my findings based on heterogeneous preferences for liquidity among long-term and short-term institutions.

3.4.8 Discussion of results

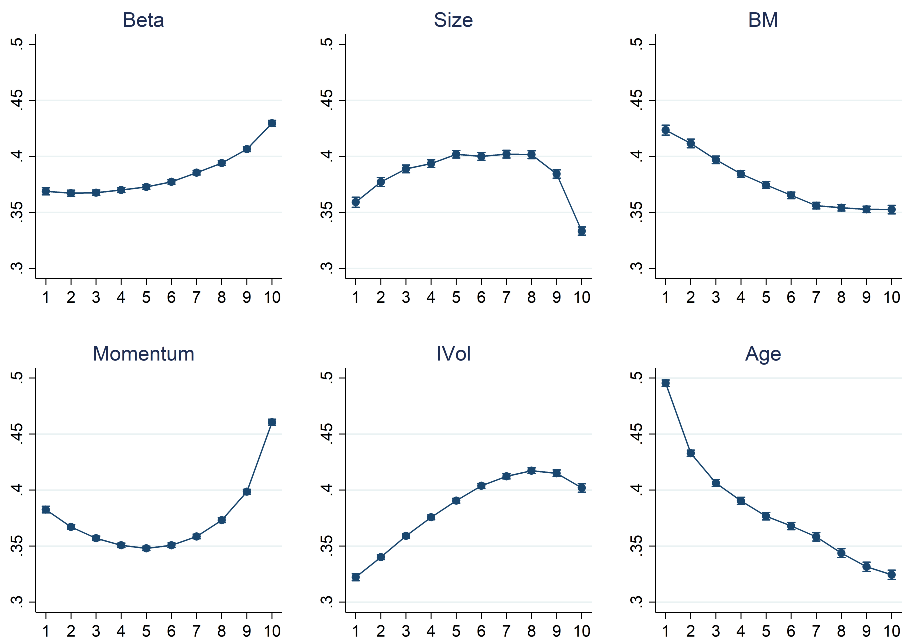
This paper's findings have several implications for asset management practice and performance evaluation. First, my results indicate that an asset's exposure to mispricing shocks provides opportunities for investors to make trading profits. If an institution can trade frequently, a low-return asset might be more attractive than a high-return asset when the low-return asset provides more trading opportunities. Moreover, if an institution is a buy-and-hold investor, such as a public pension fund, it might consider hiring short-term institutions to manage assets with high exposure to noise trader shocks or in market with tight short-selling constraints. Dyck et al. (2013) find that active asset management outperforms passive management in emerging markets, presumably because there are more noise traders and more stringent short-selling constraints in those markets. To implement these strategies in practice, one empirical challenge is to directly measure a stock's exposure to mispricing shocks. My findings suggest that ex ante short-term institutional ownership is a proxy for such exposure.

The performance evaluation of an asset manager depends on its asset allocation and trading ability. Since according to my model, short-term managers are expected to allocate more capital to low-return stocks, their performance might be negatively affected by their asset allocation decisions. Depending on the purpose of the evaluation, one might want to control for the negative correlation between expected return and expected short-term ownership. Several authors have developed methods to control for asset allocation effects. For example, Wermers (2000) decomposes a fund's return into stock picking and style picking components. Style picking reflects the fund manager's asset allocation decision, while stock picking reflects the manager's trading ability. Similarly, Kacperczyk et al. (2006a) measure the difference between the reported fund return and the return implied from prior quarter's holdings, which they call the return gap. This return gap also controls for the manager's asset allocation decision and isolates the manager's intra-quarter trading skill. Ferson and Wang (2018) develop a panel regression methodology to measure a manager's skill. They use stock fixed effects to control for a manager's return due to asset allocation decisions.

3.5 Conclusion

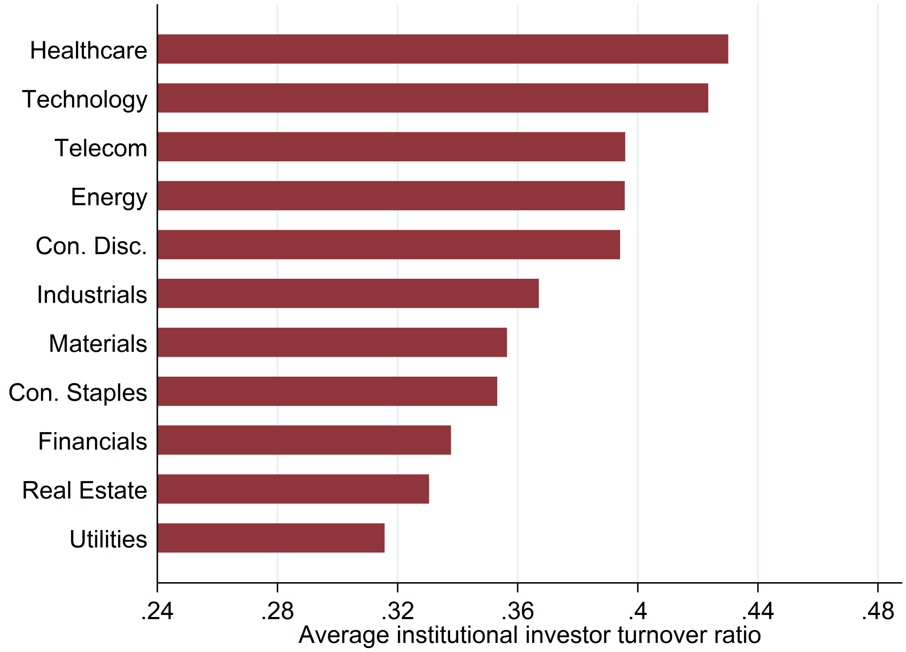
This chapter provides an empirical analysis of the asset allocation decision among institutional investors with different holding horizons. Short-term institutions prefer to invest in younger, smaller, and more volatile stocks. In addition, stocks that are primarily held by short-term institutions have lower risk-adjusted returns than stocks primarily held by long-term institutions. These empirical regularities can be explained in a model with speculative demand shocks and short-selling constraints. In the presence of short-selling constraints, future mispricing creates a resale option for the initial owners of a stock. Stocks with more exposure to these shocks have lower expected returns, because their resale options are more valuable. Since short-term institutions trade more frequently, they benefit more from resale options than long-term institutions. In equilibrium, short-term institutions overweight stocks with more valuable resale options, while long-term institutions overweight stocks with higher buy-and-hold returns. The additional demand from short-term institutions reduces the buy-and-hold returns of stocks that are more exposed to speculative demand shocks. In equilibrium, a stock's exposure to speculative demand shocks explains both its expected return and ownership structure. Furthermore, stocks primarily held by short-term institutions should have more predictable returns, and their return predictability is stronger when they become overpriced. Empirical findings strongly support these predictions. Short-term institutions outperform long-term institutions by more than 3% per year among stocks primarily held by short-term institutions, while their performance is similar among stocks primarily held by long-term institutions. My results highlight how market frictions determine the equilibrium asset allocation of institutional investors according to their holding horizons and short-term institutions benefit from holding stocks more exposed to mispricing shocks in advance. Exploring my model's implications in the international setting or other asset classes is of interest for future research.

Figure 3.1: Average institutional turnover ratio vs. stock characteristics.



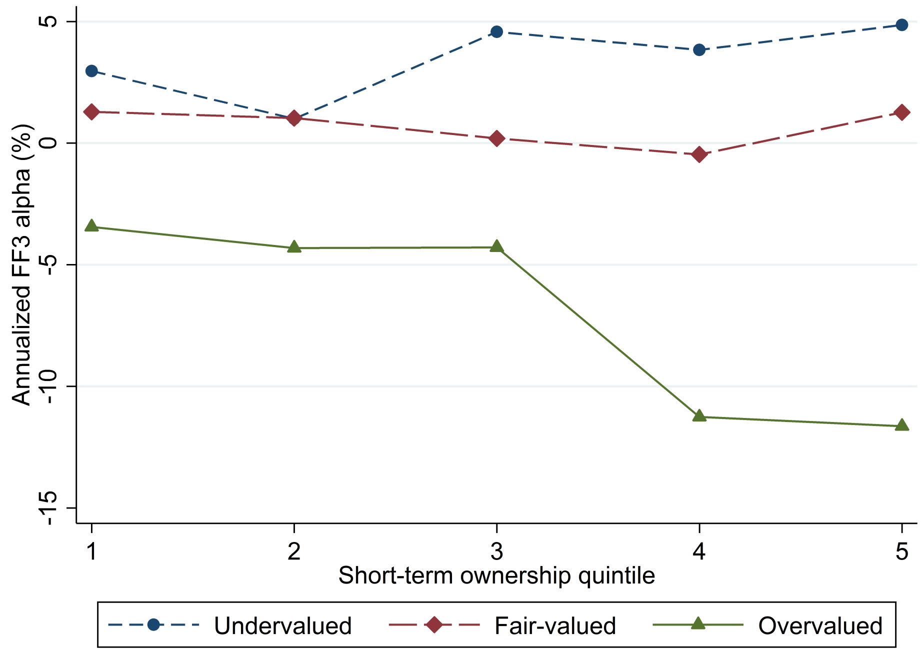
This figure presents the average turnover ratio of institutional investors for stocks in different characteristic deciles. For every stock, I measure the average turnover ratio of institutional investors that own the stock, weighted by the number of shares each institution owns. The characteristic decile is on the x-axis and the average turnover ratio is on the y-axis. The characteristics are the CAPM beta, market cap, book-to-market, momentum, idiosyncratic volatility, and stock age. The sample period is from 1981 to 2017.

Figure 3.2: Average institutional turnover ratio by sector.



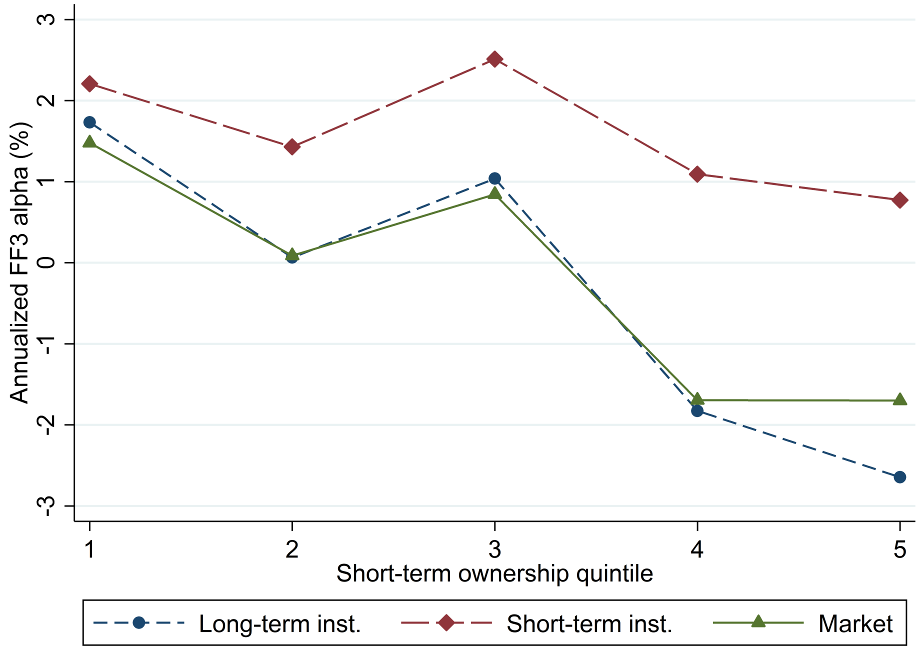
This figure presents the average institutional turnover ratio for stocks in each sector. Sector classification is based on the GIC sector code. For every stock, I measure the average turnover ratio of institutional investors that own the stock, weighted by the number of shares each institution owns. I then average these quantities within each sector. The sample period is from 1981 to 2017.

Figure 3.3: Asymmetry in return predictability.



This figure presents annualized three-factor alphas of sub-portfolios sorted by the ex ante short-term ownership and mispricing score. I first sort stocks into five quintile portfolios in the beginning of April in each year based on their prior year's short-term ownership averaged across four quarters (i.e. the ex ante short-term ownership). Short-term ownership of a stock in each quarter is proxied by the the average turnover ratio of institutional investors that own the stock. Then, within each quintile and in the beginning of each month, I sort stocks into undervalued, fair-valued and overvalued terciles based on the Stambaugh et al. (2015) mispricing score. The y-axis is the annualized abnormal return for each sub-portfolio. The top line represents underpriced stocks. The line in the middle represents fairly-priced stocks. And the bottom line represents the overpriced stocks. The return of each sub-portfolio is measured with value weights. The abnormal return is measured with respect to the Fama-French (1993) three factor model. The sample period for returns is from 1982:04 to 2016:12.

Figure 3.4: Buy-and-hold return and rebalanced return.



This figure presents the annualized Fama-French three-factor alphas for each quintile portfolio sorted by the stock's ex ante short-term ownership. I first sort stocks into five quintile portfolios in the beginning of April in each year based on their prior year's short-term ownership averaged across four quarters (i.e. the ex ante short-term ownership). Short-term ownership of a stock in each quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter. The returns of stocks in each quintile are measured with different weighting schemes: the market-cap weighted return (market), the long-term institutions' dollar weighted return, and the short-term institutions' dollar weighted return. Long-term (short-term) institutions are institutions ranked in the bottom (top) turnover ratio decile. I aggregate their holdings in the beginning of each quarter to obtain the total dollars invested in each stock by the two groups of institutions. The sample period for returns is from 1982:04 to 2017:12.

Table 3.1: Summary statistics of institutions.

A. Summary statistics

	N	Mean	Median	Std. Dev.	Min	Max
AUM (million)	1309	4,151	386	27,854	0	1,959,319
Number of holdings	1309	241	96	449	10	6074
Turnover ratio	1309	0.46	0.30	0.44	0.01	2.47

B. Persistence of turnover ratio

	(1)	(2)	(3)	(4)
VARIABLES	Turnover ratio	Turnover ratio	Turnover ratio	Turnover ratio
Lag 1 yr turnover ratio	0.90***			
	(77.13)			
Lag 5 yr turnover ratio		0.79***		
		(43.35)		
Lag 10 yr turnover ratio			0.70***	
			(32.43)	
Lag 20 yr turnover ratio				0.53***
				(11.19)
Observations	38,057	16,827	8,924	2,308
Adjusted R-squared	0.838	0.659	0.516	0.266

C. Turnover ratio by legal designations

Institutional Type	Average Turnover Ratio	Std. Dev. in Turnover Ratio
Bank Trusts	22%	14%
Corporate Pension Sponsors	33%	30%
Investment Companies	51%	45%
Insurance Companies	33%	30%
Public Pension Sponsors	19%	21%
Universities and Endowments	30%	25%
Miscellaneous and Unclassified	54%	54%

This table presents the summary statistics for institutional investors in my sample. Panel A reports the summary statistics for their asset under management (AUM), number of stock holdings, and annualized turnover ratio. The number of observations N is the time-series average number of institutions in my sample. Panel B reports the persistence of turnover ratio by regressing each year's turnover ratio on lagged turnover ratio. Panel C reports average annualized turnover ratio for institutions with different legal designations. All t-statistics (in parentheses) are based on standard errors clustered at both the institution and year level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively. The sample period is from 1981 to 2017.

Table 3.2: Summary statistics of stocks.

A. Summary statistics

	N	Mean	Median	Std. Dev.	Min	Max
Short-term Ownership	4025	0.38	0.36	0.15	0.11	0.93
Beta	3943	0.83	0.78	0.78	-1.14	3.22
Market cap	4025	2483	226	13747	0	868,880
Book-to-market	3572	0.73	0.58	0.62	0.04	3.73
Momentum	3766	0.13	0.07	0.55	-0.83	2.62
Idiosyncratic volatility	3943	0.03	0.02	0.02	0.01	0.12
Stock age	4025	15.55	10.92	15.43	0.08	92.08

B. Correlation: full sample

	ST Own	Beta	MC	BM	Mom	IVol	Age
Short-term Ownership	100%						
Beta	12%	100%					
Log(Market cap)	-2%	26%	100%				
Book-to-market	-13%	-14%	-30%	100%			
Momentum	19%	9%	17%	-9%	100%		
Idiosyncratic volatility	12%	5%	-51%	14%	-18%	100%	
Stock age	-26%	1%	38%	5%	0%	-29%	100%

C. Correlation: all-but-micro

	ST Own	Beta	MC	BM	Mom	IVol	Age
Short-term Ownership	100%						
Beta	17%	100%					
Log(Market cap)	-17%	12%	100%				
Book-to-market	-14%	-13%	-16%	100%			
Momentum	24%	6%	13%	-7%	100%		
Idiosyncratic volatility	31%	26%	-36%	-12%	-15%	100%	
Stock age	-31%	-8%	39%	14%	-3%	-32%	100%

This table reports summary statistics for stocks in my sample. Panel A reports the summary statistics for stock characteristics. Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. Definitions of other characteristics are in Appendix B. The number of observations *N* is the time-series average number of observations for each characteristic. Panel B reports the pairwise correlation of stock characteristics among all stocks in the sample. Panel C reports the pairwise correlation of stock characteristics by excluding micro-cap stocks, which are defined as stocks with a market cap less than the NYSE 20th percentile in the end of the prior year. All stock characteristics are winsorized at the 1st and 99th percentile. The sample period is from 1981 to 2017.

Table 3.3: The cross section of short-term ownership.

	(1)	(2)	(3)	(4)	(5)	(6)
		Full sample			All-but-micro	
VARIABLES	ST Own.	ST Own.	ST Own.	ST Own.	ST Own.	ST Own.
Lag 4 qtr. ST Own.	0.61***		0.56***	0.64***		0.56***
	(66.97)		(79.78)	(57.09)		(75.39)
Beta		1.42***	0.44***		1.76***	0.52***
		(12.43)	(6.15)		(10.25)	(5.26)
Log(Market cap)		0.09	-0.10*		-0.71***	-0.34***
		(0.96)	(-1.95)		(-8.03)	(-6.79)
Book-to-market		-1.12***	-0.13		-0.33*	0.70***
		(-6.68)	(-1.29)		(-1.66)	(6.26)
Momentum		5.40***	6.04***		6.62***	6.32***
		(32.93)	(30.48)		(25.94)	(24.75)
Volatility		33.93***	19.58***		124.83***	40.97***
		(4.70)	(4.17)		(11.82)	(5.70)
Stock age		-0.19***	-0.05***		-0.11***	-0.03***
		(-25.62)	(-15.93)		(-17.82)	(-9.97)
Observations	525,877	507,355	486,703	274,873	261,341	260,068
Adjusted R-squared	0.400	0.224	0.503	0.476	0.357	0.610
Industry FE		Yes	Yes		Yes	Yes
Time FE		Yes	Yes		Yes	Yes

This table reports the statistical relationship between short-term ownership and other stock characteristics. Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. Columns (1) to (3) include all stocks in the sample. Columns (4) to (6) exclude micro-cap stocks, which are stocks with prior year-end market cap smaller than the NYSE 20th percentile. Except for lagged variables, all other independent variables in the regression are measured contemporaneously as the y-variable. All stock characteristics are winsorized at the 1st and 99th percentile. All t-statistics (in parentheses) are based on standard errors clustered at both the stock and quarter level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.4: Portfolio sorts based on ex ante short-term ownership.

	Ex ante short-term ownership sorted portfolios				
	Low	2	3	4	High
Panel A: allocation					
Number of stocks	789	791	790	788	785
Total weight in the market portfolio	33%	32%	18%	11%	6%
Total weight in long-term institutions	41%	34%	15%	7%	3%
Total weight in short-term institutions	11%	22%	23%	23%	21%
Panel B: transition matrix					
	Low	2	3	4	High
Low	71	19	5	3	2
2	22	48	21	7	3
3	6	27	41	20	6
4	3	9	29	42	18
High	2	3	9	29	57

This table reports the number of stocks and their total portfolio weight in each quintile portfolio sorted by ex ante short-term ownership. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. In the end of each month, I count the number of stocks in each portfolio. I also measure the percentage of total amount of capital allocated to each portfolio by the market, low-turnover institutions, and high turnover institutions. For the market, I take the sum the market capitalization of stocks in each portfolio and divided by the total size of the market. For low and high turnover managers, I take the sum of their dollar value invested in each portfolio and then divide by the total size of their total asset. Long-term (short-term) institutions are institutions ranked in the bottom (top) turnover ratio decile. The reported numbers are the time series averages of each quantity. Panel B reports the transition probability matrix for stocks from one quintile to another between two consecutive years.

Table 3.5: Cross-sectional abnormal returns of stocks.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Panel A: value-weighted						
CAPM Alpha	0.20***	0.02	0.07	-0.22**	-0.36**	-0.56**
	(2.79)	(0.45)	(1.25)	(-2.26)	(-2.03)	(-2.36)
FF3 Alpha	0.12**	0.01	0.07	-0.14*	-0.14	-0.26*
	(2.35)	(0.16)	(1.17)	(-1.87)	(-1.33)	(-1.89)
FFC4 Alpha	0.12**	0.03	0.08	-0.12	-0.19*	-0.31**
	(2.28)	(0.60)	(1.25)	(-1.57)	(-1.68)	(-2.12)
Observations	429	429	429	429	429	429
Panel B: equal-weighted						
CAPM Alpha	0.28**	0.22*	0.12	-0.12	-0.46**	-0.74***
	(2.10)	(1.93)	(1.02)	(-0.81)	(-2.41)	(-4.64)
FF3 Alpha	0.14	0.06	0.01	-0.14	-0.36***	-0.50***
	(1.51)	(0.95)	(0.21)	(-1.46)	(-2.82)	(-4.24)
FFC4 Alpha	0.27***	0.21***	0.18***	0.08	-0.10	-0.37***
	(2.83)	(3.45)	(2.87)	(0.82)	(-0.72)	(-2.92)
Observations	429	429	429	429	429	429

This table reports the abnormal returns of portfolios sorted by ex ante short-term ownership. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. The abnormal returns are computed based on the CAPM model, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4). Panel A computes returns using value weights. Panel B computes returns using equal weights. The sample period for returns is from 1982:04 to 2017:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.6: Asymmetry in return predictability.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Undervalued stocks	0.25***	0.08	0.38***	0.32***	0.41***	0.16
	(3.36)	(1.16)	(4.18)	(2.94)	(2.94)	(0.94)
Fair-valued stocks	0.11	0.09	0.02	-0.04	0.11	-0.00
	(1.18)	(1.14)	(0.17)	(-0.39)	(0.66)	(-0.01)
Overvalued stocks	-0.29**	-0.36***	-0.36***	-0.94***	-0.97***	-0.68***
	(-1.99)	(-3.21)	(-3.14)	(-6.78)	(-6.15)	(-3.32)
Under minus overvalued	0.53***	0.44***	0.74***	1.26***	1.37***	0.84***
	(3.17)	(2.95)	(4.80)	(6.81)	(6.77)	(3.64)
Observations	417	417	417	417	417	417

This table reports the three-factor alphas of sub-portfolios sorted by the ex ante short-term ownership and mispricing score. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. Then, within each quintile and in the beginning of each month, I sort stocks into undervalued, fair-valued and overvalued terciles based on the Stambaugh et al. (2015) mispricing score. The return of each sub-portfolio is measured by value-weighting stocks in the sub-portfolio. The abnormal return is measured with respect to the Fama-French three-factor model. The sample period for returns is from 1982:04 to 2016:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.7: The cross section of trading profits of institutions.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Panel A: long-term institutions						
CAPM Alpha	0.22***	0.02	0.09	-0.23**	-0.42**	-0.64***
	(2.73)	(0.47)	(1.37)	(-2.33)	(-2.50)	(-2.75)
FF3 Alpha	0.14**	0.01	0.09	-0.15*	-0.22**	-0.36**
	(2.43)	(0.12)	(1.31)	(-1.83)	(-2.02)	(-2.55)
FFC4 Alpha	0.14**	0.03	0.09	-0.14*	-0.24**	-0.38***
	(2.35)	(0.64)	(1.32)	(-1.69)	(-2.13)	(-2.59)
Panel B: short-term institutions						
CAPM Alpha	0.25***	0.14**	0.21***	0.00	-0.17	-0.42*
	(3.51)	(2.53)	(2.69)	(0.01)	(-0.88)	(-1.76)
FF3 Alpha	0.18***	0.12**	0.21***	0.09	0.06	-0.12
	(3.11)	(2.23)	(2.76)	(0.97)	(0.55)	(-0.83)
FFC4 Alpha	0.14**	0.07	0.15*	0.02	-0.07	-0.21
	(2.33)	(1.31)	(1.84)	(0.17)	(-0.61)	(-1.43)
Panel C: short-term minus long-term						
CAPM Alpha	0.03	0.11**	0.12***	0.23***	0.25***	0.22***
	(0.64)	(2.59)	(2.74)	(3.64)	(3.78)	(3.03)
FF3 Alpha	0.04	0.11***	0.12***	0.24***	0.28***	0.25***
	(0.86)	(2.81)	(2.92)	(4.05)	(4.28)	(3.26)
FFC4 Alpha	-0.00	0.04	0.06	0.16***	0.17***	0.17**
	(-0.09)	(1.09)	(1.37)	(2.85)	(2.73)	(2.37)

This table shows the abnormal returns of long-term and short-term institutions in portfolios sorted by ex ante short-term ownership. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. Short-term (long-term) institutions are institutions in the top (bottom) turnover ratio decile. The returns of each quintile in Panel A and B are computed by weighting individual stock returns by the total dollars invested by each group of institutions. The returns in Panel C are the returns in Panel B minus the returns in Panel A. The abnormal returns are computed based on the CAPM model, the Fama-French 3 factor model (FF3), and the Fama-French-Carhart 4 factor model (FFC4). The sample period for returns is from 1982:04 to 2017:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.8: Trading profit of institutions with medium holding horizon.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Deciles 2 and 3	-0.01	-0.02	-0.04*	0.04	0.04	0.05
	(-0.33)	(-1.20)	(-1.94)	(1.13)	(0.89)	(0.91)
Deciles 4 and 5	0.00	0.01	-0.05*	0.02	0.11**	0.11**
	(0.09)	(0.56)	(-1.86)	(0.69)	(2.42)	(2.04)
Deciles 6 and 7	0.02	-0.03*	-0.05**	0.01	0.16***	0.14**
	(0.71)	(-1.70)	(-2.28)	(0.15)	(3.40)	(2.45)
Deciles 8 and 9	0.00	0.02	0.01	0.05	0.12***	0.12**
	(0.00)	(1.03)	(0.20)	(1.48)	(2.72)	(2.31)
Observations	429	429	429	429	429	429

This table shows the difference in performance between institutions from turnover deciles 2 to 9 (i.e. medium-term institutions) and institutions in the bottom turnover decile (i.e. long-term institutions). In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. I then aggregate the holdings of institutions ranked in the specified deciles. I compute the dollar-weighted returns of each portfolio institutions from decile 2 to 9. I subtract their returns by the returns of institutions from the bottom turnover decile. The abnormal return is measured with respect to the Fama-French three factor model. The sample period for returns is from 1982:04 to 2017:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.9: Time varying trading profit: sentiment index.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low	2	3	4	High	Average
Lag change in sentiment	0.28	0.36	0.07	1.44**	1.36**	0.70*
	(0.87)	(0.90)	(0.16)	(2.28)	(2.02)	(1.87)
Excess Return on the Market	0.05***	0.01	-0.01	0.01	-0.01	0.01
	(3.97)	(0.85)	(-1.11)	(0.39)	(-0.66)	(0.99)
High-Minus-Low Return	-0.01	0.01	0.01	-0.04	-0.07**	-0.02
	(-0.22)	(0.46)	(0.28)	(-0.94)	(-2.23)	(-0.84)
Small-Minus-Big Return	0.13***	0.12***	0.11***	0.16***	0.14***	0.13***
	(7.68)	(4.92)	(4.64)	(3.46)	(3.82)	(5.44)
Constant	0.04	0.11***	0.12***	0.26***	0.31***	0.17***
	(0.85)	(2.62)	(2.73)	(4.13)	(4.40)	(4.41)
Observations	403	403	403	403	403	403
Adjusted R-squared	0.224	0.148	0.114	0.169	0.130	0.253

This table reports the results of the following regression equations. The regression equation is

$$R_t = a + b\Delta S_{t-1} + cMKT_t + dSMB_t + eHML_t + \varepsilon_t$$

where ΔS_{t-1} is the change in Baker and Wurgler (2006) sentiment index and MKT_t, SMB_t, HML_t are the three Fama-French factors. In Columns 1 to 5, the dependent variables R_t are the differences in the rebalanced return between short-term and long-term institutions in ex ante short-term ownership quintiles 1 to 5. In Column 6, the dependent variable is the average of the first 5 columns. The quintiles are sorted in the beginning of April in each year. I sort stocks into five different portfolios based on their ex ante short-term ownership, which is the average short-term ownership in the prior year. Short-term ownership for a stock is measured as the average of turnover ratio of institutional investors that own the stock, weighted by the number of shares each institution owns. Long-term (short-term) institutions are institutions in the bottom (top) turnover ratio decile. I compute the rebalanced return using the aggregate holdings of each group of institutions. The sample period for returns is from 1982:04 to 2015:10. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.10: Time varying trading profit: IPO return.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low	2	3	4	High	Average
Lag IPO return	0.33	0.80*	0.82**	2.56***	1.41**	1.18***
	(1.09)	(1.65)	(2.53)	(3.45)	(2.34)	(3.07)
Excess Return on the Market	0.07***	0.02	-0.01	-0.00	-0.00	0.01
	(5.47)	(1.26)	(-0.56)	(-0.12)	(-0.22)	(1.33)
High-Minus-Low Return	0.00	0.02	0.02	-0.03	-0.06*	-0.01
	(0.10)	(0.76)	(0.57)	(-0.61)	(-1.73)	(-0.39)
Small-Minus-Big Return	0.13***	0.12***	0.11***	0.16***	0.15***	0.14***
	(7.43)	(5.12)	(5.04)	(3.71)	(4.13)	(5.75)
Constant	-0.05	-0.03	-0.03	-0.17	0.06	-0.04
	(-0.66)	(-0.33)	(-0.56)	(-1.54)	(0.56)	(-0.66)
Observations	393	393	393	393	393	393
Adjusted R-squared	0.251	0.178	0.144	0.255	0.158	0.314

This table reports the results of the following regression equations. The regression equation is

$$R_t = a + bR^{IPO}_{t-1} + cMKT_t + dSMB_t + eHML_t + \varepsilon_t$$

where R^{IPO}_{t-1} is the average first day return of IPOs. In Columns 1 to 5, the dependent variables R_t are the differences in the rebalanced return between short-term and long-term institutions in ex ante short-term ownership quintiles 1 to 5. In Column 6, the dependent variable is the average of the first 5 columns. The quintiles are sorted in the beginning of April in each year. I sort stocks into five different portfolios based on their ex ante short-term ownership, which is the average short-term ownership in the prior year. Short-term ownership for a stock is measured as the average of turnover ratio of institutional investors that own the stock, weighted by the number of shares each institution owns. Long-term (short-term) institutions are institutions in the bottom (top) turnover ratio decile. I compute the rebalanced return using the aggregate holdings of each group of institutions. The sample period for returns is from 1982:04 to 2015:12 with non-missing IPO observations. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.11: Trading profits of institutions excluding micro-cap stocks.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Panel A: long-term institutions						
CAPM Alpha	0.15**	-0.00	0.11*	-0.16	-0.46***	-0.62***
	(2.13)	(-0.05)	(1.73)	(-1.54)	(-2.67)	(-2.65)
FF3 Alpha	0.08*	-0.02	0.12*	-0.07	-0.25**	-0.34**
	(1.66)	(-0.30)	(1.75)	(-0.79)	(-2.21)	(-2.32)
FFC4 Alpha	0.09*	0.02	0.11	-0.04	-0.27**	-0.36**
	(1.80)	(0.39)	(1.59)	(-0.41)	(-2.24)	(-2.40)
Panel B: short-term institutions						
CAPM Alpha	0.21***	0.14**	0.23***	0.05	-0.22	-0.42*
	(3.10)	(2.25)	(2.87)	(0.44)	(-1.14)	(-1.76)
FF3 Alpha	0.14***	0.12*	0.24***	0.15*	0.02	-0.12
	(2.78)	(1.87)	(3.15)	(1.73)	(0.15)	(-0.82)
FFC4 Alpha	0.11**	0.07	0.18**	0.09	-0.11	-0.22
	(2.09)	(1.11)	(2.21)	(1.08)	(-0.89)	(-1.45)
Panel C: short-term minus long-term						
CAPM Alpha	0.05	0.14***	0.11**	0.21***	0.24***	0.19***
	(1.26)	(2.73)	(2.36)	(3.33)	(3.63)	(2.70)
FF3 Alpha	0.06	0.13***	0.12***	0.22***	0.27***	0.21***
	(1.53)	(2.80)	(2.68)	(3.62)	(3.98)	(2.84)
FFC4 Alpha	0.02	0.05	0.07	0.13**	0.15**	0.14*
	(0.44)	(1.13)	(1.38)	(2.40)	(2.47)	(1.92)

This table shows the abnormal returns of institutions in portfolios sorted by ex ante short-term ownership. I exclude stocks with market cap smaller than the NYSE 20th percentile. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. Long-term (short-term) institutions are institutions in the bottom (top) turnover ratio decile. The returns of each quintile in Panel A (B) are computed by weighting stock returns by the total dollars invested by long-term (short-term) institutions. The returns in Panel C are the difference between the two groups. The abnormal returns are computed based on the CAPM model, the Fama-French 3 factor model (FF3), and the Fama-French-Carhart 4 factor model (FFC4). The sample period for returns is from 1982:04 to 2017:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.12: Trading profit of institutions controlling for additional factors.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Panel A: all stocks						
FF3 + Liquidity Factor	0.05	0.11***	0.13***	0.24***	0.29***	0.24***
	(1.02)	(2.67)	(3.11)	(4.04)	(4.25)	(3.11)
FFC4 + Liquidity Factor	0.00	0.04	0.07	0.16***	0.18***	0.17**
	(0.08)	(0.97)	(1.56)	(2.82)	(2.78)	(2.30)
FF5	0.02	0.08	0.10*	0.23***	0.26***	0.23***
	(0.48)	(1.51)	(1.93)	(3.19)	(3.38)	(2.80)
Mispricing Factors	-0.02	-0.00	0.02	0.09	0.14*	0.17*
	(-0.44)	(-0.09)	(0.35)	(1.36)	(1.80)	(1.90)
Observations	417	417	417	417	417	417
Panel B: all but micro						
FF3 + Liquidity Factor	0.06	0.12***	0.13***	0.23***	0.27***	0.21***
	(1.50)	(2.59)	(2.84)	(3.71)	(3.87)	(2.73)
FFC4 + Liquidity Factor	0.02	0.04	0.08	0.14**	0.16**	0.14*
	(0.43)	(0.92)	(1.56)	(2.50)	(2.42)	(1.88)
FF5	0.05	0.06	0.11**	0.19**	0.25***	0.20**
	(1.13)	(1.05)	(2.11)	(2.54)	(3.16)	(2.43)
Mispricing Factors	0.00	-0.04	0.06	0.04	0.12	0.11
	(0.07)	(-0.75)	(1.03)	(0.65)	(1.44)	(1.35)
Observations	417	417	417	417	417	417

This table shows the difference in the performance between high-turnover institutions and low-turnover institutions, adjusting for other factor models. The models are the Fama-French three-factor model (FF3) with Pastor and Stambaugh (2003) liquidity, the Fama-French-Carhart four-factor model (FFC4) with Pastor and Stambaugh (2003) liquidity factor, the Fama-French five-factor model (FF5), and the Stambaugh and Yuan (2016) mispricing factors. Long-term (short-term) institutions are institutions in the bottom (top) turnover ratio decile. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. I compute returns of each quintile based on the total dollars invested by each group of institutions and then take the difference between the two groups. Panel A includes all stocks in the sample. Panel B excludes micro-cap stocks, which have market cap smaller than the NYSE 20th percentile. The sample period for returns is from 1982:04 to 2016:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.13: Trading profit of institutions excluding the dotcom bubble.

	Ex ante short-term ownership sorted portfolio					
	Low	2	3	4	High	Hi-Lo
Panel A: long-term institutions						
CAPM Alpha	0.20***	0.00	0.05	-0.14	-0.26*	-0.47**
	(2.80)	(0.02)	(0.84)	(-1.57)	(-1.93)	(-2.45)
FF3 Alpha	0.15***	-0.01	0.07	-0.09	-0.13	-0.29**
	(2.63)	(-0.11)	(1.04)	(-1.16)	(-1.32)	(-2.12)
FFC4 Alpha	0.14**	0.01	0.07	-0.09	-0.13	-0.28*
	(2.43)	(0.13)	(1.02)	(-1.11)	(-1.25)	(-1.97)
Panel B: short-term institutions						
CAPM Alpha	0.21***	0.05	0.13*	-0.05	-0.08	-0.29
	(3.43)	(1.05)	(1.75)	(-0.50)	(-0.52)	(-1.58)
FF3 Alpha	0.17***	0.05	0.15**	0.01	0.06	-0.11
	(3.06)	(1.01)	(1.99)	(0.10)	(0.61)	(-0.84)
FFC4 Alpha	0.13**	0.02	0.11	-0.03	-0.01	-0.14
	(2.29)	(0.36)	(1.46)	(-0.37)	(-0.13)	(-1.04)
Panel C: short-term minus long-term						
CAPM Alpha	0.01	0.05	0.08**	0.09**	0.19***	0.18**
	(0.19)	(1.37)	(2.00)	(1.98)	(3.10)	(2.57)
FF3 Alpha	0.02	0.06*	0.08**	0.10**	0.20***	0.18**
	(0.43)	(1.67)	(2.12)	(2.33)	(3.30)	(2.59)
FFC4 Alpha	-0.01	0.01	0.04	0.05	0.12**	0.13*
	(-0.29)	(0.40)	(1.20)	(1.33)	(2.01)	(1.91)

This table shows the abnormal returns of low-turnover institutions and high-turnover institutions in portfolios sorted by ex ante short-term ownership. In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. Long-term (short-term) institutions are institutions in the bottom (top) turnover ratio decile. The returns of each quintile in Panel A (B) are computed by weighting stock returns by the total dollars invested by long-term (short-term) institutions. The returns in Panel C are the returns in Panel B minus the returns in Panel A. The abnormal returns are computed based on the CAPM model, the Fama-French 3 factor model (FF3), and the Fama-French-Carhart 4 factor model (FFC4). The sample period for returns is from 1982:04 to 2017:12, excluding 1998:04 to 2001:03. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3.14: Cross-sectional abnormal return and liquidity risk.

Ex ante short-term ownership sorted portfolio						
	Low	2	3	4	High	Hi-Lo
MKT	0.84***	1.01***	1.07***	1.16***	1.25***	0.41***
	(60.64)	(81.91)	(60.47)	(52.91)	(35.13)	(8.97)
HML	0.18***	0.02	0.01	-0.20***	-0.50***	-0.69***
	(7.85)	(0.93)	(0.28)	(-5.02)	(-8.14)	(-8.82)
SMB	-0.22***	-0.12***	0.10***	0.33***	0.69***	0.91***
	(-11.34)	(-5.48)	(4.11)	(11.62)	(15.79)	(16.48)
UMD	0.00	-0.03**	-0.01	-0.03	0.05	0.05
	(0.11)	(-2.30)	(-0.70)	(-1.35)	(1.41)	(1.15)
LIQ	-0.03*	0.04***	0.08***	0.08***	0.07**	0.09**
	(-1.79)	(2.94)	(4.16)	(3.91)	(2.13)	(2.37)
Constant	0.13**	0.01	0.05	-0.15**	-0.21*	-0.34**
	(2.45)	(0.31)	(0.86)	(-2.03)	(-1.92)	(-2.38)
Observations	429	429	429	429	429	429
Adjusted R-squared	0.920	0.964	0.950	0.940	0.918	0.748

This table reports the time series regression of returns of portfolios sorted by ex ante short-term ownership on the Fama-French (1983) three factors (MKT, SMB, HML), the Carhart (1997) momentum factor (UMD), and the Pastor-Stambaugh (2003) liquidity factor (LIQ).

$$R_t = a + bMKT_t + cSMB_t + dHML_t + eUMD_t + fLIQ_t + \varepsilon_t$$

In the beginning of April in each year, I sort stocks into five different portfolios based on their prior year's short-term ownership averaged across four quarters (i.e. ex ante short-term ownership). Short-term ownership for a stock in a given quarter is proxied by the the average turnover ratio of institutional investors that own the stock in the quarter, weighted by the number of shares each institution owns. The return of each quintile is computed using value weights. The sample period for returns is from 1982:04 to 2017:12. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Chapter 4

Cheaper is Not Better: The Superior Performance of High-Fee Mutual Funds

4.1 Introduction

At the end of 2018, domestic U.S. equity mutual funds were responsible for managing \$8.65 trillion in assets. These funds continue to be the primary investment vehicle for households, with over ninety million people in the U.S. holding their shares. The average fund charges over 1% in fees, and each year investors spend billions of dollars on fund expenses, which supposedly compensate managers for their ability to generate value.[11]

Economic principles and theoretical arguments suggest that fees of a fund should be commensurate with the value it creates for investors. Skilled managers should generate better before-fee performance but capture all rents by charging higher expenses, leading to a flat relation between fund expenses and net-of-fees performance (Berk and Green, 2004). In stark contrast with the theory, empirical studies do not find a positive relation between fund expense ratios and before-fee performance. The literature concludes that net of expenses, investors in high-fee funds earn significantly worse factor-adjusted returns than do investors in low-fee funds.[12]

The seemingly poor factor-adjusted performance of high-fee funds has shaped asset allocation decisions of both retail and institutional investors. For example, in his best-selling book aimed at individual investors, Malkiel (2016) writes, "The best-performing actively managed funds have moderate expense ratios... I suggest that investors never buy actively managed funds with expense ratios above 50 basis points." More sophisticated investors also avoid high-fee funds. For instance, in a study of asset flows of defined contribution pension plans, Sialm et al. (2015) show that "plan sponsors and participants invest more in funds with lower expense ratios."

In addition to offering these billion-dollar practical implications, the inverse relation between fees and net performance raises important unanswered questions. Specifically, how should the literature square this link with the theory, which predicts a flat relation? And, why do high-fee funds continue to exist if their managers extract more economic rents than the value they add? In

[11]Statistics for the mutual fund industry are from Investment Company Fact Book 2018.

[12]See, for example, Jensen (1968), Malkiel (1995), Gruber (1996), Wermers (2000), Gil-Bazo and Ruiz-Verdú (2009), Fama and French (2010).

this paper we offer an explanation, which reconciles theory with empirics, and calls for revisiting the oft-offered practical advice to prefer low-fee funds over high-fee counterparts.

In our first set of analyses, we establish that funds with different expense ratios invest in fundamentally different stocks. In particular, relative to firms held by funds in the lowest fee decile, firms held by funds in the high-fee group grow their assets at a significantly faster rate (19% vs 12% annually) and have lower gross profit ratios (28% vs 34%). Importantly, these firms are precisely the types that conventional factor models misprice: firms with high asset growth and low profitability have significantly negative three- and four-factor alphas (Cooper et al., 2008; Novy-Marx, 2013). As a result of high-fee funds tilting their portfolios to such stocks, analyses based on conventional models lead to the premature conclusion of poor performance of these funds and the practical guidance to avoid investing in them. We re-examine the fee-performance relation through the lens of a recently proposed Fama and French (2015) five-factor model, which is designed to capture differences in average returns of stocks with different profitability and investment patterns and is hence well-suited to study factor-adjusted performance of funds with different fees.

In striking contrast with the conclusions of the prior literature, we find that high-fee funds generate significantly better factor-adjusted gross-of-expenses performance than do low-fee funds. Results of panel regressions of funds' five-factor alphas on expense ratios suggest that funds that charge 1% higher fee deliver 1% more alpha. We show that after deducting expenses, high-fee funds do not underperform low-fee funds. In other words, the seemingly poor performance of these funds documented in prior literature is but an artifact of the failure to adjust performance for the exposure to priced factors. Importantly, our results strongly support the theoretical predictions of Berk and Green (2004) that high-fee mutual funds generate higher alphas before fees, and that fees are unrelated to net-of-expenses performance because skilled managers extract rents by charging higher fees.

To better understand why high-fee funds invest more in high-investment low-profitability stocks, we consider two hypotheses. Under the naïve investor hypothesis, we conjecture that these companies appeal to unsophisticated investors who are also less price-sensitive, which allows high-fee funds to charge higher expenses. We find this is not the case: high-fee funds with more sophisticated investors exhibit similar propensities to invest in high-investment low-profitability stocks.

Alternatively, under the valuation cost hypothesis, we conjecture that fees of funds that tilt their portfolios to high-investment low-profitability companies are high because estimating intrinsic value of these stocks is more difficult. Funds that choose to specialize in investing in hard-to-value companies must spend more resources on valuation per unit of capital, for example by hiring more talented managers, which justifies the higher fees on a percentage basis. Because companies that are difficult-to-value are more likely to be the ones with fast growth rates and low profits, traditional factor models, being unable to correctly price such companies, lead to biased inferences in evaluating performance of high-fee funds. To test this hypothesis, we use several proxies for the difficulty of valuing a company. Consistent with the valuation cost hypothesis, we find that high-fee funds invest significantly more in companies that are hard-to-value: those that have high idiosyncratic volatility, high financial uncertainty, low asset tangibility, and low coverage from sell-side analysts. When we decompose a fund's expense ratio into distribution cost and asset management cost, we find that the relationship between a fund's expense ratio and proxies of the valuation cost of its underlying companies is entirely driven by the part of the expense ratio that reflects the asset management cost – that is, management fees and expenses – rather than the distribution costs such as 12b-1 fees. In other words, in line with the valuation cost hypothesis, funds investing in hard-to-value companies compensate their managers more richly by charging higher management fees.

Our results contribute to the large literature on mutual fund performance.[13] An important long-standing debate in this research is whether fund managers deliver performance that justifies the fees they charge (e.g., Daniel et al., 1997; Carhart, 1997; Berk and Green, 2004; Fama and French, 2010; Berk and Van Binsbergen, 2015). Our key contribution is to show that – consistent with the theory of Berk and Green (2004) – skilled managers indeed extract rents by charging high fees. We also extend the growing literature that investigates how anomalies associated with investment and profitability rates impact mutual funds. Several recent papers advance this research by addressing questions distinct from ours. For example, Busse et al. (2017) argue that mutual fund performance measures should control for portfolio characteristics, such as investment and profitability. Jordan and Riley (2015) show that idiosyncratic volatility can predict mutual fund performance measured with three- and four-factor models, but cannot predict five-factor alpha. Jordan and Riley (2016) find that five-factor mutual fund alphas exhibit more persistence than alphas from other models, highlighting the apparent superiority of the five-factor model over its predecessors. Our paper adds to this strand of literature by documenting the implications of exposures to the investment and profitability factors for the fee-performance relation, a central topic in the mutual fund literature.

4.2 Data

We obtain mutual fund data by linking 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 the literature, we apply several filters to form our sample (e.g., Kacperczyk et al., 2006b). We remove passive index funds by searching through fund name and index fund indicator. We then exclude mutual funds that are not U.S. domestic equity funds based on the CRSP style code, Thomson Reuters style code, and Lipper objective name. We eliminate mixed

[13] The literature has grown tremendously since Jensen (1968). See Ferson (2010), Musto (2011), and Wermers (2011) for recent comprehensive reviews.

funds or highly levered funds, which hold less than 70% or more than 130% of their assets in equity. For the analysis of holdings, we require a fund to have at least 10 stock holdings. We remove extremely small funds, i.e. funds with less than $20 million in asset in real 2017 terms, which is approximately $6 million in 1980. To estimate factor-adjusted performance for each fund, we require at least five years of return history. Our final sample contains 2,828 funds and spans the period from 1980 to 2017.[14]

If a fund has multiple share classes, we aggregate information of the different classes. Fund-level returns and expense ratios are the class size-weighted averages. We winsorize expense ratios, to which we refer interchangeably as fees, at the 99th percentile to remove extreme outliers. Fund size is the aggregate of all share classes. We drop observations where any of the fund size, return, or expense ratios is missing. We define fund age as the age of its oldest share class in our sample. To proxy for the investor sophistication of a fund, we use the fund's distribution channel and variable capturing whether it is a retail or institutional fund. Following Sun (2014), we classify a share class as broker-sold (as opposed to directly sold), if its 12b-1 fee is higher than 25 basis points or if it charges front- or back-end load fees. We define a fund's broker share as the fraction of assets in broker-sold share classes. We label a share class as institutional if its name contains words beginning with "inst", if it is of class Y or I, or if its institutional flag is Y in CRSP. Similarly, we measure a fund's institutional share as the fraction of its assets in institutional share classes. Finally, we identify funds that are in the same fund family based on their management company name and calculate fund family size as the sum of total assets of its affiliated funds. Panel A of Table 4.1 reports fund-level summary statistics. The average fund is 10.3 years old and charges a 1.22% fee. The average broker share is 49% and the average institutional share is 29%.

Our analysis of mutual fund holdings requires stock-level data, which we obtain from the CRSP, COMPUSTAT, and IBES files, restricting the sample to common stocks (share code 10 and 11). For each stock, we measure characteristics such as the CAPM beta, market capitalization, book-to-market ratio, and momentum. We also compute investment- and profitability-related characteristics such as asset growth, equity issuance, operating profitability, and stock age. To gauge whether a company is difficult to value, we construct proxies such as asset tangibility, idiosyncratic volatility, readability of financial statements, and analyst coverage. The appendix provides details on variable definitions. We winsorize firm-level variables at the top and bottom 0.5%. We take natural logarithms of growth rates and market capitalization. To study portfolio-level attributes of the funds, we take position-weighted averages of characteristics of stocks they hold at the beginning of each year. Panel B of Table 1 shows summary statistics of these stock characteristics.

[14] In Section 6, we show that the results remain similar if we use only three-year windows to estimate risk loadings, leaving us with 3,261 unique funds.

4.3 Mutual funds fees and investment styles

In this section we uncover systematic differences in the investment strategies of high-fee and low-fee funds.

Fund prospectuses provide valuable information on fund's investment strategies (Abis, 2017). To get a first sense of whether high- and low-fee funds follow distinct investment approaches, we examine the differences in the "Principal Investment Strategies" (PIS) section of prospectus forms 497K available from EDGAR. To the extent that high- and low-fee funds differ in their investment styles, we expect to observe differences in the language in that section.

We find that high-fee funds tend to describe their investment strategies differently from low-fee funds. A typical PIS section of high-fee funds reads:

> [The fund] utilizes a growth approach to choosing securities based upon fundamental research which attempts to identify companies whose earnings growth rate exceeds that of their peer group, exhibit a competitive advantage in niche markets, or do not receive significant coverage from other institutional investors. (Emerald Mutual Fund)

By contrast, a typical low-fee fund describes its investment strategy as follows:

> The Fund invests, under normal circumstances, primarily in U.S. common stocks that are considered by the Fund's subadvisers to have above-average potential for growth. The subadvisers emphasize stocks of well-established medium- and large-capitalization firms. (The Vantagepoint Funds)

In addition, we look at fund holdings to see whether there are systematic differences between high-fee and low-fee mutual funds. We compute average characteristics of stock holdings of funds with different expense ratios. In addition to the commonly considered stock characteristics such as size, book-to-market ratio, and momentum, we investigate asset growth rate, operating profitability, equity issuance rate, and stock age. For every fund at the first observation of each year, we take position-weighted averages across all stocks in its portfolio to calculate average characteristics of stockholdings. We then run the following panel regression:

$$Avg\,char_{j,t} = b_0 + b_1 Expense\,ratio_{j,t-1} + c' Controls_{j,t-1} + FE_t + \varepsilon_{j,t} \tag{4.1}$$

where $Avg\,char_{j,t}$ is one of the above-mentioned stock characteristics for fund j in year t, *Expense ratio* is the fund's expense ratio in year $t-1$, and $Controls_{j,t-1}$ include the natural logarithm of fund size, fund age (in months), and the size of other affiliated funds in the same family. Since our focus is on the cross-sectional comparison between high-fee and low-fee funds, we include year fixed effects to control for time series trends in the mutual fund industry. We cluster standard errors at the fund level and scale all variables by their standard deviations annually to better facilitate the interpretation of the magnitudes of the coefficients.

Our main focus in this test is on the coefficient on the expense ratio. For example, for asset growth rate, a positive coefficient indicates that high-fee funds tilt their holdings to companies with high asset growth rates. Table 4.2 shows that the coefficients on the expense ratio are significant for seven out of eight characteristics we study. With respect to commonly considered characteristics, regressions (1)-(4) establish high-fee funds invest more in high-beta stocks, small stocks, and high momentum stocks. Specifications (5) and (6) show that high-fee funds also invest more in stocks with high asset growth rates and high equity issuance rates. Finally, regressions (7) and (8) shows that high-fee funds invest more in young stocks and stocks with low profitability. Overall, the results of this analysis suggest that funds charging different fees have systematically different investment preferences. Broadly speaking, high-fee funds prefer younger firms in a stage of rapid expansion that have not yet achieved high profitability.

In terms of the economic significance, we observe that the absolute magnitude of the coefficient in regressions (5)-(8) is often greater than that in specification (1)-(4), indicating that growth- and profitability-related characteristics are economically more important in capturing portfolio differences among funds charging different fees. To better gauge the economic magnitude of tilts by high-fee funds, we plot average asset growth rates, equity issuance rates, operating profitability and stock age against fund fee deciles in Figure 4.1. The benefit of this plot is that it does not impose a linear structure between fee and stock characteristics, which better demonstrates the reliability of fee as an indicator of tilt towards certain characteristics. The figure shows that stock characteristics change strikingly and monotonically with fees. The average asset growth rate of companies invested by funds in the bottom decile is about 12% a year, while in the highest decile is about 19%. The difference of 7% represents a half of the average asset growth rate of all companies. The plot also reveals that companies held by bottom decile funds on average achieve operating profitability that is 6 percentage points higher than that of companies held by top decile funds.

The landscape of the mutual fund industry and academic understanding of the determinants of asset returns have both changed significantly since the 1990s. It is possible that the preference of high-fee funds for different types of stocks has changes over time. To test this conjecture, we run regression (4.1) annually and plot the time series of the coefficients on the expense ratio in Figure 4.2. The coefficients are more volatile during the early part of the sample, potentially because of the smaller number of observations. Importantly, the preference of funds with higher fees for low-profitability high-growth firms is persistent over time.

4.4 Mutual fund fee-performance relation

The persistent preference of high-fee funds for fast-growing, low-profitability stocks has important implications for the relation between expenses and performance of mutual funds. To the extent that these stock characteristics are associated with lower expected returns, as recent literature has shown (Fama and French, 2015; Hou et al., 2015), failure to account for these characteristics can lead to erroneous conclusions on the relation between fees and fund performance. Such failure would be analogous to using CAPM to evaluate the performance of a large-cap growth fund: without explicitly accounting for loadings on size and value factors, the performance of this fund would appear poor on average. In our context, accounting for exposures to asset growth and profitability factors of funds with different fees is necessary to get a clearer picture of the relation between expenses and performance of mutual funds.

To control for exposures to asset growth and profitability factors, we use the five-factor model of Fama and French (2015). To contrast our results with those of prior literature, we also use commonly considered models such as the CAPM as well as the three- and four-factor models and evaluate robustness to other models in section 6. For each performance model and in each month t, we regress a fund's monthly return in the previous five years on factors to obtain loadings β_{jt}^{Model}. We compute monthly alphas as

$$\alpha_{j,t}^{Model} = r_{j,t}^{e} - \beta_{j,t}^{Model'} r_t^{Factor} \tag{4.2}$$

where r_{jt}^{e} is fund j's excess return before fee or after fee, and r_t^{Factor} is a vector of realized factor returns in each model. We measure a fund's gross monthly alpha using its gross return, which is net return plus the annual expense ratio divided by 12.

4.4.1 Empirical evidence

Figure 4.3 summarizes future performance of funds grouped into deciles on the basis of fees disclosed in the most recent fiscal year end. Panel A plots before-fee alphas from different models. The results from the CAPM, three- and four-factor models confirm the findings of the prior literature: gross fund performance is unrelated to fees. By contrast, alphas from the five-factor model display a very different pattern: they increase significantly with fees.

Panel B shows that irrespective for the model, actively managed mutual funds with both high and low expense ratios achieve poor net-of-fees factor-adjusted performance. In addition, consistent with the previously established results, net-of-expenses fund performance as measured by the CAPM, three-, and four-factor models, deteriorates with fees. Strikingly, this negative relation is absent when we use five-factor alphas. The difference in five-factor performance of funds with high and low expense ratios is economically small and statistically indistinguishable from zero.

Taken together, the evidence in Figure 4.3 provides one missing support of the prediction of Berk and Green (2004) that skilled managers extract rents by charging higher fees, and consequently actively managed funds deliver similar net-of-fees performance.

The sort-based results in Figure 4.3 are informative, but to evaluate the fee-performance relation more formally, we run the following panel regression:

$$\alpha_{j,t} = d_0 + d_1 Expense_{j,t-1} + h' Control_{j,t-1} + F_t + \varepsilon_{j,t} \tag{4.3}$$

where $Expense_{j,t-1}$ is the fund j's expense ratio measured at the most recent fiscal year end, and $Control_{j,t-1}$ is a vector controls measured at the same time as fees, including the logarithm of fund size, fund age (in months), and the total size of other affiliated funds in the family. To facilitate presentation, we divide the control variables by 10. We include month fixed effects and cluster standard errors by month.

Panel A of Table 4.3 reports the results of regression (4.3) with before-fee alphas. Specifications (1)-(3) show funds that charge higher fees do not provide better performance as measured by conventional factor models. However, in regression (4), which controls for fund exposure to the investment and profitability factors, the coefficient on the Expense ratio is significantly positive, suggesting that high-fee funds deliver better performance.

Panel B of Table 4.3 repeats the analysis using after-fee alphas. Consistent with prior literature, regressions (1)-(3) show that the coefficients on the *Expense ratio* are large and negative, suggesting that performance – measures using conventional models – declines with fees. Crucially, and consistent with the theoretical arguments that skilled managers extract rents by charging higher fees (Berk and Green, 2004), specification (4) shows that the coefficient on *Expense ratio* is statistically insignificant from zero. In other words, expenses are not related to future after-fee performance when investment and profitability factors are controlled for.

Why does the performance of high-fee funds improve after controlling for investment and profitability factors? The reason is that the stocks in which high-fee funds invest most heavily have high asset growth rates and low profitability. Thus, high-fee funds should have low loadings on the investment and profitability risk factors, both of which carry positive factor premia. Table 4.4 reports this result in a formal test. Columns (1) and (2) show the coefficients on *Expense ratio* are negative and significant after controlling for fund characteristics. Columns (3) and (4) shows that the coefficients are significantly negative after controlling for fund characteristics and loadings on the other risk factors, such as the market, size, and value factors. This finding suggests that high-fee funds tend to load less on the investment and profitability factors. The realized risk premia of the investment factor and the profitability factor are 0.25% and 0.36% per month in the 1985 to 2017 period. Based on the magnitude of the coefficients in columns (1) and (2), a 1 percentage point increase in fee would reduce the required rate of return by 0.86 percentage point (i.e. 1.15×0.25%+1.6×0.36%=0.86) in the five-factor model. These differences in risk loadings explain why high-fee funds appear to have poor performance in the traditional models.

4.4.2 Sub-sample analysis of the fee-performance relationship

We next investigate whether the relation between expense ratios the performance varies across different sub-sample of funds. To this end, we separate funds into two groups based on each of their size, age, family size, turnover ratio, institutional indicator, or broker sold indicator. Specifically, for each of these fund level characteristics, we define a dummy variable equal to one if the variable is greater than the sample median in each year. We then regress the five-factor alpha on the expense ratio, a characteristic dummy, and an interaction term of the dummy variable and expense ratio, controlling for other fund attributes. The coefficient of the expense ratio measures the fee-alpha relationship for the baseline group of funds with their dummy variable equal to 0. Its sum with the coefficient on the interaction term indicates the fee-alpha relationship for the second half of funds.

Table 4.5 reports the results of this test with before-fee alpha.[15] Across all columns, irrespective of the particular fund type used to define the dummy variable, the coefficients on *Expense ratio* remain statistically and economically significant. The performance of high-fee funds as measured by the five-factor alpha thus appears consistent across different types of funds. Especially in Columns (1) to (3) and Column (6), the fee-alpha relationship exceeds 1 for smaller funds, younger funds, funds offered by smaller families and funds sold directly to investors. A coefficient greater than 1 means, for any additional fee that investors pay for these funds, investors are obtaining positive net benefit after fee, which suggests for some types of funds, managers are not extracting all the rents generated from their skill. The coefficients on the interaction terms in columns (1) and (2) are also significantly negative, indicating that smaller and younger funds have steeper fee-alpha relationship than larger and older funds. The higher fee-alpha relationship could be due to several reasons. For example, smaller and younger funds are less well-known, investors might need to incur positive search cost to find these funds. Theoretically, as predicted by Gârleanu and Pedersen (2018), investors should be compensated by higher alpha for their search effort. Alternatively, Chevalier and Ellison (1997) have shown that the response of flow to performance is more sensitive for younger and smaller funds. Therefore, skilled managers of these funds might be willing to charge a lower fee to build a track record.

4.5 Explanation

We now consider two hypotheses to understand why mutual fund expense ratios relate systematically to funds' propensities to invest in firms with certain asset growth and profitability profiles.

[15] Results obtained using after-fee alphas are similar and are omitted for brevity.

4.5.1 Naive investor hypothesis

The behavioral finance literature has postulated that naïve investors overinvest in fast-growing companies due to cognitive biases. For example, Lakonishok et al. (1994) and Porta et al. (1997) argue that unsophisticated investors over-extrapolate high growth rate of a company into its future, causing it to be overpriced. In a related study, Frazzini and Lamont (2008) document a dumb money effect in retail investor flows. They find retail investors display positive sentiment towards growth stocks and allocate more capital to funds that hold more such stocks.

Motivated by this literature, we propose the naïve investor hypothesis, which conjectures that fast-growing companies are more appealing to naïve investors, who are also less likely to be price sensitive about mutual fund fees. These companies can be expected to have a high rate of asset growth, low profitability, and high equity issuance to finance the growth. If such companies attract unsophisticated investors, we would expect that some fund managers invest more in high-growth and low-profitability stocks to attract more unsophisticated investors. Since unsophisticated investors tend to be less price sensitive, the fund manager can charge higher fees than what is justified by the performance.[16]

To test the naïve investor hypothesis, we construct two measures of a fund's investor sophistication. The first proxy is the fraction of a fund's asset that belongs to institutional share classes. It is well recognized that institutional investors are more sophisticated than retail investors. The second proxy is broker share, defined as the fraction of a fund's asset that is sold through broker channels instead of being sold directly to investors. Funds sold through brokers charge investors higher sales loads, which do not contribute to the management of the fund. Prior literature has shown that investors who purchase mutual fund through brokers are less performance-sensitive than investors who purchase mutual funds directly and, in addition, brokers' incentives are more aligned with fund families (Guercio and Reuter, 2014; Sun, 2014). Therefore, the higher the broker share of a fund, the less sophisticated the fund's investors are. We re-run regression (1) of average portfolio characteristics on the expense ratio, either investor sophistication proxy, and their interaction.

Table 4.6 summarizes regression results for each of the investor sophistication proxy in four separate panels. Under the naïve investor hypothesis, we expect to see that sophisticated high-fee funds have weaker tilt towards stock characteristics appealing to naïve investors, which implies that the coefficient on the interaction term of expense ratio and institutional share should be of the opposite sign to that on the expense ratio. With broker share, the coefficients on the interaction term should have the same sign as the coefficient on the expense. We find that it is not the case.

[16]Indeed, the literature has explored how fund managers set fees strategically to exploit investors who are less sensitive to price. Christoffersen and Musto (2002) find that retail money funds tend to increase fees after a large amount of outflow. They propose that outflows are an indication of performance-sensitive investors leaving the fund, which also signals a decrease in the average price sensitivity among investors remaining in the fund, causing the managers to subsequently raise fees.

In Panel A, the coefficients on the interaction term between expense ratio and institutional share all have the same sign as the coefficient on the expense ratio. In Panel B, the coefficients on the interaction term between expense ratio and broker share all have the opposite sign as the coefficient on the expense ratio and are all statistically significant.

In contrast to the predictions of the hypothesis, we find that high-fee institutional funds have a stronger tilt towards high-growth and low-profitability companies, while high-fee broker-sold funds have a weaker tilt towards such companies. In other words, among funds with more sophisticated investors, the association between expense ratio and growth-related characteristics is the same, if not stronger. Overall, the results summarized in Table 8 suggest that the naïve investor hypothesis does not explain the link between expense ratios and portfolio stock characteristics of mutual funds.

4.5.2 Valuation cost hypothesis

We now consider the hypothesis that funds investing in high-growth and low-profitability stocks charge high fees because their valuation is considerably more difficulty and demands more time and effort from fund managers per unit of capital. The high valuation cost, in turn, necessitates higher fees on a percentage basis. In other words, funds charge high fees because they invest in difficult-to-value stocks characterized by high growth and low profitability. We label this alternative explanation the valuation cost hypothesis. Under this hypothesis, we would expect to observe that high-fee funds invest more in companies that are more difficult to value.

To test the valuation cost hypothesis, we use four measures to identify whether a company is hard to value. Our first measure is idiosyncratic volatility (Ang et al., 2006), which has been linked to valuation difficulty (e.g., Kumar, 2009). Our second measure is based on the textual analysis of a company's annual reports.[17] Following Loughran and McDonald (2011), we construct an uncertainty index by counting the uncertainty words such as 'almost' and 'appears', and dividing it by the total number of words in each annual report. The index is higher if the annual report contains more uncertain words. We deem a company as opaque if its uncertainty index is high. The third measure we consider is tangibility: valuing a firm whose intangible assets represent a large portion of its asset base can be difficult (e.g., Baker and Wurgler, 2006). Our last measure is the number of analysts that have earning forecasts for a firm from the IBES database. Stocks with more analyst coverage likely have better information available and are thus less challenging to price. We aggregate each company-level measure of valuation cost to the fund level using portfolio weights of a fund.

Panel A of Table 4.7 shows our results from regressions of valuation cost proxies of funds' stockholdings on their expense ratios. Lending support to the valuation cost hypothesis, the results

[17] The word list is available from Bill McDonald's website: http://www3.nd.edu/~mcdonald/.

suggest that fund fees relate positively to each of the valuation difficulty proxies we consider. To further test the hypothesis, we split a fund's reported expense ratio into the part that represents its asset management cost and the part that represents marketing and distribution cost. A typical fund's expense ratio consists of three main components, including 12b-1 fee, management fee, and other operating expenses. Management fee and other operating expenses cover the cost of fund managers and daily operations, while 12b-1 fee is mainly used for the fund's marketing and distribution, e.g., compensation to brokers who sell the fund to investors. Under the valuation cost hypothesis, funds investing in harder-to-value stocks should charge higher management fees to compensate managers for their efforts, but we do not expect marketing and distribution fees to relate to valuation difficulty of the stockholdings. We find this to be the case. In Panel B of Table 4.7, the coefficient on the asset management cost is positively related with the valuation cost of the underlying companies, while 12b-1 fee is negatively related or unrelated to the valuation cost of stocks, lending support for the valuation cost hypothesis.

To further investigate the valuation cost hypothesis, we conduct textual analysis of the PIS sections. Specifically, we construct a "*research index*" to capture a fund's research activities by calculating the fraction of words that are related to research. We include the following words in list: analysis, analyze, analyzes, analyzed, bottom-up, fundamentally-based, fundamentals-based, and research. The text data is then merged with fund variables using the links in SEC's Investment Company Series and Class information. The textual analysis covers the period is from 2010 until 2016 due to data availability.

To test whether high- and low-fee funds differ significantly in describing research activities central to their trading strategies, we regress the *research index* on the expense ratio and control variables. Table 4.8 shows that the coefficients on the expense ratio are positive and significant in all specifications. This result provides an indication that high-fee funds focus more on research in formulating their investment strategies. This finding provide further support for the valuation cost hypothesis.

4.6 Robustness and additional results

To evaluate robustness of our results, in this section we conduct several tests modifying various aspects of our empirical methods. In Panel A of Table 4.9, we assess whether the propensity of high-fee funds to hold high-growth low-profitability stocks, as established in Table 4.2, is driven by the omission of other stock characteristics as controls. Specifically, we re-run the regression of average portfolio characteristics on expense ratios and other variables after adding averages of CAPM beta, market capitalization, momentum, and B/M ratio of the stockholdings as regressors. Our results remain similar to those in the base-case analysis summarized in Table 4.2.

We also perform several robustness tests for the fee-alpha relationship. In Panel A of Table

4.10, we perform Fama-MacBeth regressions by regressing monthly alpha measured with different models on the most recent expense ratio. We find that the relationship between the expense ratio and the before-fee alpha measured with the Fama-French five factor model, the six-factor model that adds the momentum factor, and Hou et al. (2015) four-factor model are significantly positive. In Panel B of Table 4.10, we perform the same regression as in Table 4.3 for the sample period of 1998 to 2017. The results are quantitatively the same as Table 4.3. In Panel C of Table 4.10, we use a shorter three-year rolling window to calculate factor loadings of the funds. The results are quantitatively similar to Table 4.3. Overall, we show that after controlling for exposures to profitability and investment factors, high-fee funds significantly outperform low-fee funds before deducting expenses, and perform equally well net of fees.

We also control for any potential non-linearity effects in fee-performance regression. Table 4.11 presents the results by regressing alphas on expense ratio and expense ratio squared. The results are quantitatively similar to Table 4.3. Before-fee alphas measured under the CAPM, the Fama-French three-factor, and the Fama-French-Carhart four-factor models are not significantly related with fees, but before-fee alpha under the Fama-French five-factor model is positively related with fees. There is some evidence the before-fee alpha under the Fama-French five-factor model has a non-linear relationship with fees, which remains to be explained in future research. Similarly, after-fee alphas under the CAPM, the three-factor, and the four-factor models are negatively associated with fees, but not under the five factor model.

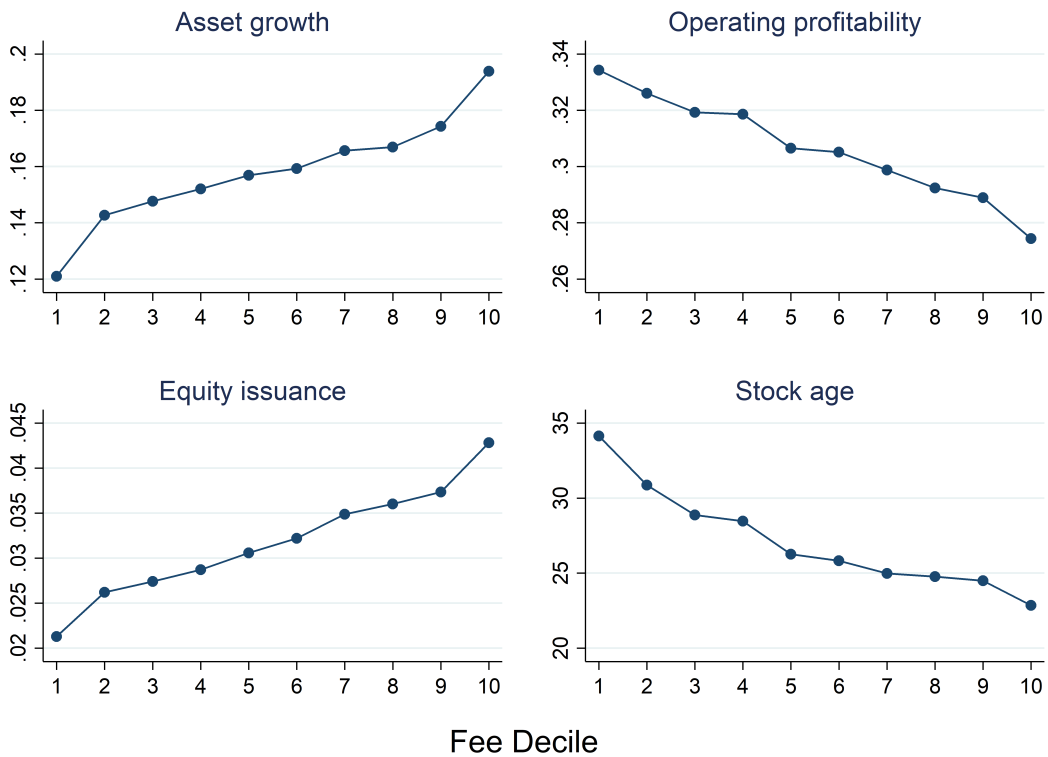
4.7 Conclusion

Previous literature uncovers a robust inverse relation between fees charged by actively managed mutual funds and future after-fee fund performance. Before deducting expenses, high-fee funds have been found to perform just as well as do low-fee funds. Theoretically, this result is puzzling as it suggests that managers of high-fee funds extract more rents than the value they add. Empirically, the apparent negative relation between expenses and net-of-fees performance has helped to guide allocations of billions of dollars of retail and institutional investors, who shun high-fee funds. The relation is also puzzling as it calls into question the continued existence of high-fee funds.

This paper resolves the puzzle by showing that factor models used to establish the prior fee-performance results are inadequate to control for differences in performance of funds with different fees. High-fee funds exhibit a strong preference for stocks with high investment rates and low profitability, characteristics that have been recently shown to associate with low expected returns. The commonly used three- and four-factor models produce large negative alphas for these types of stocks, leading to a premature conclusion that high-fee funds underperform net of expenses.

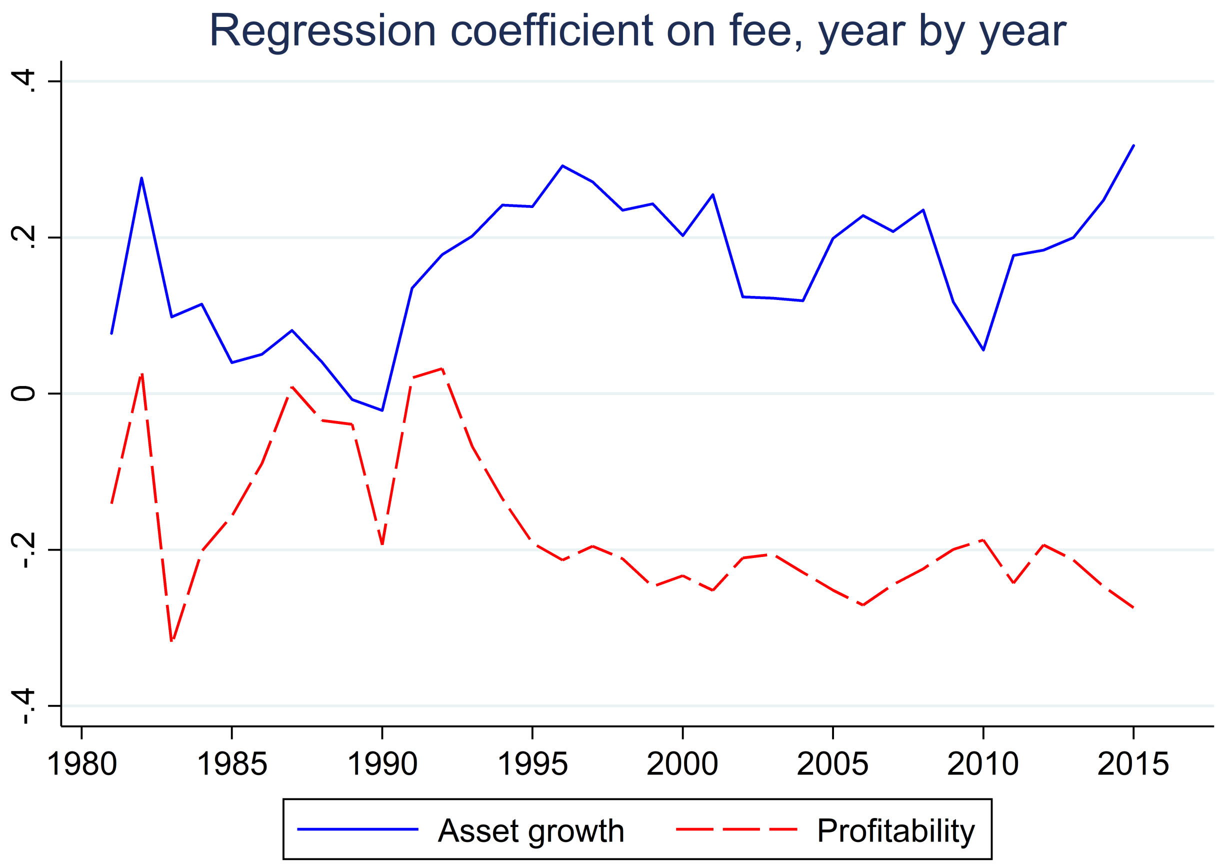
We evaluate the fee-performance relation using the recently proposed five-factor model that controls for exposures to the investment and profitability factors. The results we obtain stand in stark contrast with those in the prior literature. We find that high-fee funds significantly outperform low-fee funds before deducting expenses, and do equally well net of fees. Our findings support the theoretical prediction that skilled managers extract rents by charging high fees, and call into question the widely offered advice to avoid high-fee funds.

Figure 4.1: Characteristics of stock portfolios of funds charging different fees.



This figure plots average characteristics of stocks held by mutual funds grouped into deciles on the basis of expense ratio. For each fund, we calculate its stock characteristics as the position-weighted averages across companies held by the fund. The characteristics, defined in detail in the Appendix, are the asset growth rate, operating profitability, equity issuance rate, and stock age. The sample period is 1980-2015.

Figure 4.2: Fund fees and time series dynamics of fund portfolio characteristics.

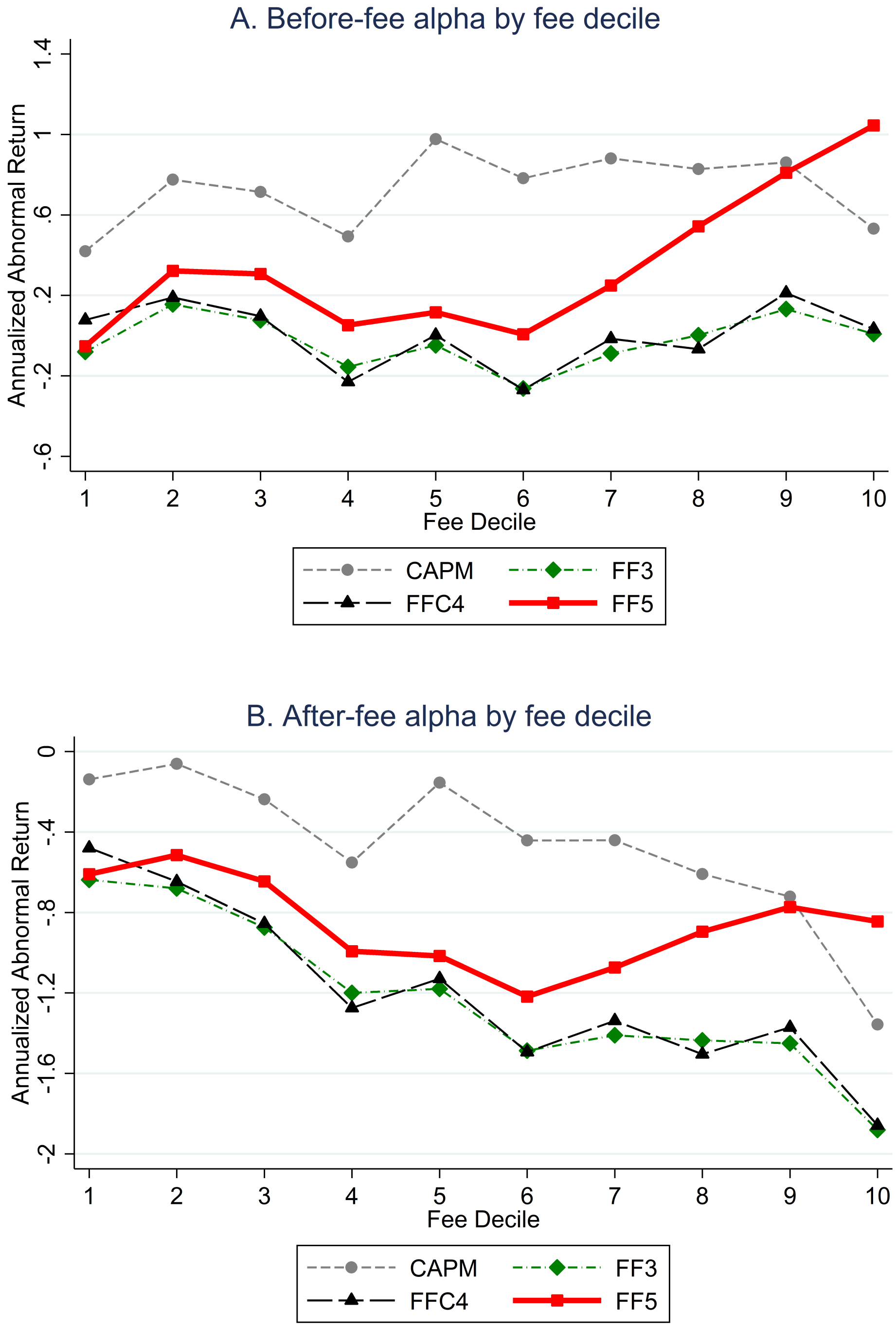


This figure presents the time series dynamics of the relation between fund fees and portfolio characteristics. For each characteristic, we plot the time series of coefficients on the fee variable from annual cross-sectional regressions

$$Average\,characteristics_{j,t} = b_0 + b_1 fee_{j,t-1} + b' Controls_{j,t-1} + \varepsilon_{j,t}$$

where $Average\,characteristics_{j,t}$ is one of the measures of stock characteristics (asset growth rate and operating profitability) for fund j in year t; $fee_{j,t-1}$ is the fund j's expense ratio in year $t-1$; $Controls_{j,t-1}$ are fund level control variables, including the natural log of fund age (in months), fund size, and fund family size. For each fund, we calculate its stock characteristics as the position-weighted averages across companies held by the fund. Detailed variable definitions are provided in the Appendix. All variables are scaled by their standard deviation and demeaned in each year. The sample period if from 1980 to 2015.

Figure 4.3: Mutual fund fee-performance relationship.



This figure plots expected alphas, in percent per year, of funds grouped into deciles on the basis of expense ratio reported in the most recent fiscal year. We measure alpha with four benchmark models: the CAPM, the Fama-French three-factor, the Fama-French-Carhart four-factor, and the Fama-French five-factor. A fund's alpha in month t is the difference between the fund's excess return in month t and its expected return, calculated as the sum of the products of factor returns in t and factor loadings estimated from rolling regressions on five years of monthly data. Panel A plots the average before-fee alphas against the fee decile, and Panel B shows the corresponding plot for after-fee alphas. The sample period for alphas is from 1980-2017.

Table 4.1: Summary statistics for fund and portfolio characteristics.

	Mean	Median	SD	p5	p25	p75	p95
Panel A. Fund characteristics							
Expense ratio	1.22%	1.18%	0.44%	0.57%	0.95%	1.47%	2.01%
Fund size (million)	1,304	234	5,034	22	73	851	5,042
Fund age, years	10.3	8.7	7.7	0.9	4.2	14.9	25.3
Family size (million)	32,931	4,660	87,043	51	693	21,139	216,838
Turnover ratio	84%	63%	80%	11%	33%	107%	229%
Broker-sold share	49%	45%	45%	0%	0%	100%	100%
Institutional share	29%	5%	38%	0%	0%	61%	100%
12b-1 fee	0.18%	0.07%	0.23%	0.00%	0.00%	0.29%	0.67%
Panel B. Portfolios characteristics							
Stock age	12.9	8.6	13.9	0.7	3.3	17.3	41.1
CAPM beta	0.94	0.86	0.92	-0.32	0.37	1.41	2.61
Market cap	1,795	115	11,179	4	26	585	5,827
Book-to-market	0.80	0.61	0.73	0.11	0.33	1.01	2.16
Momentum	11%	5%	59%	-70%	-25%	35%	118%
Asset growth rate	13%	7%	38%	-35%	-3%	21%	85%
Operating probability	8%	19%	55%	-77%	4%	30%	55%
Equity issuance rate	5%	0%	14%	-6%	0%	3%	32%
Idiosyncratic volatility	4%	3%	3%	1%	2%	5%	9%
Tangibility	26%	18%	24%	1%	6%	39%	77%
Financial uncertainty	1.36%	1.37%	0.35%	0.78%	1.11%	1.62%	1.92%
Number of analysts	3	0	5	0	0	3	14

This table reports the summary statistics for fund characteristics (Panel A) and portfolio characteristics (Panel B). Fund size and fund family size are measured in nominal terms in millions. Broker-sold share is the estimated percentage of a fund's assets in share classes sold through brokers. Institutional share is the estimated percentage of a fund's assets in share classes sold to institutional investors. Detailed definitions are in the Appendix. The sample period is from 1980 to 2017.

Table 4.2: Fund fees and characteristics of stock holdings.

Panel A. FFC4 factor related characteristics

	(1) CAPM Beta	(2) B/M	(3) Size	(4) Momentum
Expense ratio$_{t-1}$	0.20***	-0.03	-0.20***	0.09***
	(14.43)	(-1.52)	(-11.25)	(7.33)
Log fund size$_{t-1}$	0.04***	0.00	0.09***	-0.02*
	(2.68)	(0.21)	(4.79)	(-1.79)
Log fund age$_{t-1}$	-0.03**	-0.06***	0.01	0.00
	(-2.47)	(-3.73)	(0.90)	(0.13)
Log fund family size$_{t-1}$	0.06***	-0.03	-0.00	0.05***
	(3.88)	(-1.54)	(-0.12)	(3.57)
Observations	35,134	35,131	35,134	35,132
Adj. R^2	0.833	0.189	0.387	0.664
Year FEs	Yes	Yes	Yes	Yes

Panel B. Other stock characteristics

	(1) Asset growth	(2) Equity Issuance	(3) Profitability	(4) Stock age
Expense ratio$_{t-1}$	0.19***	0.21***	-0.21***	-0.27***
	(13.68)	(17.01)	(-14.05)	(-16.05)
Log fund size$_{t-1}$	-0.01	0.01	0.01	0.01
	(-0.83)	(1.18)	(0.34)	(0.69)
Log fund age$_{t-1}$	0.03**	-0.01	0.02	-0.00
	(2.48)	(-0.89)	(1.31)	(-0.18)
Log fund family size$_{t-1}$	0.07***	0.08***	-0.06***	-0.05***
	(4.77)	(6.37)	(-3.93)	(-3.06)
Observations	35,132	35,132	35,131	35,134
Adj. R^2	0.134	0.284	0.430	0.130
Year FEs	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in the column heading) on the fund's attributes lagged by one year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. All variables are scaled by their cross-sectional standard deviations in each year. Regressions include year fixed effects. The sample period is from 1980 to 2015. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.3: Mutual fund fee-performance relation: Panel regressions.

Panel A. Before-fee alpha	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FFC4}	(4) α_t^{FF5}
Expense ratio$_{t\text{-}1}$	-0.15	0.11	-0.07	1.08***
	(-0.26)	(0.31)	(-0.19)	(3.62)
Log fund size$_{t\text{-}1}$	-0.23***	-0.08	-0.11*	0.02
	(-3.38)	(-1.35)	(-1.91)	(0.29)
Log fund age$_{t\text{-}1}$	0.27*	0.21*	0.28**	0.13
	(1.81)	(1.72)	(2.35)	(1.11)
Log fund family size$_{t\text{-}1}$	0.06*	0.06**	0.05*	0.09***
	(1.88)	(2.31)	(1.70)	(3.13)
Observations	321,414	321,414	321,414	321,414
Adj. R^2	0.110	0.074	0.083	0.075
Month FE	Yes	Yes	Yes	Yes

Panel B. After-fee alpha	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FFC4}	(4) α_t^{FF5}
Expense ratio$_{t\text{-}1}$	-1.09*	-0.83**	-1.01***	0.14
	(-1.93)	(-2.43)	(-2.78)	(0.46)
Log fund size$_{t\text{-}1}$	-0.23***	-0.07	-0.11*	0.02
	(-3.33)	(-1.29)	(-1.85)	(0.35)
Log fund age$_{t\text{-}1}$	0.27*	0.20*	0.27**	0.12
	(1.77)	(1.67)	(2.30)	(1.06)
Log fund family size$_{t\text{-}1}$	0.06*	0.06**	0.05*	0.09***
	(1.91)	(2.35)	(1.73)	(3.16)
Observations	321,414	321,414	321,414	321,414
Adj. R^2	0.110	0.074	0.083	0.074
Month FEs	Yes	Yes	Yes	Yes

This table presents the results of panel regressions of fund alphas on expense ratios, both in percent per month, and other fund characteristics. Alphas are computed using the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart four-factor model (FFC4), and the Fama-French five-factor model (FF5). Alphas are calculated using factor loadings estimated from a five-year rolling window regression. In Panel A (B), alpha is computed using before-fee (after-fee) returns. Independent variables are measured as of the most recent fiscal year of the fund. All regressions include month fixed effects and cluster standard errors by month. The sample period is from 1980 to 2017. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.4: Fund fees and loadings on the investment (CMA) and profitability (RMW) factors.

	(1) CMA loading	(2) RMW loading	(3) CMA loading	(4) RMW loading
Expense ratio$_{t-1}$	-1.15***	-1.60***	-0.78***	-1.32***
	(-7.68)	(-11.61)	(-5.37)	(-11.15)
Log fund size$_{t-1}$	-0.05	-0.03	-0.07**	-0.03
	(-1.63)	(-0.99)	(-2.44)	(-1.08)
Log fund age$_{t-1}$	-0.13	-0.08	-0.16**	-0.01
	(-1.63)	(-1.14)	(-2.08)	(-0.23)
Log fund family size$_{t-1}$	0.00	-0.08***	0.01	-0.06***
	(0.02)	(-6.39)	(0.47)	(-4.58)
FF5 market factor loading$_t$			-0.22***	-0.02
			(-7.22)	(-0.60)
FF5 HML factor loading$_t$			-0.03*	0.31***
			(-1.74)	(19.65)
FF5 SMB factor loading$_t$			-0.14***	-0.02**
			(-13.19)	(-2.06)
Observations	25,636	25,636	25,636	25,636
Adj. R^2	0.091	0.050	0.135	0.183
Year FEs	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of funds' investment or profitability factors loadings in the beginning of each year on annual expense ratios and other fund characteristics. To obtain the loadings, we regress a fund's monthly before-fee return in the previous five years on Fama-French five-factor portfolios and use the coefficients as risk loadings. Control variables include the log of fund size, fund age (in months), and fund family size, measured from the most recent fiscal year, as well as contemporaneous loadings on market, size, and value factors. Regressions include year fixed effects. Standard errors are clustered at the fund level. The sample period is from 1980 to 2017. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.5: Fee-performance relation and different fund characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
			α_t^{FF5}			
Expense $\text{ratio}_{t\text{-}1}$	1.39***	1.23***	1.24***	0.82***	0.94***	1.24**
	(4.58)	(4.07)	(3.36)	(3.28)	(2.84)	(2.55)
Size dummy	0.07**					
	(2.57)					
Expense $\text{ratio}_{t\text{-}1}$ × Size dummy	-0.76***					
	(-2.83)					
Age dummy		0.03				
		(1.13)				
Expense $\text{ratio}_{t\text{-}1}$ × Age dummy		-0.41*				
		(-1.68)				
Family size dummy			0.03			
			(1.28)			
Expense $\text{ratio}_{t\text{-}1}$ × Family dummy			-0.33			
			(-1.16)			
Turnover dummy				-0.02		
				(-0.73)		
Expense $\text{ratio}_{t\text{-}1}$× Turnover dummy				0.42		
				(1.14)		
Institutional share dummy					-0.03	
					(-1.03)	
$\text{Fee}_{t\text{-}1}$× Inst. dummy					0.03	
					(0.10)	
Broker share dummy						-0.00
						(-0.09)
$\text{Fee}_{t\text{-}1}$× Broker share dummy						-0.13
						(-0.36)
Observations	321,414	321,414	321,414	315,411	284,212	306,522
Adj. R^2	0.075	0.075	0.075	0.075	0.071	0.074
Fund level controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes

This table presents results of regressions of the monthly before-fee gross Fama-French Five-Factor alpha on the fund's monthly expense ratio, i.e. fee, and its interactions with fund characteristic dummies. For each of characteristics, i.e. fund size, age, family size, turnover ratio, institutional share, and broker share, we create a dummy variable to be 1 or 0 if the characteristic value is above or below the cross-sectional median. We also include other fund level control variables, which are the log of fund size, fund age (in months), and fund family size. All independent variables are measured as of the most recent fiscal year end of the fund. Regressions include month fixed effects and cluster standard errors by month. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.6: Fund fees and characteristics of stock holdings: Investor sophistication.

Panel A. Institution share	(1) Asset growth	(2) Equity issuance	(3) Profitability	(4) Stock age
Expense ratio$_{t-1}$	0.23***	0.24***	-0.25***	-0.35***
	(13.76)	(16.39)	(-13.57)	(-17.28)
Institution share$_{t-1}$	0.08***	0.07***	-0.06***	-0.15***
	(4.56)	(4.72)	(-3.43)	(-7.24)
Expense ratio$_{t-1}$× Institution share$_{t-1}$	0.03	0.02	-0.01	-0.09***
	(1.57)	(1.53)	(-0.34)	(-4.68)
Log fund size$_{t-1}$	-0.01	0.02	-0.02	-0.01
	(-0.91)	(1.12)	(-1.15)	(-0.49)
Log fund age$_{t-1}$	0.05***	-0.00	0.01	-0.00
	(3.30)	(-0.02)	(0.87)	(-0.07)
Log fund family size$_{t-1}$	0.07***	0.08***	-0.06***	-0.05***
	(4.42)	(5.44)	(-3.62)	(-2.71)
Observations	26,730	26,731	26,729	26,732
Adj. R^2	0.140	0.294	0.358	0.134
Year FEs	Yes	Yes	Yes	Yes

Panel B. Broker share	(1) Asset growth	(2) Equity issuance	(3) Profitability	(4) Stock age
Expense ratio$_{t-1}$	0.24***	0.24***	-0.26***	-0.35***
	(14.91)	(16.86)	(-14.07)	(-18.99)
Broker share$_{t-1}$	-0.06***	-0.03**	0.05***	0.11***
	(-3.88)	(-2.43)	(3.21)	(6.35)
Expense ratio$_{t-1}$× Broker share$_{t-1}$	-0.03**	-0.04***	0.06***	0.09***
	(-2.36)	(-3.71)	(3.95)	(5.53)
Log fund size$_{t-1}$	-0.01	0.02*	-0.00	-0.01
	(-0.39)	(1.67)	(-0.14)	(-0.27)
Log fund age$_{t-1}$	0.04***	-0.01	0.01	-0.01
	(2.64)	(-0.81)	(0.93)	(-0.40)
Log fund family size$_{t-1}$	0.07***	0.08***	-0.07***	-0.07***
	(5.13)	(6.31)	(-4.48)	(-3.72)
Observations	32,410	32,410	32,409	32,412
Adj. R^2	0.138	0.294	0.408	0.151
Year FEs	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in column heading) on the fund's expense ratio, a proxy of investor sophistication, and the interaction of the two, controlling for other fund level characteristics. All independent variables are measured at the most recent fiscal year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. In Panel A, the proxy for investor sophistication is institutional share, which measures the fraction of a fund's asset from institutional share classes. In Panel B, the proxy for investor sophistication is broker share, which measures the fraction of a fund's asset from share classes that are sold through brokers. All independent variables are scaled by the cross-sectional standard deviation and de-meaned in each year. Regressions include year fixed effects and cluster standard errors at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.7: Fund fees and the valuation cost of stock holdings.

Panel A. Expense ratio and valuation cost

	(1) Idiosyncratic volatility	(2) Financial uncertainty	(3) Asset tangibility	(4) Number of analysts
Expense ratio$_{t-1}$	0.28***	0.22***	-0.11***	-0.16***
	(16.99)	(13.66)	(-6.23)	(-8.82)
Log fund size$_{t-1}$	-0.02	0.00	-0.02	0.04**
	(-1.49)	(0.28)	(-1.08)	(2.22)
Log fund age$_{t-1}$	-0.02	-0.00	0.00	0.04**
	(-1.32)	(-0.06)	(0.18)	(2.39)
Log family size$_{t-1}$	0.05***	0.07***	0.02	0.03
	(3.13)	(4.52)	(0.94)	(1.64)
Observations	35,134	29,794	35,131	33,239
Adj. R^2	0.293	0.952	0.078	0.097
Year FEs	Yes	Yes	Yes	Yes

Panel B. Asset management fee and valuation cost

	(1) Idiosyncratic volatility	(2) Financial uncertainty	(3) Asset tangibility	(4) Number of analysts
Management fee$_{t-1}$	0.45***	0.32***	-0.17***	-0.30***
	(25.06)	(18.30)	(-9.09)	(-15.30)
12b-1 fee$_{t-1}$	-0.06***	-0.02	0.02	0.09***
	(-3.66)	(-1.43)	(0.77)	(5.31)
Log fund size$_{t-1}$	0.06***	0.05***	-0.05***	-0.02
	(3.45)	(3.07)	(-2.76)	(-1.35)
Log fund age$_{t-1}$	-0.03**	-0.00	0.01	0.05***
	(-2.02)	(-0.13)	(0.61)	(2.98)
Log family size$_{t-1}$	0.11***	0.12***	-0.01	-0.02
	(6.97)	(7.48)	(-0.24)	(-1.46)
Observations	32,412	29,794	32,409	32,412
Adj. R^2	0.317	0.953	0.039	0.133
Year FEs	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in the column heading) on the fund's attributes measured at the most recent fiscal year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. Panel A regresses on expense ratio. Panel B regresses on management fee and 12b-1 fee, which add up to expense ratio. All variables are scaled by their cross-sectional standard deviations and de-meaned in each year. Regressions include year fixed effects. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.8: Textual analysis of mutual fund prospectus.

	(1) Research Index	(2) Research Index	(3) Research Index
Expense ratio	0.16***	0.13***	0.15***
	(4.91)	(3.41)	(3.87)
Constant	0.01***	-0.01***	-0.01***
	(23.90)	(-5.30)	(-6.14)
Observations	6,036	6,036	6,036
Adj. R^2	0.004	0.030	0.036
Controls	No	Yes	Yes
Year FEs	No	No	Yes

This table reports a textual analysis of fund prospectus. We extract the text of "Principal Strategies" from 497K filings from EDGAR database and construct a "research index" by calculating the fraction of words that are research-related. The control variables used in Column (3) include fund size, fund age, and family size. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.9: Robustness check about fund fees and characteristics of stock holdings.

	(1) Asset growth	(2) Equity issuance	(3) Profitability	(4) Stock age
Expense ratio$_{t-1}$	0.07***	0.08***	-0.08***	-0.06***
	(10.01)	(8.86)	(-7.65)	(-7.49)
Avg. CAPM beta$_t$	0.07***	0.08***	-0.08***	-0.06***
	(10.01)	(8.86)	(-7.65)	(-7.49)
Avg. B/M ratio$_t$	(15.84)	(17.24)	(-20.81)	(-30.12)
	-0.52***	-0.03**	-0.21***	0.29***
Avg. market cap$_t$	(-41.90)	(-2.10)	(-13.21)	(24.13)
	-0.28***	-0.24***	0.39***	0.74***
Avg. momentum$_t$	(-29.37)	(-18.04)	(31.62)	(84.29)
	0.18***	0.20***	0.02	-0.05***
Observations	35,129	35,129	35,129	35,129
Adj. R^2	0.552	0.483	0.643	0.754
Fund level controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in column heading) on the fund's attributes lagged fund expense ratio. Additional control variables include log of fund size, fund age (in months), and fund family size, all measured at the same time as the expense ratio. All variables are scaled by their cross-sectional standard deviations in each year. Control variables also include contemporaneous portfolio characteristics. Regressions include year fixed effects. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.10: Robustness of the mutual fund fee-performance relation: additional models

	(1)	(2)	(3)	(4)	(5)	(6)
		Gross alpha			Net alpha	
	FF5	FFC6	HXZ4	FF5	FFC6	HXZ4
Panel A: Fama-MacBeth regression						
Expense ratio	0.79**	0.56*	0.92**	-0.12	-0.35	0.01
	(2.43)	(1.85)	(2.15)	(-0.38)	(-1.17)	(0.02)
Panel B: sample period 1998 to 2017						
Expense ratio	1.06***	0.87***	0.72	0.10	-0.09	-0.24
	(3.18)	(2.74)	(1.41)	(0.31)	(-0.29)	(-0.46)
Adjusted R^2	0.075	0.086	0.060	0.075	0.086	0.060
Month FE and controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: three-year rolling window						
Expense ratio	1.32***	0.84**	1.30**	0.38	-0.09	0.37
	(3.44)	(2.59)	(2.31)	(0.99)	(-0.28)	(0.65)
Adj. R^2	0.073	0.082	0.056	0.073	0.082	0.056
Month FEs and controls	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of regressions of fund alphas on lagged expense ratios, both in percent per month. Alphas are computed using the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart four-factor model (FFC4), the Fama-French five-factor model (FF5), Fama-French five-factor augmented with Carhart momentum factor model (FFC6), and Hou, Xue, and Zhang four-factor model (HXZ4). In Panel A, regressions are Fama-MacBeth regressions with expense ratio as the only independent variable and standard errors are adjusted for 4 lags of auto-correlation. In Panel B, the results are based on the 1998-2017 sample with fund level control variables and month fixed effects. Factor loadings for each fund in each month in both Panel A and B are based on five-year rolling regression windows. In Panel C, we measure factor loadings using three-year rolling window. Standard errors in Panel B and C are clustered at the month level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4.11: Robustness of the mutual fund fee-performance relation: non-linearity test

Panel A. Before-fee alpha	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FFC4}	(4) α_t^{FF5}
Expense ratio$_{t-1}$	-0.04	0.08	-0.12	0.97***
	(-0.07)	(0.24)	(-0.32)	(3.09)
Expense ratio$^2_{t-1}$	-7.22	1.69	3.07	7.07**
	(-1.63)	(0.49)	(0.90)	(2.15)
Log fund size$_{t-1}$	-0.23***	-0.08	-0.12*	0.01
	(-3.34)	(-1.36)	(-1.93)	(0.22)
Log fund age$_{t-1}$	0.25	0.21*	0.29**	0.15
	(1.64)	(1.78)	(2.43)	(1.30)
Log fund family size$_{t-1}$	0.06*	0.06**	0.05*	0.09***
	(1.92)	(2.30)	(1.68)	(3.07)
Observations	321,414	321,414	321,414	321,414
Adj. R^2	0.110	0.074	0.083	0.075
Month FE	Yes	Yes	Yes	Yes

Panel B. After-fee alpha	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FFC4}	(4) α_t^{FF5}
Expense ratio$_{t-1}$	-0.98*	-0.86**	-1.06***	0.02
	(-1.71)	(-2.54)	(-2.91)	(0.08)
Expense ratio$^2_{t-1}$	-6.81	2.09	3.47	7.49**
	(-1.54)	(0.61)	(1.02)	(2.28)
Log fund size$_{t-1}$	-0.23***	-0.07	-0.11*	0.02
	(-3.30)	(-1.31)	(-1.87)	(0.27)
Log fund age$_{t-1}$	0.24	0.21*	0.28**	0.15
	(1.61)	(1.74)	(2.40)	(1.27)
Log fund family size$_{t-1}$	0.06*	0.06**	0.05*	0.09***
	(1.95)	(2.33)	(1.71)	(3.10)
Observations	321,414	321,414	321,414	321,414
Adj. R^2	0.110	0.074	0.083	0.074
Month FEs	Yes	Yes	Yes	Yes

This table presents the results of panel regressions of fund alphas on expense ratios, both in percent per month, and other fund characteristics. Alphas are computed using the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart four-factor model (FFC4), and the Fama-French five-factor model (FF5). Alphas are calculated using factor loadings estimated from a five-year rolling window regression. In Panel A (B), alpha is computed using before-fee (after-fee) returns. Independent variables are measured as of the most recent fiscal year of the fund. Both Expense Ratio and Expense Ratio^2 (i.e. expense ratio squared) are cross-sectionally de-meaned at the monthly level. All regressions include month fixed effects and cluster standard errors by month. The sample period is from 1980 to 2017. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Chapter 5

Conclusion

This thesis addresses several questions about institutional investors. In the first essay, Chapter 2, I theoretically investigate how the holding horizon of an institution determines its portfolio choice and the related asset pricing implications. Institutional investors different significantly in their holding horizon or their trading frequency. Empirically, institutions with different holding horizons also prefer to invest in different types of stocks. To analyze this phenomenon, I develop a model in which short-term institutions can make more frequent portfolio rebalancing than long-term institutions, and stocks in the cross section experience different degrees of speculative demand shocks. In equilibrium, short-term institutions prefer to invest in stocks with greater exposure to speculative demand shocks. The additional demand from short-term institutions reduces the buy-and-hold returns of these speculative stocks, making them less desirable for long-term institutions to hold. My model rationalizes why short-term institutions overweight low-return stocks and predicts these institutions generate additional returns by trading these stocks actively. Furthermore, stocks primarily held by short-term institutions should have more predictable returns, and their return predictability is stronger when they become overpriced.

In the second essay, Chapter 3, I construct empirical measures to test the main predictions of my theoretical model. Empirically, short-term institutions prefer to invest in younger, smaller, and more volatile stocks. Furthermore, stocks primarily held by short-term institutions should have more predictable returns, and their return predictability is stronger when they become overpriced. Empirical findings strongly support these predictions. Short-term institutions outperform long-term institutions by more than 3% per year among stocks primarily held by short-term institutions, while their performance is similar among stocks primarily held by long-term institutions. Both Chapter 2 and 3 enhance our understanding of the behaviors of institutional investors with different holding horizons.

In Chapter 4, a joint work with Jinfei Sheng and Mike Simutin, we re-examine the fee performance relationship of active mutual funds. Previous literature uncovers a robust inverse relation between fees charged by actively managed mutual funds and future after-fee fund performance. Before deducting expenses, high-fee funds have been found to perform just as well as do low-fee funds. This paper resolves the puzzle by showing that factor models used to establish the prior fee-performance results are inadequate to control for differences in performance of funds with different fees. High-fee funds exhibit a strong preference for stocks with high investment rates and low profitability, characteristics that have been recently shown to associate with low expected returns. The commonly used three- and four-factor models produce large negative alphas for these types of stocks, leading to a premature conclusion that high-fee funds underperform net of expenses. We evaluate the fee-performance relation using the recently proposed five-factor model that controls for exposures to the investment and profitability factors. The results we obtain stand in stark contrast with those in the prior literature. We find that high-fee funds significantly outperform low-fee funds before deducting expenses and do equally well net of fees. Our findings support the theoretical prediction that skilled managers extract rents by charging high fees, and call into question the widely offered advice to avoid high-fee funds.

5.1 Future work

The three essays in this thesis could be extended along several dimensions. First of all, the theory that I develop in Chapter 2 offers more predictions that are not tested in Chapter 3. Empirically verifying these additional predictions could further the understanding of institutional investors and the mechanism that allows them to set asset prices. Second, the empirical asset pricing literature has identified many variables that predict the stock returns in the cross section. Chapter 2 offers a new non-risk based interpretation of why a variable can predict stock return. Distinguishing whether a variable predicts stock return through the risk channel or the speculative demand channel is an interesting area of future research. Finally, Chapter 4 highlights the challenges of measuring mutual fund performance by showing that performance evaluation is sensitive to the choice of benchmark model. Should any variable that predicts stock return be controlled for in performance evaluations? Should all mutual funds be evaluated by the same factor model? These questions require more future research.

Bibliography

Abel, A. B., Eberly, J. C., Panageas, S., 2007. Optimal inattention to the stock market. American Economic Review 97 (2), 244–249.

Abel, A. B., Eberly, J. C., Panageas, S., 2013. Optimal inattention to the stock market with information costs and transactions costs. Econometrica 81 (4), 1455–1481.

Abis, S., 2017. Man vs. machine: Quantitative and discretionary equity management. Unpublished working paper. Columbia Business School.

Abreu, D., Brunnermeier, M. K., 2002. Synchronization risk and delayed arbitrage. Journal of Financial Economics 66 (2-3), 341–360.

Abreu, D., Brunnermeier, M. K., 2003. Bubbles and crashes. Econometrica 71 (1), 173–204.

Almazan, A., Brown, K. C., Carlson, M., Chapman, D. A., 2004. Why constrain your mutual fund manager? Journal of Financial Economics 73 (2), 289–321.

Alti, A., Tetlock, P. C., 2014. Biased beliefs, asset prices, and investment: A structural approach. The Journal of Finance 69 (1), 325–361.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17 (2), 223–249.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. The Journal of Finance 61 (1), 259–299.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. The Journal of Finance 61 (4), 1645–1680.

Barber, B. M., Odean, T., 2007. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The Review of Financial Studies 21 (2), 785–818.

Barberis, N., Shleifer, A., 2003. Style investing. Journal of Financial Economics 68 (2), 161–199.

Basak, S., Pavlova, A., 2013. Asset prices and institutional investors. American Economic Review 103 (5), 1728–58.

Beber, A., Driessen, J., Neuberger, A., Tuijp, P., 2018. Pricing liquidity risk with heterogeneous investment horizons. Available at SSRN 1964709.

Ben-David, I., Franzoni, F., Moussawi, R., Sedunov, J., 2019. The granular nature of large institutional investors. Tech. rep., CEPR Discussion Papers.

Berk, J. B., Green, R. C., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112 (6), 1269–1295.

Berk, J. B., Van Binsbergen, J. H., 2015. Measuring skill in the mutual fund industry. Journal of Financial Economics 118 (1), 1–20.

Blume, M. E., Keim, D. B., et al., 2014. The changing nature of institutional stock investing. Critical Finance Review 6, 1–41.

Borochin, P., Yang, J., 2017. The effects of institutional investor objectives on firm valuation and governance. Journal of Financial Economics 126 (1), 171–199.

Brunnermeier, K. M., Nagel, S., 2004. Hedge funds and the technology bubble. The Journal of Finance 59 (5), 2013–2040.

Bushee, B. J., 2001. Do institutional investors prefer near-term earnings over long-run value? Contemporary Accounting Research 18 (2), 207–246.

Busse, J. A., Jiang, L., Tang, Y., 2017. Double-adjusted mutual fund performance. Available at SSRN 2516792.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance 52 (1), 57–82.

Cespa, G., Vives, X., 2015. The beauty contest and short-term trading. The Journal of Finance 70 (5), 2099–2154.

Chevalier, J., Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. Journal of Political Economy 105 (6), 1167–1200.

Christoffersen, S. E., Musto, D. K., 2002. Demand curves and the pricing of money management. The Review of Financial Studies 15 (5), 1499–1524.

Christoffersen, S. E., Simutin, M., 2017. On the demand for high-beta stocks: Evidence from mutual funds. The Review of Financial Studies 30 (8), 2596–2620.

Cooper, M. J., Gulen, H., Schill, M. J., 2008. Asset growth and the cross-section of stock returns. The Journal of Finance 63 (4), 1609–1651.

Cremers, M., Pareek, A., 2016. Patient capital outperformance: The investment skill of high active share managers who trade infrequently. Journal of Financial Economics 122 (2), 288–306.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of finance 52 (3), 1035–1058.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. The Journal of Finance 53 (6), 1839–1885.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990. Noise trader risk in financial markets. Journal of Political Economy 98 (4), 703–738.

Duffie, D., Garleanu, N., Pedersen, L. H., 2002. Securities lending, shorting, and pricing. Journal of Financial Economics 66 (2-3), 307–339.

Dyck, A., Lins, K. V., Pomorski, L., 2013. Does active management pay? new international evidence. The Review of Asset Pricing Studies 3 (2), 200–228.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33 (1), 3–56.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. The Journal of Finance 51 (1), 55–84.

Fama, E. F., French, K. R., 2008. Dissecting anomalies. The Journal of Finance 63 (4), 1653–1678.

Fama, E. F., French, K. R., 2010. Luck versus skill in the cross-section of mutual fund returns. The Journal of Finance 65 (5), 1915–1947.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116 (1), 1–22.

Ferson, W. E., 2010. Investment performance evaluation. Annu. Rev. Financ. Econ. 2 (1), 207–234.

Ferson, W. E., Wang, J. L., 2018. Holdings-based fund performance measures: Estimation and inference.

Frazzini, A., Lamont, O. A., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88 (2), 299–322.

French, K. R., 2008. Presidential address: The cost of active investing. The Journal of Finance 63 (4), 1537–1573.

Froot, K. A., Scharfstein, D. S., Stein, J. C., 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. The Journal of Finance 47 (4), 1461–1484.

Gârleanu, N., Pedersen, L. H., 2018. Efficiently inefficient markets for assets and asset management. The Journal of Finance 73 (4), 1663–1712.

Gaspar, J.-M., Massa, M., Matos, P., 2005. Shareholder investment horizons and the market for corporate control. Journal of Financial Economics 76 (1), 135–165.

Giannetti, M., Kahraman, B., 2017. Open-end organizational structures and limits to arbitrage. The Review of Financial Studies 31 (2), 773–810.

Gil-Bazo, J., Ruiz-Verdú, P., 2009. The relation between price and performance in the mutual fund industry. The Journal of Finance 64 (5), 2153–2183.

Griffin, J. M., Harris, J. H., Shu, T., Topaloglu, S., 2011. Who drove and burst the tech bubble? The Journal of Finance 66 (4), 1251–1290.

Griffin, J. M., Xu, J., 2009. How smart are the smart guys? a unique view from hedge fund stock holdings. The Review of Financial Studies 22 (7), 2531–2570.

Gruber, M. J., 1996. Another puzzle: The growth in actively managed mutual funds. The Journal of Finance 51 (3), 783–810.

Guercio, D. D., Reuter, J., 2014. Mutual fund performance and the incentive to generate alpha. The Journal of Finance 69 (4), 1673–1704.

Hanson, S. G., Shleifer, A., Stein, J. C., Vishny, R. W., 2015. Banks as patient fixed-income investors. Journal of Financial Economics 117 (3), 449–469.

Harrison, J. M., Kreps, D. M., 1978. Speculative investor behavior in a stock market with heterogeneous expectations. The Quarterly Journal of Economics 92 (2), 323–336.

Hong, H., Scheinkman, J., Xiong, W., 2006. Asset float and speculative bubbles. The Journal of Finance 61 (3), 1073–1117.

Hong, H., Sraer, D. A., 2016. Speculative betas. The Journal of Finance 71 (5), 2095–2144.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance 54 (6), 2143–2184.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28 (3), 650–705.

Hou, K., Xue, C., Zhang, L., 2017. Replicating anomalies. Tech. rep., National Bureau of Economic Research.

Ibbotson, R. G., Sindelar, J. L., Ritter, J. R., 1994. The market's problems with the pricing of initial public offerings. Journal of Applied Corporate Finance 7 (1), 66–74.

Jensen, M. C., 1968. The performance of mutual funds in the period 1945–1964. The Journal of Finance 23 (2), 389–416.

Jordan, B. D., Riley, T. B., 2015. Volatility and mutual fund manager skill. Journal of Financial Economics 118 (2), 289–298.

Jordan, B. D., Riley, T. B., 2016. Skill and persistence in mutual fund returns: Evidence from a six-factor model. Available at SSRN 2717091.

Kacperczyk, M., Sialm, C., Zheng, L., 2006a. Unobserved actions of mutual funds. The Review of Financial Studies 21 (6), 2379–2416.

Kacperczyk, M., Sialm, C., Zheng, L., 2006b. Unobserved actions of mutual funds. The Review of Financial Studies 21 (6), 2379–2416.

Kacperczyk, M., Van Nieuwerburgh, S., Veldkamp, L., 2016. A rational theory of mutual funds' attention allocation. Econometrica 84 (2), 571–626.

Kamara, A., Korajczyk, R. A., Lou, X., Sadka, R., 2016. Horizon pricing. Journal of Financial and Quantitative Analysis 51 (6), 1769–1793.

Koijen, R. S., Yogo, M., 2018. A demand system approach to asset pricing.

Kumar, A., 2009. Hard-to-value stocks, behavioral biases, and informed trading. Journal of Financial and Quantitative Analysis 44 (6), 1375–1401.

Lakonishok, J., Shleifer, A., Vishny, R. W., 1994. Contrarian investment, extrapolation, and risk. The Journal of Finance 49 (5), 1541–1578.

Lan, C., Moneta, F., Wermers, R., 2015. Holding horizon: A new measure of active investment management. In: American Finance Association Meetings.

Lewellen, J., 2011. Institutional investors and the limits of arbitrage. Journal of Financial Economics 102 (1), 62–80.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. The Journal of Finance 66 (1), 35–65.

Malkiel, B. G., 1995. Returns from investing in equity mutual funds 1971 to 1991. The Journal of finance 50 (2), 549–572.

Miller, E. M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of finance 32 (4), 1151–1168.

Musto, D. K., 2011. The economics of mutual funds. Annu. Rev. Financ. Econ. 3 (1), 159–172.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78 (2), 277–309.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108 (1), 1–28.

Nutz, M., Scheinkman, J. A., 2018. Shorting in speculative markets.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111 (3), 642–685.

Pástor, L., Stambaugh, R. F., Taylor, L. A., 2017. Do funds make more when they trade more? The Journal of Finance 72 (4), 1483–1528.

Pastor, L., Stambaugh, R. F., Taylor, L. A., August 2017. Fund tradeoffs. Working Paper 23670, National Bureau of Economic Research.

Porta, R. L., Lakonishok, J., Shleifer, A., Vishny, R., 1997. Good news for value stocks: Further evidence on market efficiency. The Journal of Finance 52 (2), 859–874.

Scheinkman, J. A., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of Political Economy 111 (6), 1183–1220.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk*. The Journal of Finance 19 (3), 425–442.

Sharpe, W. F., 1991. The arithmetic of active management. Financial Analysts Journal 47 (1), 7–9.

Sheng, J., Simutin, M., Zhang, T., 2019. Cheaper is not better: On the superior performance of high-fee mutual funds.

Shleifer, A., Vishny, R. W., 1997. The limits of arbitrage. The Journal of Finance 52 (1), 35–55.

Sialm, C., Starks, L. T., Zhang, H., 2015. Defined contribution pension plans: Sticky or discerning money? The Journal of Finance 70 (2), 805–838.

Sims, C. A., 2003. Implications of rational inattention. Journal of Monetary Economics 50 (3), 665–690.

Stambaugh, R. F., 2014. Presidential address: Investment noise and trends. The Journal of Finance 69 (4), 1415–1453.

Stambaugh, R. F., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104 (2), 288–302.

Stambaugh, R. F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. The Journal of Finance 70 (5), 1903–1948.

Stambaugh, R. F., Yuan, Y., 2016. Mispricing factors. The Review of Financial Studies 30 (4), 1270–1315.

Sun, Y., 2014. The effect of index fund competition on money management fees. Available at SSRN 2432361.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. The Journal of Finance 55 (4), 1655–1695.

Wermers, R., 2011. Performance measurement of mutual funds, hedge funds, and institutional accounts. Annu. Rev. Financ. Econ. 3 (1), 537–574.

Yan, X., Zhang, Z., 2007. Institutional investors and equity returns: Are short-term institutions better informed? The Review of Financial Studies 22 (2), 893–924.

Appendix A

Appendix to Chapter 2: Proof of Propositions

A.0.1 Proof of Proposition 1

The proof applies to any stock i. To simplify presentation, I drop the stock index i. Denote the expected final pay-off of a stock $E[v_2]$ as $\bar{v}$. The optimal demand of short-term institutions at $t = 1$ is

$$x_1^S(p_1) = \begin{cases} \frac{\bar{v}-p_1}{q} & \bar{v} \geq p_1 \\ \frac{\bar{v}-p_1}{\theta q} & \bar{v} < p_1 \end{cases} \tag{A.1}$$

Based on the market clearing condition

$$\lambda x_1^S + u = \kappa \tag{A.2}$$

The price at $t = 1$ is

$$p_1 = \begin{cases} \bar{v} + \frac{q}{\lambda}(u-\kappa) & u \leq \kappa \\ \bar{v} + \frac{\theta q}{\lambda}(u-\kappa) & u > \kappa \end{cases} = \bar{v} + \frac{q}{\lambda}(u-\kappa) + \frac{(\theta-1)q}{\lambda}\max(u-\kappa, 0) \tag{A.3}$$

Taking expectation

$$E[p_1] = \bar{v} - \frac{q}{\lambda}\kappa + \frac{(\theta-1)q}{\lambda}C(\kappa,\sigma) \tag{A.4}$$

where, by direct integration,[18]

$$C(\kappa,\sigma) = E[\max(u-\kappa,0)] = \frac{\sigma^2}{\sqrt{2\pi\sigma^2}}e^{-\frac{\kappa^2}{2\sigma^2}} - \kappa\left(1-\Phi\left(\frac{\kappa}{\sigma}\right)\right) \tag{A.5}$$

Consider equilibrium at $t = 0$, the demand of short-term institutions is

$$x_0^S(p_0) = \begin{cases} \frac{E[p_1]-p_0}{q} & E[p_1] \geq p_0 \\ \frac{E[p_1]-p_0}{\theta q} & E[p_1] < p_0 \end{cases} \tag{A.6}$$

[18] Note that function Φ is the cumulative distribution function of a standard normal random variable.

The demand of long-term institutions is

$$x_0^L(p_0) = \begin{cases} \frac{\bar{v}-p_0}{2q} & \bar{v} \geq p_0 \\ 0 & \bar{v} < p_0 \end{cases} \tag{A.7}$$

There are four cases to consider: 1) $E[p_1] \geq p_0$ and $\bar{v} \geq p_0$, 2) $E[p_1] \geq p_0$ and $\bar{v} < p_0$, 3) $E[p_1] < p_0$ and $\bar{v} \geq p_0$, and 4) $E[p_1] < p_0$ and $\bar{v} < p_0$. In the first case, both short-term institutional demand and long-term institutional demand are positive,

$$\lambda x_0^S + (1-\lambda)x_0^L = 1 \tag{A.8}$$

Solve for κ, p_0, and $E[p_1]$ based on equations (A.4), (A.6), and (A.7) we have

$$\kappa = \lambda + \frac{(\theta-1)(1-\lambda)}{2}C(\kappa,\sigma) \tag{A.9}$$

In the second case, we have $x_0^L = 0$, then $\kappa = 1$. This case happens when the solution to (A.9) is greater than 1. The third case is not possible, which can be shown by contradiction. Suppose it were true, then $\kappa < 0$ and

$$E[p_1] - p_0 = \bar{v} - p_0 - \frac{q}{\lambda}\kappa + \frac{(\theta-1)q}{\lambda}C(\kappa,\sigma) > 0 \tag{A.10}$$

contradicting the condition $E[p_1] - p_0 < 0$. The last case is not possible either, since if $x_0^S < 0$ and $x_L = 0$, the market does not clear at $t = 0$. Therefore, in equilibrium, the ex ante short-term ownership is

$$\kappa = \min\left(1, \lambda + \frac{(\theta-1)(1-\lambda)}{2}C(\kappa,\sigma)\right) \tag{A.11}$$

The right-hand-side of (A.9) is monotonically decreasing in κ, since

$$\frac{\partial C}{\partial \kappa} = -\left(1 - \Phi\left(\frac{\kappa}{\sigma}\right)\right) < 0 \tag{A.12}$$

By the intermediate value theorem, a unique root to equation (A.9) exists. Q.E.D

A.0.2 Proof of Lemma 2

The utility of each institution is the sum of its utility derived from each stock. This lemma can be proved by showing that the utility derived from each stock for long-term institutions is increasing in the fraction of short-term institutions λ and for short-term institutions is decreasing in λ. To simplify presentation, I drop the stock index i. The utility for long-term institutions from stock i is

$$U_L = \max E[x_L(v_2 - p_0) - 2Q(x_L)] \tag{A.13}$$

Also, by the first order condition and the definition of ex ante short-term ownership κ, I have

$$\frac{1-\kappa}{1-\lambda} = x_L = \frac{\bar{v} - p_0}{2q} \tag{A.14}$$

Assuming that long-term demand is not zero, I can rewrite a long-term institution's utility as

$$U_L = qx_L^2 = q\left(\frac{1-\kappa}{1-\lambda}\right)^2 \tag{A.15}$$

Differentiate U_L with respect to λ,

$$\frac{\partial U_L}{\partial \lambda} = \frac{2q(1-\kappa)}{(1-\lambda)^2}\left(\frac{1-\kappa}{1-\lambda} - \frac{\partial \kappa}{\partial \lambda}\right) \tag{A.16}$$

Based on (A.9),

$$\frac{1-\kappa}{1-\lambda} = 1 - \frac{\theta - 1}{2}C > 0 \tag{A.17}$$

Differentiate κ with respect to λ based on Equation (A.9),

$$\frac{\partial \kappa}{\partial \lambda} = 1 - \frac{\theta-1}{2}C + \frac{(1-\lambda)(\theta-1)}{2}\frac{\partial C}{\partial \kappa}\frac{\partial \kappa}{\partial \lambda} \tag{A.18}$$

$$= \frac{1 - \frac{\theta-1}{2}C}{1 - \frac{(\theta-1)(1-\lambda)}{2}\frac{\partial C}{\partial \kappa}} \tag{A.19}$$

$$> 0 \tag{A.20}$$

Given that $\frac{\partial C}{\partial \kappa} < 0$ as shown in Proposition (1), we have

$$\frac{1-\kappa}{1-\lambda} - \frac{\partial \kappa}{\partial \lambda} = -\frac{(1-\lambda)(\theta-1)}{2}\frac{\partial C}{\partial \kappa}\frac{\partial \kappa}{\partial \lambda} > 0 \tag{A.21}$$

Hence,

$$\frac{\partial U_L}{\partial \lambda} > 0 \tag{A.22}$$

The utility of a long-term institution is the sum of its utility derived from each stock. Therefore, the utility of long-term institution increases with λ.

The utility of a short-term institution from stock i is

$$U_S = \max E[x_0^S(p_1 - p_0) + x_1^S(v_2 - p_1) - Q(x_0^S) - Q(x_1^S)] \tag{A.23}$$

Based on the first order condition and the definition of κ, I can write

$$x_0^S = \frac{\kappa}{\lambda} = \frac{E[p_1] - p_0}{q} \tag{A.24}$$

$$x_1^S = \begin{cases} \frac{\bar{v}-p_1}{q} & \bar{v} \geq p_1 \\ \frac{\bar{v}-p_1}{\theta q} & \bar{v} < p_1 \end{cases} \tag{A.25}$$

Substituting into the above equation,

$$U_S = \frac{q\kappa^2}{2\lambda^2} + \frac{1}{2q}\int_{-\infty}^{\kappa}(\bar{v}-p_1)^2 f(u)du + \frac{1}{2q\theta}\int_{\kappa}^{\infty}(\bar{v}-p_1)^2 f(u)du \tag{A.26}$$

$$= \frac{q\kappa^2}{2\lambda^2} + \frac{q}{2\lambda^2}E[(\kappa-u)^2] + \frac{q(\theta-1)}{2\lambda^2}\int_{\kappa}^{\infty}(\kappa-u)^2 f(u)du \tag{A.27}$$

$$= \frac{q(2\kappa^2+\sigma^2)}{2\lambda^2} + \frac{q(\theta-1)}{2\lambda^2}\int_{\kappa}^{\infty}(\kappa-u)^2 f(u)du \tag{A.28}$$

where $f(u)$ is the probability density function of the speculative demand shock u.

By direct integration

$$\int_{\kappa}^{\infty}(\kappa-u)^2 f(u)du = (\kappa^2+\sigma_u^2)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right) - \frac{\sigma_u^2\kappa}{\sqrt{2\pi\sigma_u^2}}e^{-\frac{\kappa^2}{2\sigma_u^2}} \tag{A.29}$$

$$= \sigma_u^2\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right) - \kappa C(\kappa,\sigma) \tag{A.30}$$

$$> 0 \tag{A.31}$$

Hence,

$$U_S = \frac{q(2\kappa^2+\sigma^2)}{2\lambda^2} + \frac{q(\theta-1)}{2\lambda^2}\left[\sigma_u^2\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right) - \kappa C(\kappa,\sigma)\right] \tag{A.32}$$

I can denote this equation as

$$U_S = A + BH \tag{A.33}$$

where

$$A = \frac{q(2\kappa^2+\sigma^2)}{2\lambda^2} > 0 \tag{A.34}$$

$$B = \frac{q(\theta-1)}{2\lambda^2} > 0 \tag{A.35}$$

$$H = \sigma_u^2\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right) - \kappa C(\kappa,\sigma) > 0 \tag{A.36}$$

To show that U_S decreases with λ, it is suffice to show that A, B, and H decrease with λ, given that A, B, and H are all positive. I can show that

$$\frac{\partial}{\partial\lambda}\frac{q(2\kappa^2+\sigma^2)}{2\lambda^2} = \frac{2q\kappa\lambda\left(\lambda\frac{\partial\kappa}{\partial\lambda}-\kappa\right)}{\lambda^4} - \frac{q\sigma^2}{\lambda^3} \tag{A.37}$$

$$< \frac{2q\kappa\lambda\left(\lambda-\kappa\right)}{\lambda^4} - \frac{q\sigma^2}{\lambda^3} \tag{A.38}$$

$$< 0 \tag{A.39}$$

The first inequality is based on

$$\frac{\partial\kappa}{\partial\lambda} = 1 - \frac{\theta-1}{2}C + \frac{(1-\lambda)(\theta-1)}{2}\frac{\partial C}{\partial\kappa}\frac{\partial\kappa}{\partial\lambda} < 1 \tag{A.40}$$

The second inequality is based on the fact that $\kappa \geq \lambda$.

In addition,

$$\frac{\partial}{\partial\lambda}\frac{q(\theta-1)}{2\lambda^2} = -\frac{q(\theta-1)}{\lambda^3} < 0 \tag{A.41}$$

Finally,

$$\frac{\partial}{\partial\lambda}\left[\sigma_u^2\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)-\kappa C\right] = -\frac{\sigma^2}{\sqrt{2\pi\sigma^2}}e^{-\frac{\kappa^2}{2\sigma^2}}\frac{\partial\kappa}{\partial\lambda} - C\frac{\partial\kappa}{\partial\lambda} - \kappa\frac{\partial C}{\partial\kappa}\frac{\partial\kappa}{\partial\lambda} \tag{A.42}$$

$$= -\left[\frac{\sigma^2}{\sqrt{2\pi\sigma^2}}e^{-\frac{\kappa^2}{2\sigma^2}} + C + \kappa\frac{\partial C}{\partial\kappa}\right]\frac{\partial\kappa}{\partial\lambda} \tag{A.43}$$

$$= -\left[\frac{\sigma^2}{\sqrt{2\pi\sigma^2}}e^{-\frac{\kappa^2}{2\sigma^2}} + C - \kappa\left(1-\Phi\left(\frac{\kappa}{\sigma}\right)\right)\right]\frac{\partial\kappa}{\partial\lambda} \tag{A.44}$$

$$= -2C(\kappa,\sigma)\frac{\partial\kappa}{\partial\lambda} \tag{A.45}$$

$$< 0 \tag{A.46}$$

Hence, U_S is decreasing in λ. The utility of a short-term institution is the sum of its utility derived from each stock. Therefore, the utility of short-term institution decreases with λ. Q.E.D.

A.0.3 Proof of Proposition 3

Lemma (2) has established that the utility of short-term institutions decrease with λ and the utility of long-term institutions increase with λ. Hence, the difference in their utility decreases with λ. Now, I show that as λ approaches 0. The utility of short-term institutions approaches infinity, while the utility of long-term institutions remain finite. Based (A.32)

$$U_S > \frac{q\sigma^2}{2\lambda^2} \tag{A.47}$$

Hence,

$$\lim_{\lambda\to 0} U_S \geq \lim_{\lambda\to 0} \frac{q\sigma^2}{2\lambda^2} = \infty \tag{A.48}$$

The utility of long-term institutions is maximized when $\lambda = 1$. When $\lambda = 1$, the utility of long-term institutions is finite. Therefore, as λ approaches 0, the utility of long-term institutions is finite. Hence, the differential of their utilities approaches infinity. By the intermediate value theorem, for any large cost c, there exists a positive λ such that the after cost utility of short-term institutions equals to the utility of long-term institutions when $\lambda < 1$. For small c, the utility of short-term institutions will be greater than the utility of long-term institutions even if $\lambda = 1$. Hence, all institutions will be short-term institutions Proposition (1) has established the existence and uniqueness of stock level equilibrium for any given λ. Therefore, the equilibrium of this model exists and is unique. Q.E.D.

A.0.4 Proof of Proposition 4

A stock's ex ante short-term ownership κ is the solution to the equation (2.10). From (A.5), we have

$$\frac{\partial C}{\partial \sigma} = \frac{\sigma^2}{\sqrt{2\pi\sigma^2}} e^{-\frac{\kappa^2}{2\sigma^2}} - \kappa\left(1 - \Phi\left(\frac{\kappa}{\sigma}\right)\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\kappa^2}{2\sigma^2}} > 0 \tag{A.49}$$

$$\frac{\partial C}{\partial \kappa} = -\left(1 - \Phi\left(\frac{\kappa}{\sigma}\right)\right) < 0 \tag{A.50}$$

Hence, based on (A.9),

$$\frac{\partial \kappa}{\partial \sigma_u} = \frac{\frac{(\theta-1)(1-\lambda)}{2}\frac{\partial C}{\partial \sigma}}{1 - \frac{(\theta-1)(1-\lambda)}{2}\frac{\partial C}{\partial \kappa}} \geq 0 \tag{A.51}$$

Therefore, stocks with higher σ have higher ex ante short-term ownership. From the first order condition of long-term institutions, the buy-and-hold return of a stock is

$$E[v_2 - p_0] = 2qx_0^L = 2q\frac{1-\kappa}{1-\lambda} \tag{A.52}$$

It is immediate that the buy-and-hold return decreases with σ (i.e., decreases with κ). Q.E.D.

A.0.5 Proof of Proposition 5

By definition, the trading profit of long-term institutions is always 0 for each stock. The trading profit of short-term institutions for stock i is

$$R_S^T \equiv x_0(p_1-p_0)+x_1(v_2-p_1)-x_0(v_2-p_0)=(x_1-x_0)(v_2-p_1) \tag{A.53}$$

Taking expectation

$$E[(x_1-x_0)(v_2-p_1)]=E[x_1(v_2-p_1)]-E[x_0(v_2-p_1)] \tag{A.54}$$

Evaluate each component separately

$$E[x_1(v_2-p_1)]=\frac{q}{\lambda^2}E[(\kappa-u)^2]+\frac{q(\theta-1)}{\lambda^2}\int_{\kappa}^{\infty}(\kappa-u)^2 f(u)du \tag{A.55}$$

$$=\frac{q}{\lambda^2}(\kappa^2+\sigma^2)+\frac{q(\theta-1)}{\lambda^2}\left[\sigma_u^2\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)-\frac{2\kappa(\kappa-\lambda)}{(\theta-1)(1-\lambda)}\right] \tag{A.56}$$

$$=\frac{q}{\lambda^2}\left[\kappa^2-\frac{2\kappa(\kappa-\lambda)}{1-\lambda}\right]+\frac{q}{\lambda^2}\sigma^2\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] \tag{A.57}$$

The second equality is based on (A.30).

$$E[x_0(v_2-p_1)]=\frac{\kappa}{\lambda}\left(\frac{q}{\lambda}\kappa-\frac{(\theta-1)q}{\lambda}C\right) \tag{A.58}$$

$$=\frac{q}{\lambda^2}\left(\kappa^2-\frac{2\kappa(\kappa-\lambda)}{1-\lambda}\right) \tag{A.59}$$

Combining the two terms, I have

$$E[(x_1-x_0)(v_2-p_1)]=\frac{q}{\lambda^2}\sigma_u^2\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] \tag{A.60}$$

It is clear that $\frac{q}{\lambda^2}\sigma_u^2$ increases with σ_u. It is suffice to show that $\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right]$ also increases with σ_u. Differentiate it with respect to σ_u

$$\frac{\partial}{\partial\sigma_u}\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right]=-\frac{(\theta-1)}{\sigma_u^2}\phi\left(\frac{\kappa}{\sigma_u}\right)\left(\sigma_u\frac{\partial\kappa}{\partial\sigma_u}-\kappa\right) \tag{A.61}$$

where ϕ is the probability density function of standard normal distribution. I can show that

$$\sigma_u \frac{\partial \kappa}{\partial \sigma_u} = \sigma_u \frac{\frac{(\theta-1)(1-\lambda)}{2} \frac{\partial C}{\partial \sigma_u}}{1 - \frac{(\theta-1)(1-\lambda)}{2} \frac{\partial C}{\partial \kappa}} \tag{A.62}$$

$$= \frac{\frac{(\theta-1)(1-\lambda)}{2} \frac{\sigma_u^2}{\sqrt{2\pi\sigma_u^2}} e^{-\frac{\kappa^2}{2\sigma_u^2}}}{1 + \frac{(\theta-1)(1-\lambda)}{2} \left(1 - \Phi\left(\frac{\kappa}{\sigma_u}\right)\right)} \tag{A.63}$$

$$< \frac{\frac{(\theta-1)(1-\lambda)}{2} C}{1 + \frac{(\theta-1)(1-\lambda)}{2} \left(1 - \Phi\left(\frac{\kappa}{\sigma_u}\right)\right)} \tag{A.64}$$

$$< \kappa \tag{A.65}$$

where the first inequality is based on equation for the value of the resale option, Equation (A.5), and the second inequality is based on the equation for κ, Equation (A.9). Hence,

$$\frac{\partial}{\partial \sigma_u} \left[1 + (\theta - 1) \left(1 - \Phi\left(\frac{\kappa}{\sigma_u} \right) \right) \right] > 0 \tag{A.66}$$

By the product rule,

$$\frac{\partial}{\partial \sigma_u} E[(x_1 - x_0)(v_2 - p_1)] > 0 \tag{A.67}$$

Q.E.D.

A.0.6 Proof of Proposition 6

It is clear from Lemma (2) that the difference in utility between long-term and short-term institutions is monotonic in the fraction of short-term institutions. As the cost of becoming a short-term institutions increases, the break-even utility differential also increases, which means that the fraction of short-term institutions declines.

Now let me compare two economies with two different fractions of short-term institutions. In economy 1, the fraction of short-term institutions is λ_1 and in economy 2, the fraction is λ_2. Suppose $\lambda_1 > \lambda_2$, I show that the dispersion of ex ante short-term ownership, i.e. $Var(\kappa_{1i})$, in economy 1 is smaller than the dispersion in economy 2. Start with the equilibrium condition

$$\kappa = \lambda + \frac{(\theta - 1)(1 - \lambda)}{2} C(\kappa, \sigma) \tag{A.68}$$

First, I show that

$$\frac{\partial^2}{\partial \sigma \partial \lambda} \kappa < 0 \tag{A.69}$$

From equation (A.51), we know

$$\frac{\partial \kappa}{\partial \sigma_u} = \frac{\frac{\partial C}{\partial \sigma}}{\frac{2}{(\theta-1)(1-\lambda)} - \frac{\partial C}{\partial \kappa}} \tag{A.70}$$

Differentiate with respect to λ

$$\frac{\partial^2}{\partial \sigma \partial \lambda} \kappa = -\frac{\partial C}{\partial \sigma} \left(\frac{2}{(\theta-1)(1-\lambda)} - \frac{\partial C}{\partial \kappa} \right)^{-2} \frac{2}{(\theta-1)(1-\lambda)^2} < 0 \tag{A.71}$$

We also have

$$\frac{\partial \kappa}{\partial \lambda} = \frac{1}{1 - \frac{\theta-1}{2}\frac{\partial C}{\partial \kappa}} > 0 \tag{A.72}$$

Hence, κ_{1i} is greater than κ_{2i} for every stock i, but the difference, $\kappa_{1i} - \kappa_{2i}$, is decreasing in σ_{ui}. Denote the difference between the two as δ_i. We have

$$\kappa_{2i} = \kappa_{1i} - \delta_i \tag{A.73}$$

Given that κ_{1i} is increasing in σ_{ui}, κ_{1i} and δ_i must have negative co-variance. Hence,

$$\begin{aligned} Var(\kappa_{2i}) &= Var(\kappa_{1i} - \delta_i) && \text{(A.74)} \\ &= Var(\kappa_{1i}) + Var(\delta_i) - 2Cov(\kappa_{1i}, \delta_i) && \text{(A.75)} \\ &> Var(\kappa_{1i}) && \text{(A.76)} \end{aligned}$$

The expected return of each stock is a linear function of ex ante short-term ownership κ. Hence, the variance in the cross section of expected return is also greater in economy 2 than in economy 1. The trading profit is

$$E[(x_1 - x_0)(v_2 - p_1)] = \frac{q}{\lambda^2}\sigma^2 \left[1 + (\theta - 1)\left(1 - \Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] \tag{A.77}$$

Given that κ is increasing in λ,

$$\frac{\partial}{\partial \lambda} \left[1 + (\theta - 1)\left(1 - \Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] < 0 \tag{A.78}$$

$$\frac{\partial}{\partial \lambda} \left[\frac{q}{\lambda^2}\sigma^2 \right] < 0 \tag{A.79}$$

Based on the chain rule,

$$\frac{\partial}{\partial \lambda} E[(x_1 - x_0)(v_2 - p_1)] < 0 \tag{A.80}$$

The trading profit of short-term institutions in economy 2 is greater than that in economy 1. Q.E.D.

A.0.7 Proof of Proposition 7

Consider two economies, 1 and 2. Economy 1 has more stringent short-selling constraint θ_1, while economy 2 has less stringent short-selling constraint θ_2, i.e. $\theta_1 > \theta_2$. Similar to Proposition 6,

$$\frac{\partial^2}{\partial\sigma\partial\theta}\kappa = \frac{\partial C}{\partial\sigma}\left(\frac{2}{(\theta-1)(1-\lambda)} - \frac{\partial C}{\partial\kappa}\right)^{-2}\frac{2}{(1-\lambda)(\theta-1)^2} > 0 \tag{A.81}$$

We also have

$$\frac{\partial\kappa}{\partial\theta} = \frac{\frac{1-\lambda}{2}C(\kappa,\sigma)}{1-\frac{(\theta-1)(1-\lambda)}{2}\frac{\partial C}{\partial\kappa}} > 0 \tag{A.82}$$

Denote the difference between κ_{2i} and κ_{1i} as δ_i ($\delta_i > 0$)

$$\kappa_{1i} = \kappa_{2i} + \delta_i \tag{A.83}$$

We have that δ_i is increasing in σ_i. Hence, the co-variance between κ_{2i} and δ_i is positive,

$$Var(\kappa_{1i}) = Var(\kappa_{2i} + \delta_i) \tag{A.84}$$

$$= Var(\kappa_{2i}) + Var(\delta_i) + 2Cov(\kappa_{2i}, \delta_i) \tag{A.85}$$

$$> Var(\kappa_{2i}) \tag{A.86}$$

Similarly, the expected return of each stock is a linear function of ex ante short-term ownership κ. Hence, the variance in the cross section of expected return is also greater in economy 1 than in economy 2. Q.E.D.

A.0.8 Proof of Proposition 8

It is clear from Equation (A.9) that ex ante short-term ownership is not affected by changes in q. Given that long-term return is

$$E[v_2] - p_0 = 2q\frac{1-\kappa}{1-\lambda} \tag{A.87}$$

An increase in q increases the cross-sectional variation in expected return. The trading profit of short-term institutions also increases with q, since

$$\frac{\partial}{\partial q}E[(x_1-x_0)(v_2-p_1)] = \frac{\partial}{\partial q}\frac{q}{\lambda^2}\sigma^2\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] \tag{A.88}$$

$$= \frac{\sigma^2}{\lambda^2}\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] \tag{A.89}$$

$$> 0 \tag{A.90}$$

Q.E.D.

A.0.9 Proof of Proposition 9

Based on the market clearing condition at $t=0$, an exogenous increase in either short-term demand or long-term demand will increase the price of the stock at $t=0$, reducing its buy-and-hold return. Now consider return volatility, given that the price at $t=1$ is

$$p_1 = \bar{v} + \frac{q}{\lambda}(u-\kappa) + \frac{(\theta-1)q}{\lambda}\max(u-\kappa, 0) \tag{A.91}$$

clearly, we can see that holding constant σ_u, an increase (decrease) in κ will reduce (increase) $Var(p_1)$ by reducing (increasing) the variance of $\max(u-\kappa,0)$. Given that trading profit is

$$E[(x_1-x_0)(v_2-p_1)] = \frac{q}{\lambda^2}\sigma^2\left[1+(\theta-1)\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right)\right] \tag{A.92}$$

holding constant σ_u, an increase (decrease) in κ will reduce (increase) the trading profit of short-term institutions. Q.E.D.

A.0.10 Proof of Proposition 10

To compute the expected second-period return for overpriced and under-priced stocks, I take the conditional expectation of the second period return based on (A.3),

$$R_+ \equiv E[v_2-p_1|u<0] = \frac{q}{\lambda}\kappa - \frac{q}{\lambda}E[u|u<0] = \frac{q}{\lambda}\kappa + \frac{q\sqrt{2}}{\lambda\sqrt{\pi}}\sigma \tag{A.93}$$

$$R_- \equiv E[v_2-p_1|u>0] = \frac{q}{\lambda}\kappa - \frac{q}{\lambda}E[u|u>0] - \frac{q(\theta-1)}{\lambda}E[u-\kappa|u>0] \tag{A.94}$$

$$= \frac{q}{\lambda}\kappa - \frac{q\sqrt{2}}{\lambda\sqrt{\pi}}\sigma - \frac{2q(\theta-1)}{\lambda}C \tag{A.95}$$

Differentiate R_+ with respect to σ_u and since $\frac{\partial\kappa}{\partial\sigma} \geq 0$

$$\frac{\partial R_+}{\partial\sigma} = \frac{q}{\lambda}\frac{\partial\kappa}{\partial\sigma} + \frac{q\sqrt{2}}{\lambda\sqrt{\pi}} > 0 \tag{A.96}$$

To find the derivative of $R_-$with respect to σ_u, first substitute C using equation (A.9)

$$R_- = -\frac{(3+\lambda)q}{(1-\lambda)\lambda}\kappa - \frac{q\sqrt{2}}{\lambda\sqrt{\pi}}\sigma + \frac{4q}{1-\lambda} \tag{A.97}$$

Hence,

$$\frac{\partial R_-}{\partial \sigma} = -\frac{(3+\lambda)q}{(1-\lambda)\lambda}\frac{\partial \kappa}{\partial \sigma} - \frac{q\sqrt{2}}{\lambda\sqrt{\pi}} < 0 \tag{A.98}$$

The difference in the absolute value of these two derivatives is

$$\left|\frac{\partial R_-}{\partial \sigma}\right| - \left|\frac{\partial R_+}{\partial \sigma}\right| = \frac{2(1+\lambda)q}{(1-\lambda)\lambda}\frac{\partial \kappa}{\partial \sigma} \geq 0 \tag{A.99}$$

Hence, the return predictability is stronger for overpriced stocks than under-priced stocks as σ increases. Q.E.D.

A.0.11 Proof of Proposition 11

Since the additional utility that short-term institutions obtain from each stock is positive, increase in the number of stocks increases the total extra utility that short-term institutions obtain, increasing the incentive for institutions to switch to be short-term investors. Hence, the fraction of short-term institutions λ increases with the number of stocks N. From Lemma 2, I have that

$$\begin{aligned} U_S &= \frac{q(2\kappa^2+\sigma^2)}{2\lambda^2} + \frac{q(\theta-1)}{2\lambda^2}\int_\kappa^\infty (\kappa-u)^2 f(u)du && \text{(A.100)} \\ &= \frac{q(2\kappa^2+\sigma^2)}{2\lambda^2} + \frac{q(\theta-1)}{2\lambda^2}\left[\sigma_u^2\left(1-\Phi\left(\frac{\kappa}{\sigma_u}\right)\right) - \kappa C(\kappa,\sigma)\right] && \text{(A.101)} \end{aligned}$$

It is easy to see that

$$\frac{\partial U_S}{\partial q} = \frac{(2\kappa^2+\sigma^2)}{2\lambda^2} + \frac{(\theta-1)}{2\lambda^2}\int_\kappa^\infty (\kappa-u)^2 f(u)du > 0 \tag{A.102}$$

Therefore, an increase in q increases the utility of short-term institutions, resulting in higher λ. Q.E.D.

A.0.12 Proof of Proposition 12

At $t=1$, short-term investors

$$x_1^S(p_1) = \begin{cases} \frac{\bar{v}-d\beta-p_1}{q} & \bar{v} \geq p_1 \\ \frac{\bar{v}-d\beta-p_1}{\theta q} & \bar{v} < p_1 \end{cases} \tag{A.103}$$

Price at $t=1$

$$p_1 = \begin{cases} \bar{v}-d\beta+\frac{q}{\lambda}(u-\kappa) & u \leq \kappa \\ \bar{v}-d\beta+\frac{\theta q}{\lambda}(u-\kappa) & u > \kappa \end{cases} = \bar{v}-d\beta+\frac{q}{\lambda}(u-\kappa)+\frac{(\theta-1)q}{\lambda}\max(u-\kappa,0) \tag{A.104}$$

$$E[p_1] = \bar{v} - d\beta - \frac{q}{\lambda}\kappa + \frac{(\theta-1)q}{\lambda}C \tag{A.105}$$

At $t = 0$, long-term demand

$$x_0^L = \frac{\bar{v} - 2d\beta - p_0}{2q} = \frac{1-\kappa}{1-\lambda} \tag{A.106}$$

$$x_0^S = \frac{E[p_1] - d\beta - p_0}{q} = \frac{\kappa}{\lambda} \tag{A.107}$$

Solve for κ and p_0, we have the expected stock return and short-term ownership as

$$\frac{\bar{v} - p_0}{2} = d\beta + \frac{q}{1-\lambda}(1-\kappa) \tag{A.108}$$

$$\kappa = \lambda + \frac{(\theta-1)(1-\lambda)}{2}C(\kappa, \sigma) \tag{A.109}$$

Q.E.D.

Appendix B

Appendix to Chapter 3: Variable Definition

Turnover ratio of institutional investors: quarterly turnover ratio is defined as the minimum of purchases and sales in a quarter divided by the average asset. The turnover ratio of an institution as of quarter t is the sum of its turnover ratios in four most recent consecutive quarters. Purchases and sales are computed as changes in the number of shares between two quarter ends multiplied by the last quarter-end price.

$$Turn_{jt} = \sum_{\tau=t-3}^{t} \frac{\min(Purchase_{\tau}, Sales_{\tau})}{\frac{1}{2}(Size_{\tau-1} + Size_{\tau})} \tag{B.1}$$

Short-term ownership: short-term ownership of stock i in quarter t is defined as the weighted average of turnover ratios of institutions that invest in the stock, weighted by the number of shares each institution owns

$$ST\ Own_{it} = \frac{\sum_{j=1}^{N} Shares_{ijt} \times Turn_{jt}}{\sum_{j=1}^{N} Shares_{ijt}} \tag{B.2}$$

Ex ante short-term ownership: defined as the average short-term ownership of a stock over four quarters in the prior year.

Beta: measured as the regression coefficient of a stock's daily excess return on the daily market excess return in each quarter.

Idiosyncratic volatility: measured as the residual volatility of regressing a stock's daily excess return on daily Fama-French three-factor returns in each quarter.

B/M ratio: the ratio of a stock's book equity at the end of its fiscal year to its December market capitalization. Book equity is measured as common equity plus deferred taxes (if available). If common equity is not available, I replace it with total asset minus liability minus preferred equity (if available).

Momentum: the cumulative return of a stock from month $t-12$ to month $t-2$.

Mispricing score: constructed by Stambaugh et al. (2015), it is the average percentile ranking of eleven anomaly characteristics, which include financial distress, O-Score, net stock issuance, momentum, etc. Jianfeng Yu provides detailed documentation about this mispricing score on his personal website.[19]

[19] https://sites.google.com/site/yujianfengaca/

Appendix C

Appendix to Chapter 4: Variable Definition

CAPM beta: Following Lewellen and Nagel (2006), we measure a stock's daily CAPM beta as the sum of the slope coefficients from a regression of the stock excess return in day t on the market excess returns in t, t-1, and average market excess return during t-4 through t-2. We estimate the betas annually using one calendar year of data.

Market capitalization: The natural logarithm of stock i's market capitalization, measured in the end of December of each year.

B/M ratio: The ratio of stock i's book equity at the end of its fiscal year to its December end market capitalization. We adjust market capitalization for any share issuance between the fiscal and calendar year end. Following Fama and French (2008), book equity is common equity plus deferred taxes (if available). If common equity is not available, we replace it with total asset minus liability minus preferred equity (if available). The formula for B/M ratio is

$$B/M_{i,t} = \frac{Book\,Equity_{it}}{Market\,Equity_{it}} \tag{C.1}$$

Momentum: The cumulative return of a stock from January to November of each year.

Asset growth: The asset growth rate of company i in year t is defined as the natural logarithm of the ratio of its total asset in year t to total asset in year t-1. Total asset is measured as of the fiscal year end

$$AG_{i,t} = \ln \frac{Asset_{it}}{Asset_{it-1}} \tag{C.2}$$

Equity issuance: Equity issuance: equity issuance for company i in year t is defined as the natural logarithm of the ratio of number of shares outstanding in year t to the number of shares outstanding in year t-1. Number of shares outstanding is measured as of December of each year. We adjust for stock splits between two year ends. The formula is

$$EI_{it} = \ln \frac{Adjusted\,shares\,outstanding_{it}}{Adjusted\,shares\,outstanding_{it-1}} \tag{C.3}$$

Operating profitability: For company i year t, we measure its operating profitability following Fama and French (2015). Specifically, profitability is measured as of the end of fiscal year as revenue minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense, all divided by the book equity. The formula is

$$OP_{it} = \frac{(REV - COGS - SG\&A - INT\,EXP)_{it}}{Book\,Equity_{it}} \tag{C.4}$$

Stock age: Number of years a stock is publicly listed

Sales growth: The sales growth rate of company i in year t is defined as the natural logarithm of the ratio of its total sales in year t to total sales in year t-1.

Uncertain words: Loughran and MacDonald (2011) firm level uncertainty index.

Tangibility: For company i in year t, its tangibility is measured as the ratio of the amount of property, plant and equipment to its total asset.

Number of analysts: Number of analysts that provides earnings forecasts for a stock.

Idiosyncratic volatility: For company i in year t, IVOL is measured as the standard deviation of the residual of daily Fama-French three-factor regression as in Ang et al. (2006).