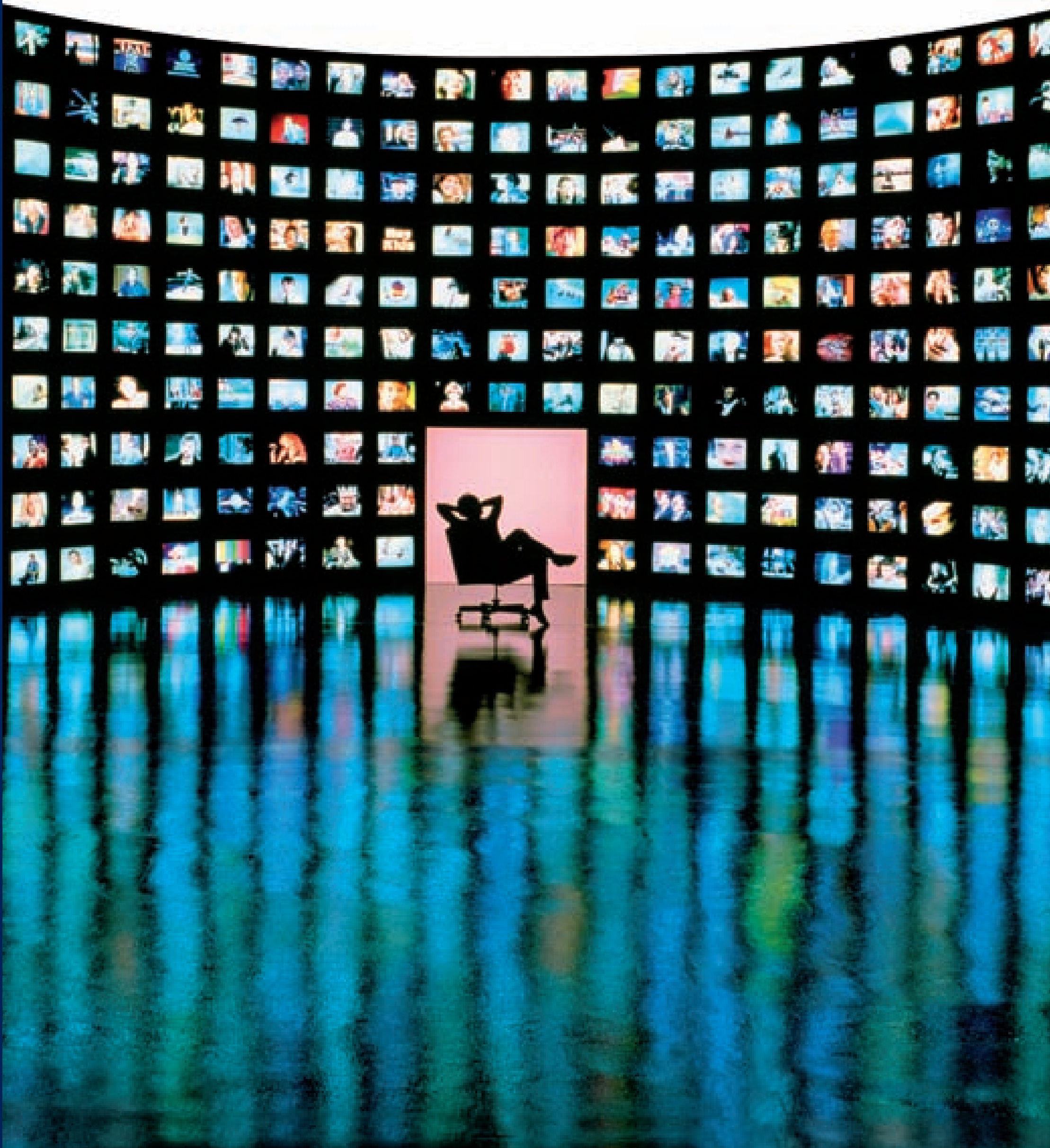
YU WANG

Information Content of Mutual Fund Portfolio Disclosure



Information Content of Mutual Fund Portfolio Disclosure

Yu Wang

Information Content of Mutual Fund Portfolio Disclosure

De informatieve waarde van openbare informatie
over de portefeuilles van belegginsgondsen

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born in Tianjin, China

ERASMUS UNIVERSITEIT ROTTERDAM

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FSC

To my beloved

In loving memory of my mother

Preface

Back in 2008 when I became part of this research project, the majority of the academic studies on mutual funds used return-based performance measurement. The general consensus of this line of research was a puzzle that the fast-growing actively managed mutual funds on average generate disappointing net performance, underperforming passive benchmark indices. Do mutual fund managers who aggressively add stocks to (or liquidate stocks from) their portfolios add value? This is a question over which there has been a longstanding dispute in both academia and financial industry. Fortunately, we have seen more and more papers attempting to gain deeper understanding of this issue by examining performance at the security level based on portfolio holdings. This PhD thesis is among one of them. I thank Marno Verbeek, my supervisor, for initiating this fascinating and challenging research project. I hope my research efforts in the past three years can shed some light on the topic of active asset management.

The very first paper of our project, the basis for Chapter 2 of this book, is a very important step in my PhD life. This paper looks at the impact of reporting frequency on the profitability of a free-riding strategy, i.e. the simplest way in which holdings information can be used by outsiders. What I learned along the path of achieving this paper, not only the research skills but also how to face intellectual challenges will be an estate for my life. I am so grateful to Marno, who guided me through the entire project, for his patient guidance, generous understanding, and most importantly, endless encouragement. Thanks to Marno, I came to understand what an excellent researcher means: creative, conscientious, independent, and never give up! Marno is a great econometrician, a committed supervisor and a trustworthy coauthor. This book would not have been completed without his trust and support, whenever I needed. Another very important person who has a tremendous influence on my academic research is Hao Jiang, one of my coauthors. We cooperated on my second paper (Chapter 3 of the book) that examines the informational role of active mutual funds in financial markets by relating active fund investments to asset prices. My interactions with Hao steered the focus of my research into the information content of fund portfolio decisions, the main message this whole book aspires to deliver. I owe him many many thanks for his inspiring ideas, openness to discussions, and selfless help throughout the whole process. Hao is a very clever researcher, but he is also a very supportive friend in life. I am also indebted to my coauthor Rui Shen, a key contributor to my third research paper in which we further explore the nature of the information possessed by fund managers. I thank him for introducing me to the accounting literature on security fundamental analysis and for the many valuable research insights he gave me. Brainstorming with Rui was always a pleasant experience, even on a basketball court.

My special thanks go to other members of my doctoral committee, Mathijs van Dijk, Willem Verschoor, Lars Norden, Gerard Mertens, from *Erasmus University*, Alessandro Beber, from *University of Amsterdam*, Jenke ter Horst from *University of Tilburg*, and Russ Wermers from *University of Maryland*. I would like to express my gratitude again to Russ for his kind suggestions on programming tools when I started my PhD. Many of his research works use holdings data and he has broken new ground for fund performance evaluation. This book owes an enormous intellectual debt to all of the many people who have taken the time to give me comments at seminars and conferences. I thank all my colleagues at RSM for creating an enjoyable and productive working environment. I appreciate several generations of finance PhD students at RSM who brought a lot of fun to my work and life, especially Jingnan, Tao, Eric, Olga, Oliver, Henry, Xiaohong, Melissa, Ruben, Pooyan, Dimitrios, Manuel, Dominique, Teng, and Teodor. I am also grateful to ERIM and the *Department of Finance* of RSM for providing generous financial support, which made international conference presentations possible.

My parents deserves a special place in this preface. Their unconditional support and endless love have been the most precious treasure in my life. I always hope that one day I could achieve something that they can be proud of. My deepest gratitude goes to my mother who left me forever when I just started my PhD. I miss her so much. This book is dedicated to my dearest mother.

Yu Wang
Rotterdam, The Netherlands
April, 2011

Contents

Chapter 1

Introduction

The enviable pace of growth of the U.S. mutual fund industry for much of the past decades has witnessed the increasing investors' reliance on professional investment advice. The U.S. mutual fund industry–with $11.1 trillion in assets under management at year-end 2009–has become one of the largest groups of investors in U.S. companies, holding 24 percent of the outstanding shares of U.S.-issued stocks by the end of year 2009 (2010 Investment Company Institute). Investor demand for mutual funds is influenced by a variety of factors, one of which is the return-generating ability of fund managers who presumably, as a group, are supposed to possess superior private information regarding security mispricing.

Academic financial economists have been keenly interested in the value of active portfolio management since the seminal paper of Jensen (1968). The general consensus that mutual funds on average fail to outperform market and their passive benchmarks does not preclude finding subgroups of skilled managers.[1] From the perspective of equilibrium accounting, the aggregate portfolio of actively managed U.S. equity mutual funds is close to the market portfolio (Fama and French, 2010). This means the active investment must be a zero sum game—-active funds with positive true alpha are balanced by other funds with negative alpha. A skilled active fund manager will exhibit portfolio tilts consistent with the private information he receives concerning future stock returns. The present thesis examines such information through an analysis of disclosed fund holdings. Performance evaluation at the security level allows us to gain a more comprehensive understanding of the value of active money management and decompose various security-selection talents. The thesis further provides insight into the informational role that active fund managers play in financial markets.

[1]Studies of mutual fund returns generally report disappointing fund performance (e.g., Jensen, 1968, Malkiel, 1995, Carhart, 1997, Fama and French, 2010). For evidence supporting the value of active investing, see Avramov and Wermers (2006) and Wermers, Yao, and Zhao (2007).

1.1 Motivation

The U.S. Securities and Exchange Commission requires each mutual fund to periodically disclose a complete portfolio holdings schedule to investors. If the reported holdings unveil valuable investment opportunities and more importantly such opportunities are not transitory, outside investors who trade on such information would be able to share the benefits of fund research without incurring the actual cost of owning the fund shares. In 2004, the SEC adopted enhanced regulations that increased the frequency of portfolio disclosure from semi-annually to quarterly. On the one hand, more frequent portfolio disclosure by mutual funds would allow investors to better monitor the extent of their portfolio diversification and hence make more informed asset allocation decisions. On the other hand, under a more frequent disclosure mandate, predatory trading practices would increase and adversely affect fund performance by preventing a fund from fully realizing the potential benefits of its research efforts. The first part of this thesis addresses the question to what extent fund portfolio disclosure reveals valuable information for outsiders and whether the enhanced SEC regulations have increased the potential for outsiders to benefit. These questions are important to increase our understanding of the simplest way in which disclosed holdings information can be exploited by individual investors.

Despite the increasing importance of mutual fund industry, the informational role that mutual funds play in determining security prices remains ambiguous. Given the large amount of resources active funds spend on security analysis and research, we might expect them to be good candidates for informed investors, whose costly information acquisition helps impound information into asset prices (Grossman and Stiglitz, 1980). Prior literature on fund performance, however, has painted a disheartening picture of active funds' performance at the aggregate level. Can we reconcile this in a fully rational framework? Berk and Green (2004) outline a model in which managers collect fees as a fixed percentage of assets under management and thus attempt to maximize fund assets. In their model, managers mix their alpha-generating ideas with a benchmark portfolio. Their information-based investments in an individual stock will push the price of that stock toward fair value. Hence, the amount of profit that a manager can extract from a given investment idea is limited. In equilibrium each manager will raise assets until the fees are equal to the alpha that can be extracted from his private information. This leaves individual investors with a return close to the benchmark. With portfolio holdings data at hand, we are interested in evaluating the performance of the information-driven portion of active funds' investments and understanding how effectively active fund managers can exploit market inefficiencies based on their superior information concerning future stock returns. To better assess whether active fund managers attain informational advantages in discovering valuable investment opportunities, the second part of the thesis examines the active portion of fund investments, that is, the portfolio deviations from the benchmark.[2] This is because a mutual fund manager can attempt to outperform its benchmark only by deviating from it.

If active fund managers are able to make advantageous portfolio bets based on their informational advantages, what is the nature of such information? In stock markets, the cornerstone of investing is fundamental analysis, a technique that attempts to determine a securitys intrinsic value by focusing on underlying factors that affect a company's actual business and its future prospects. When information and trading costs are not trivial in reality, stock prices may diverge from their intrinsic values (e.g., Shiller (1984), Summers (1986), DeBondt and Thayler (1987), Lakonishok, Shleifer, and Vishny (1994), and Shleifer and Vishny (1997)). If investors have superior information on a firm's fundamental prospects or more comprehensive ways of processing such information, they will trade on such information and thus help mitigate the mispricing relative to stock intrinsic values. Do active mutual funds rely on fundamental analysis? If so, can they profit from it? Furthermore, what are the implications of funds' exploitation of fundamental information on asset prices? The third part of the thesis will investigate these issues in more detail.

1.2 Outline of the Thesis

The three essays presented in this book constitute an empirical investigation of the information content of mutual fund portfolio disclosure. Chapter 2 studies the value of active funds' portfolio disclosure from an outside investor's perspective. Chapter 3 and Chapter 4 attempt to relate active fund investments to asset prices and further explore the role of active mutual funds in bringing about price efficiency in financial markets.

Chapter 2 constructs hypothetical copycat funds to investigate the performance of free-riding strategies that duplicate the disclosed asset holdings of actively managed mutual funds. We measure the relative success of free-riding by comparing the performance between a copycat fund with its target active fund. Analyzing disclosed holdings of 3,046 active U.S. equity funds over the 1985-2008 period, we find that copycat funds on average can generate performance that is comparable to their actively managed counterparts, after trading costs and expenses. More interestingly, their relative success increased significantly after 2004 when the SEC imposed

[2]Cremers and Petajisto (2009) document a rapid increase in closet indexers whose portfolios largely resemble those of their benchmarks while still claiming to be active.

quarterly disclosure regulations on all mutual funds. The stabilizing pattern is especially salient for the subsample of mutual funds that have experienced and survived past the policy change. The improvement in net relative returns for those copycat funds amounts to 0.05% per month. The improved tracking performance after the policy change in 2004 is associated with a steady increase in the representativeness of fund portfolio disclosure, i.e. the extent to which a fund's disclosed holdings are representative of its true investment style in the recent past. We measure the representativeness by the tracking error of a mutual fund relative to a characteristic-based benchmark. These findings confirm our expectations that requiring more frequent portfolio disclosure expands the opportunities for potential free-riders to successfully track or even beat their actively managed counterparts. In this chapter, we also document a substantial cross-sectional dispersion in the relative success of copycat funds. A copycat strategy targeted at past winning funds provides investors with a cheap momentum strategy. Further, the representativeness of holdings also appears to be a powerful predictor of the relative success of copycat funds. Copycat strategies exploiting 'more representative' holdings tend to outperform not only their actively managed counterparts but also the vast majority of active funds. The superior performance of such selective copycat strategies helps to identify those active target funds that provide the most attractive free-riding opportunities. Distinct from prior studies, our work evaluates the effectiveness of the disclosure policy change in 2004 and the impact of mandating more frequent disclosure on the tracking performance. This chapter provides insights into how investors could use disclosed fund holdings and to what extent free-riders gain at the expense of fund shareholders.

Chapter 3 establishes a robust relation between the active funds' deviations from benchmarks and future stock returns. We study the information content of the active portion of fund investments by creating a stock-level measure that seeks to aggregate various pieces of information scattered among active funds, as revealed through their over- and underweighting decisions. Specifically, we compare the portfolio holdings of an active fund with its benchmark index and compute the excess weight for each stock on top of the benchmark portfolio. Then we use the simple average of these excess weights on one stock across all active funds to characterize the consensus active bet of fund managers on that stock, which we label funds' Deviations From Benchmarks, DFB. We find that DFB strongly and positively predicts future stock returns. The return premium on stocks heavily overweighted by mutual funds, relative to their underweighted counterparts, reaches more than 7% per year even after adjustments for their loadings on the market, size, value, momentum, and liquidity factors. These results are also robust to the various specifications of Fama and MacBeth's (1973) cross-sectional regressions with common stock return predictors, to the Daniel, Grinblatt, Titman, and Wermers (1997) characteristic-adjustment procedure, for different weighting schemes, to the exclusion of IPO allocations, and across various subperiods. A significant portion of this premium occurs around corporate earnings announcements, which suggests that part of the active funds' superior information relates to firms' fundamental prospects. However, there is evidence that mutual funds tend to herd (Wermers, 1999; Sias, 2004). To differentiate an alternative interpretation based on price pressure from our story of informed fund managers, we examine the dynamics of changes in DFB, the return persistence of high-DFB stocks, and the possible influence of future demand shocks. The results uniformly support our information-based story. In addition, we find that the return forecasting power of DFB is stronger among mid-cap firms that have higher idiosyncratic volatilities and those that attract fewer mutual fund investors. Our results are more pronounced for past-winning funds and growth-oriented funds. Finally, we find that in aggregate, mutual funds invest less than 10% of their assets in high-DFB stocks but approximately 34% in low DFB stocks. Therefore, a large four-factor alpha of 6–7% per year on high DFB stocks translates into a small mutual fund alpha of less than 1% per year. These results are consistent with the prediction of Berk and Green (2004) on the equilibrium behavior of mutual fund managers. Different from previous studies, our measure of deviations from benchmarks is less subject to the influence of fund flows. Moreover, we connect mutual fund investing to asset prices without assuming any a priori links between firms and funds.

Chapter 4 explores the relation between active mutual funds' trading behavior and stock price divergence from intrinsic value. Over the 1981 to 2008 period, we find that mutual funds in aggregate tend to buy (sell) underpriced (overpriced) stocks as measured by a V/P ratio, where V denotes the intrinsic value estimated by a residual income valuation model. We attribute the mutual funds' exploitation of a stock's intrinsic value to their superior expertise in forecasting and processing fundamental information (Cheng, Liu and Qian, 2006). To characterize the portfolio choices of mutual funds based on V/P and assess how successfully they exploit such information, we construct a fund-level V/P-timing measure, VPT, in the spirit of Grinblatt, Titman, and Wermers (1995). VPT is the weighted average V/P decile rank of all stocks held by a mutual fund. A high value of VPT indicates that the fund manager actively trades on fundamentals and tilts her portfolio toward underpriced stocks (with high V/P ratios). In univariate portfolio sorts, D10 funds with the highest VPT have an average return of 1.19% per month over a six-month horizon and significantly outperform the lowest-VPT funds in D1 by 0.55% per month. The results are robust to various forms of factor risk adjustments. Hence, mutual funds that actively exploit the fundamental mispricing are able to benefit from such information and generate both statistically and economically significant profits. This confirms the findings that mutual funds benefit from fundamental-relevant information in Campbell, Ramadorai, and Schwartz (2009) and Baker, Litov, Wachter, and Wurgler (2010). Finally, we find that the V/P effect is more pronounced among stocks with less intense past mutual funds' exploitation. We find that high-V/P stocks with the lowest mutual funds' ownership upon the release of accounting information continue to generate a significant 4-factor alpha of 0.42% per month in the subsequent one year. Furthermore, we also show that high-V/P stocks that have been heavily sold by mutual funds in the recent past can generate even higher future performance. Our evidence supports the view that the tendency of mutual funds to trade in the direction of V/P mitigates mispricing and facilitates impounding fundamental information into stock prices. This study is among the first to empirically test the trading behavior of delegated informed traders using a stock mispricing measure based on a comprehensive valuation model. Our findings that mutual funds tend to exploit mispricing opportunities are consistent with the theoretical prediction of Grossman and Miller (1988), De Long, Shleifer, Summers, Waldman (1990) and Campbell and Kyle (1993).

Chapter 2

Better than the Original? The Relative Success of Copycat Funds*

2.1 Introduction

Mutual funds are required to periodically disclose their portfolio holdings. In 2004, the SEC adopted enhanced regulations that increased the frequency of portfolio disclosure from semi-annually to quarterly. The amendment was designed to provide investors more frequent access to portfolio information to monitor whether a fund is complying with its stated investment objective, and, if so, how. As discussed by Wermers (2001), Frank et al. (2004) and Parida and Teo (2010), more frequent disclosure potentially imposes new costs on mutual funds. For example, it can become easier for other investors to exploit information on fund flows to front-run the fund's trades (Coval and Stafford, 2007). Moreover, disclosure can allow outside investors to share the benefits of fund research without incurring the actual cost of owning the fund shares. Investors can simply "free-ride" on mutual fund investment strategies through the direct mimicking of disclosed portfolio holdings, even though this information is typically two months old at the time of publication.[1] The reported holdings can thus unveil valuable investment opportunities. For example, Daniel et al. (1997) examine fund holdings and show that certain groups of mutual

*This chapter is based on the article by Verbeek and Wang (2011). I am grateful to John Adams, Stefano Bubellini, Susan Christofferson, Richard Fu, Hao Jiang, Tarun Ramadorai, Jan Wrampelmeyer, Russ Wermers and the participants of the Midwest Finance Association Meeting (Las Vegas, 2010), Eastern Finance Association Meeting (Miami, 2010), EFMA Conference (Aarhus, 2010), FMA European Conference (Hamburg, 2010), the 4th Professional Asset Management Conference (Rotterdam, 2010) and the FMA Annual Meeting (New York, 2010) for helpful comments and suggestions. This paper received the Outstanding Research Award in Investments at the Eastern Finance Association Meetings in Miami, Florida, April 2010. I also wish to thank Kenneth French and Russ Wermers for making their data available through their websites.

[1]Chen, Jegadeesh and Wermers (2000) and Wermers (2001) find that profits from fund research tend to accrue over periods ranging from 12 to 18 months after the date a newly acquired stock is first added to a fund's portfolio.

funds exhibit selectivity ability. If such opportunities are not transitory, investors who trade on such information, even with a time lag, would be able to make a substantial profit. In this paper we address the question to what extent portfolio disclosures reveal valuable information for outsiders and whether the enhanced SEC regulations have increased the potential for such free-riding strategies. These questions are important to increase our understanding of the simplest way in which disclosed holdings information can be exploited and to establish the potential costs of disclosure to mutual funds.

To address these issues, we construct hypothetical copycat funds by strictly duplicating the active funds' disclosed portfolios and rebalancing whenever new holdings are reported. We measure the relative success of free-riding by comparing the performance between a copycat fund and the target active fund. Analyzing disclosed holdings of 3,046 active U.S. equity funds over the 1985-2008 period, we find that copycat funds on average can generate returns that are close to their actively managed counterparts, after trading costs and expenses. More interestingly, the average relative performance of copycat funds stabilizes and increases significantly after the SEC requires more frequent portfolio disclosure in 2004. The pattern is especially salient for a subsample of mutual funds that have experienced and survived past the policy change. The improvement in net relative returns for those copycat funds amounts to 0.05% per month, which is statistically significant. The improved tracking performance after the policy change in 2004 is associated with a steady increase in the representativeness of fund portfolio disclosure, i.e. the extent to which a fund's disclosed holdings are representative of its true investment style in the recent past. We measure the representativeness by the tracking error of a mutual fund relative to a characteristic-based benchmark. These findings confirm our expectations that requiring more frequent portfolio disclosure expands the opportunities for potential free-riders to successfully track or even beat their actively managed counterparts.

A potentially interesting free-riding strategy focuses on the holdings reported by certain types of mutual funds, for example, funds with a proven track record of success. Outside investors might apply various techniques to returns and holdings data to infer the stock-picking talents of active funds. In this paper we document a substantial cross-sectional dispersion in the relative success of copycat funds. A copycat strategy targeted at past winning funds provides investors with a cheap momentum strategy that significantly outperforms the majority of the mutual fund universe after trading costs and expenses. Further, the representativeness of holdings also appears to be a powerful predictor of the relative success of copycat funds. Copycat strategies exploiting 'more representative' holdings tend to outperform not only their actively managed counterparts but also the vast majority of active funds. The superior performance of such selective copycat strategies helps to identify those active target funds that provide the most attractive free-riding opportunities.

An extensive literature has examined mutual fund performance and new money growth based on holdings data or trades derived from holdings.[2] Few studies have focused on the tracking performance of a free-riding strategy and the association of portfolio disclosure with fund performance and investor reactions.[3] Our study evaluates the effectiveness of the disclosure policy change in 2004 and the impact of mandating more frequent disclosure on the tracking performance. To enhance the practical relevance of our study we take into account the possible transaction costs for copycat funds. Further, we investigate the cross-sectional variation in the performance of copycat funds. Brown and Schwarz (2010) examine the use of hedge funds' 13(f) filings by market participants and find that mandatory disclosure of hedge fund portfolio positions provides little long-term benefit to investors who seek to free-ride on the information released in these disclosures. Kacperczyk, Sialm and Zheng (2008) investigate the impact of unobserved actions of U.S. equity funds on future fund performance by defining the 'return gap' between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. Our work differs from theirs in that we shift the object of study from active funds to potential free-riders who expect to track the active fund's performance. More importantly, we aim at measuring the extent to which outdated holdings are valuable. Our study provides insights into how investors could use disclosed fund holdings and to what extent free-riders gain at the expense of fund shareholders.

The remainder of the chapter proceeds as follows. Section 2.2 briefly reviews the dynamics of U.S. disclosure regulations for mutual funds and describes the data used in this study. Section 2.3 presents the main methodology to construct copycat portfolios and defines a measure for the representativeness of disclosed holdings. In Section 2.4, we examine the effect of mandating more frequent portfolio disclosure in 2004 on the tracking performance of copycat funds. Section 2.5 focuses on the determinants of the relative success of copycat funds and analyzes the cross-sectional variation in the performance of copycat funds. Section 2.6 concludes.

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[2] The literature includes, among others, Grinblatt and Titman (1989), Grinblatt, Titman and Wermers (1995), Daniel, Grinblatt, Titman and Wermers (1997), Wermers (1997, 1999, 2000, 2001, 2003), Chen, Jegadeesh, Wermers (2000), Kacperczyk, Sialm and Zheng (2005, 2008), Cohen, Coval and Pastor (2005), Kosowski, Timmermann, Wermers and White (2006), Baks, Busse and Green (2006), Ge and Zheng (2006), Cremers and Petajisto (2009).

[3] An exception is Frank et al. (2004), which analyzes the average tracking performance of copycat funds based on the semi-annually reported holdings of 20 high-expense mutual funds in the 1990s.

2.2 Institutional Background and Data

The Investment Company Act historically required all registered U.S. investment management companies to transmit reports to their shareholders and to file these shareholder reports with the SEC within 10 days after transmission to shareholders. These fund reports have long served as the primary vehicle to communicate information regarding both fund performance and portfolio composition to investors. Since 1985 the SEC required under Rule 30b1-1 that all registered investment companies file their portfolio holdings within 60 days after the end of each fiscal six-month period. Aiming at improving the effectiveness of such information disclosure, many petitioners had suggested ways to improve the disclosure regime by the end of 2003.[4] They believed that investors could benefit from the enhanced transparency by both increasing the frequency with which mutual funds are required to disclose their portfolio holdings and streamlining the portfolio schedules delivered to shareholders. In their petitions they also argued that more frequent portfolio disclosure by mutual funds would allow investors to better monitor the extent of their portfolio diversification and consequently enable them to make more informed asset allocation decisions. In addition, the transparency supporters believed that investors would have better information to check how a fund was complying with its stated investment objective, so as to identify style-drifting funds. In their opinions, more frequent disclosure would also shed light on the problems of portfolio manipulation such as 'window dressing' and 'portfolio pumping'[5]. In response to the demand for more effective portfolio disclosure regulation, the SEC issued a release proposing rule amendments under SA of 1933, SEA of 1934 and ICA of 1940 on December 18, 2002. By February 14, 2003, the SEC had received 65 comment letters from industry members, investor advocacy groups, consultants and academics. Some of these letters supported the SEC's proposal to improve the transparency of the periodic portfolio disclosures provided to investors. By contrast, other petitioners, including members of the investment management groups, raised concerns that frequent portfolio disclosure with a short reporting delay might encourage predatory trading practices in the market.[6]

[4]The SEC received six rule-making petitions by May 10, 2004. See "Shareholder Reports and Quarterly Portfolio Disclosure of Registered Management Investment Companies; Final Rule", 17 CFR Parts 210, 239, 249, 270, and 274, available from `http://www.sec.gov/rules/final/33-8393.htm`.

[5]"Window Dressing" is defined as buying or selling portfolio securities shortly before the date as of which a fund's holdings are publicly disclosed, to convey an impression that the manager has been investing in companies that have had exceptional performance during the reporting period. "Portfolio Pumping" is defined as buying shares of stock the fund already owns on the last day of the reporting period, to drive up the price of the stocks and inflate the fund's performance results. See Lakonishok, Shleifer, Thaler and Vishny (1991), Sias and Starks (1997), Musto (1999), O'Neal (2001) and Meier and Schaumburg (2006), Duong and Meschke (2009).

[6]The commenters from ICI and Fidelity argued that free-riding could be achieved and facilitated by more frequent disclosures of fund holdings. See letter from Craig S. Tyle, General Counsel, ICI, to the SEC (February 14,

More frequent portfolio disclosure would facilitate the ability of professional traders and other opportunists to expropriate the results of mutual funds' proprietary research and investment acumen. Such exploitation of reported holdings could lead to additional costs that will be passed on to fund shareholders in the form of sacrificed fund performance and the consequent erosion of market share. Wermers (2001) examines the potentially harmful consequences of requiring more frequent portfolio disclosure and concludes that under a more frequent disclosure mandate abusive activities such as free-riding would increase and adversely affect fund performance by preventing a fund from fully realizing the potential benefits of its research efforts. In an attempt to strike a balance between the benefits and costs associated with disclosing fund holdings, the Commission decided to adopt a quarterly disclosure requirement with a 60-day filing delay in the final amendments that took effect in May of 2004. Accordingly, our analysis is also motivated by the desire to understand the impact of increased mandatory reporting frequency on fund performance. Examining the information content of the disclosure per se allows us to gain a deeper insight into the value of outdated portfolio data for free-riding activities and the possible responses by mutual funds to such predatory trading practices.

Our empirical analysis employs data on stock prices, mutual funds and their holdings extracted from three major sources: the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (MFDB), the Thomson Financial CDA/Spectrum S12 equity holdings data, and the CRSP stock files. Our sample spans the 24-year period from January 1985 to December 2008. The CRSP mutual fund database provides monthly fund net returns, TNAs, and annual data on portfolio turnover ratios, 12b1 fees, expense ratios and other fund characteristics (investment styles, asset allocations, etc.) for all open-end mutual funds. The second mutual fund database contains a history of quarterly/semi-annual portfolio holdings for all U.S. equity mutual funds, and lists the number of shares of each stock held by a fund and the self-declared investment objective at the beginning of each calendar quarter. The SEC filings, together with the voluntary quarterly fund reports to shareholders and informal reports to CDA constitute the main source of this database. The third database contains stock prices and returns from the CRSP NYSE/AMEX/Nasdaq stock files. We merge the CRSP MFDB with the TFN CDA/Spectrum holdings data using the MFLINKS database provided by WRDS to obtain a complete record of stock holdings of a given mutual fund along with the fund's net returns and other characteristics.[7] To concentrate our analysis on open-end U.S. domestic active equity mutual funds, for which the holdings data are most complete and reliable, we eliminate bond, money market, international and sector funds, as well

2003) 'Re: Shareholder Reports and Quarterly Portfolio Disclosure of Registered Management Investment Companies'.

[7]The MFLINKS data set is maintained by Russ Wermers and the Wharton Research Data Services (WRDS).

as funds not primarily invested in equity. We also exclude index funds that target to (more or less passively) replicate an equity index. For funds with multiple share classes, we eliminate the duplicate funds sharing one underlying portfolio. Appendix A provides details on the sample selection (based on investment objectives and portfolio equity concentration) and the merging process of the aforementioned three databases.

Panel A of Table 2.1 reports the summary statistics for our mutual fund database. Our sample includes 3,046 distinct U.S. equity mutual funds over the period from 1985 to 2008. The mutual funds in our sample on average invest 95.06% of their assets in common stocks and less than 5% in other asset classes. Therefore, our sample well represents the universe of U.S. domestic funds with an investment focus on equity. Besides the investment composition, Table 2.1 also summarizes other fund attributes that are used in the analyses below. An average mutual fund in our database has a TNA of $876 million, expense ratio of 1.30% per year and turnover of 91.6% per year. The relatively high expense ratios of active funds facilitate the potential free-riders' relative success by taking the most of their cost advantage. In our sample, the average fund age is 12.63 years which is higher than the median fund age of 7.75 years due to the existence of several old funds, such as Massachusetts Investors Trust introduced in 1924.

In Panel B of Table 2.1 we report the summary statistics for all common stocks held by mutual funds in our sample. Size refers to the market capitalization of the stock. On average, 0.74% of the stock market capitalization is traded every month. The book-to-market ratio is determined for each stock at the end of each calendar year using the book value of the fiscal year end and the market value at the end of the calendar year. Momentum is defined as the cumulative stock return over the past one year (month t-11 to t-1). Size and momentum scores, ranging from 1 to 5, are calculated by assigning all stocks into quintile portfolios at the end of each month using NYSE breakpoints, with a score of 1 for the lowest quintile. BM ratio scores are calculated in a similar way except that the quintile portfolios are rebalanced at the end of each year. On average, mutual fund portfolios have a slight tilt toward small, growth and momentum stocks

2.3 Constructing Copycat Funds

This section describes the construction of copycat funds, taking into account trading costs and expenses. It also introduces a measure of representativeness for disclosed portfolio holdings, which appears an important characteristic to describe the relative success of copycat strategies.

Table 2.1: **Summary Statistics for Merged Mutual Fund Database**

Panel A of this table presents the summary statistics for the sample of U.S. equity mutual funds over the period 1985 to 2008. Merging the Thomson Financial/CDA database, CRSP MFDB and CRSP stock files results in a sample of 3,046 distinct funds. 12(b)1 fees are the actual 12(b)1 fees in the CRSP Mutual Fund Database and the maximum 12(b)1 fees in case the actual 12(b)1 fees are missing. Proportion of investments in each asset class is from the CRSP mutual fund summary database. We average the expense ratios, turnover ratios, 12(b)1 fees and other proportion of investments characteristics at the end of each year. TNAs and fund ages are averaged using monthly data. Panel B reports the summary statistics for the U.S. common stocks held by our sample of U.S. equity mutual funds. Stock size is the product of the stock price and the number of outstanding shares. Book-to-Market ratio is determined for each stock at the end of last calendar year using the book value of last fiscal year end and the market value of the stock at the end of last calendar year. Momentum is defined as the cumulative stock return over the past one year ($t-11$ to $t-1$). Size and momentum scores are calculated by assigning all stocks into quintile portfolios at the end of the each month using NYSE breakpoints with score of 1 for the quintile of the lowest characteristic values and vice versa. BM ratio scores are calculated in a similar way except rebalancing the quintile portfolios at the end of each year.

Panel A: Mutual Funds	Mean	25% percentile	Median	75% percentile	Standard Deviation
Total Net Assets (millions)	875.70	25.10	107.50	448.95	3827.41
Expense Ratio (% per year)	1.30	0.95	1.20	1.50	1.12
Fund Turnover Ratio (% per year)	91.58	35.70	67.00	114.00	120.22
12(b)1 fees (% per year)	0.29	0.00	0.25	0.30	0.31
Common Stock Investments (%)	95.06	93.25	97.23	99.75	6.99
Fund Age (years)	12.63	3.92	7.75	15.09	13.91
Panel B: Stocks Held by Mutual Funds	**Mean**	**25% Percentile**	**Median**	**75% Percentile**	**Standard Deviation**
Volume/Size (% per month)	0.74	0.13	0.32	0.79	2.06
Size (Millions)	2070.83	88.59	271.78	966.45	10690.09
Size Score (1∼5)	2.23	1.00	2.00	3.00	1.35
Book-to-Market Ratio	0.69	0.31	0.55	0.90	0.61
Book-to-Market Ratio Score (1∼5)	2.71	1.00	3.00	4.00	1.46
Momentum (%)	21.97	-10.42	11.44	37.69	80.62
Momentum Score (1∼5)	3.11	2.00	3.00	4.00	1.46

2.3.1 Measuring Copycat Portfolio Gross Returns

We compute the gross return for a copycat fund as the total return of a hypothetical buy-and-hold portfolio that invests in the most recently disclosed fund asset positions and is rebalanced at the next disclosure date. The gross monthly holding period return for a copycat fund targeting mutual fund j is defined as

$$GR_t^j = \sum_{i=1}^{N} \widetilde{w}_{i,t-1}^j R_{i,t}, \tag{2.1}$$

where $R_{i,t}$ denotes the return on asset i, and the value weights are given by

$$\widetilde{w}_{i,t-1}^j = \frac{N_{i,t-\tau}^j P_{i,t-1}}{\sum\limits_{i=1}^{N} N_{i,t-\tau}^j P_{i,t-1}}, \tag{2.2}$$

where $N_{i,t-\tau}^j$ denotes the number of shares of stock i held by mutual fund j at the most recent disclosure date at time $t - \tau$, and $P_{i,t-1}$ is the stock price at the end of the previous month. Different from Kacperczyk, Sialm and Zheng (2008), we do not use the snapshot dates (RDATE in the TFN/CDA database) to rebalance our portfolio because we are constructing a practically implementable copycat strategy. Typically, the disclosure dates are less than 60 days after the end of each fiscal quarter. Considering the amount of work and degree of difficulty for individual investors to access the SEC's EDGAR filings, we assume that a disclosure date is 60 days after each snapshot date to ensure that all the holdings data are available to individual investors at the time of portfolio construction. Our copycat portfolio for each active fund is rebalanced on each disclosure date. Accordingly, copycat funds are at least two months out of date in tracking the active mutual fund's portfolio. We also adjust the number of shares and the stock prices across months in each holding period for stock splits and other share adjustment using the accumulative adjustment factor given by CRSP.

The TFN/CDA holdings database only contains common stock positions and excludes other non-equity holdings. To adjust the copycat fund returns for the various asset classes, we proxy for these assets' returns using published indexes. We assume all bonds and preferred stocks held by mutual funds earn the Barclays Lehman Brothers Aggregate Bond Index returns and all cash and other asset classes earn the Treasury-bill monthly return. The value weights for all other asset classes are collected from the CRSP mutual fund summary database.

2.3.2 Estimating Trading Costs and Expenses of Copycat Funds

The copycat fund returns defined above ignore transaction costs and other expenses. We estimate the trading costs for copycat funds based on the studies by Keim and Madhavan (1997), Wermers (2000) and Kacperczyk, Sialm and Zheng (2008). Keim and Madhavan (1997) provide fitted regressions to estimate the total institutional (explicit and implicit) execution costs for a sample of mutual funds during the period 1991-1993. Wermers (2000) re-computes the coefficients in this regression, excluding trader dummies, since trader types for fund transactions are hard to collect. We start by calculating the numbers of trading orders (both buy and sell) for each stock by comparing the fund's holdings at two consecutive disclosure dates. For simplicity, we assume that the copycat fund is managing the same amount of assets as its primitive fund.[8] We then follow Kacperczyk, Sialm and Zheng (2008) and compute the execution costs for each trade using

$$C_{i,t}^{B} = 1.098 + 0.336D_{i,t}^{Nasdaq} + 0.092Trsize_{i,t} - 0.084Log(mcap_{i,t}) + 13.807(\frac{1}{P_{i,t}}), \quad (2.3)$$

$$C_{i,t}^{S} = 0.979 + 0.058D_{i,t}^{Nasdaq} + 0.214Trsize_{i,t} - 0.059Log(mcap_{i,t}) + 6.537(\frac{1}{P_{i,t}}), \quad (2.4)$$

where $C_{i,t}^{B}$ is the total costs (in percentage of the trade value) of buying stock i during period t, while $C_{i,t}^{S}$ is the total costs (in percentage of the trade value) of selling stock i during period t; $Trsize$ is the trade size (dollar value of the stock trade divided by market capitalization of the stock); $Log(mcap_{i,t})$ is the natural logarithm of the market capitalization of the stock (in thousands); $P_{i,t}$ is the stock price; $D_{i,t}^{Nasdaq}$ is a dummy variable that equals one if the trade occurs on Nasdaq (as opposed to NYSE or AMEX). Having computed the costs of all trades for a fund at a certain disclosure date, we estimate the total trading costs for that fund by summing the costs of all trades and dividing by the total value of the fund's stock portfolio at the beginning of the period. In addition, we winsorize the estimated trading costs in percentage of the trade value or asset value at the 1% tails to remove the contaminating effect of outliers. Monthly transaction costs are calculated by dividing the aggregate transaction costs at a given disclosure date by the number of months since the previous disclosure date.

By assumption, copycat funds do not spend anything on research. Accordingly, they can operate with relatively low levels of expenses. Following Frank et al. (2004), we assume that

[8] In unreported results, we find that the trading costs of maintaining a copycat fund that is 25%, 50%, 75% and 100% as large as the target active fund would only differ in the second decimal place in percentages. This finding justifies our construction of copycat funds buying the same amount of assets as the active funds in the present study. Smaller copycat funds could perform slightly better than the numbers reported in this paper.

they incur expenses equal to those of the Vanguard Total Stock Market Index fund in 2002, 20 basis points. This index fund invests in both large and small capitalization stocks, so its expense ratio should be able to represent a broad cross-section of potential copycat funds. Nevertheless, because this fund is an extreme example of efficiency, some readers may prefer to impose higher expense ratios, and this will lead to straightforward adjustments in our calculations.

2.3.3 Representativeness of Fund Portfolio Disclosure

A potentially important element for the relative success of copycat funds is the validity of the information contained in each portfolio disclosure. A mutual fund manager might have different incentives to either reduce or increase the information revealed by portfolio disclosures hoping to revise the investors' impression on the fund beyond what has been revealed in past returns, e.g. by 'window dressing' or 'portfolio pumping'. Besides, mutual funds that expect large money flows can also attempt to conceal their true positions because predatory traders may be able to front-run on their trades (Coval and Stafford, 2007; Chen, Hanson, Hong and Stein, 2008). Other funds may just engage in active interim trading so that their disclosed holdings hardly represent their average investment styles in the recent past. In short, reported holdings may not be representative of the true underlying investment style of a mutual fund. It is therefore useful for any investor to evaluate the accuracy and representativeness of the disclosed holdings. In our study, we measure the representativeness of the reported holdings by computing the tracking error between the reported fund returns and the returns on a characteristics-based benchmark. The higher the tracking error, the lower is the holdings' representativeness.

To define a benchmark for each mutual fund, we follow Daniel, Grinblatt, Titman and Wermers (1997, DGTW), Chan, Karceski and Lakonishok (1998) and Chan, Chen and Lakonishok (2002). A fund's style is determined by the characteristics of the fund's portfolio holdings along three dimensions: market capitalization, value-growth orientation and momentum. At the end of June, all stocks meeting the selection requirements for both the CRSP stock file and Compustat database are triple-sorted into 125 fractile portfolios based on size, book-to-market (BM) ratio and momentum, where the BM-ratios are industry-adjusted using 48 Fama-French industry groupings. The value-weighted portfolio returns are then computed for each portfolio in the post-ranking months. This provides a set of 125 characteristics-based benchmark portfolio returns. At each disclosure date, we match a stock in a disclosed portfolio to one of the 125 characteristic portfolios to which it belonged on the snapshot date. Next, we calculate the fund style benchmark returns for the disclosed portfolio over the 5 months prior to the disclosure date using the disclosed portfolio weights calculated on the snapshot date and the characteristics-based benchmark returns.

Inspired by Brown, Harlow and Zhang (2009), for each disclosure date t the representativeness of the portfolio holdings disclosed by mutual fund j are measured by

$$TrackingError_t^j = \sigma\langle \widetilde{R}_{j,t-s} - \sum\nolimits_i \widetilde{w}_{i,t-2}\widetilde{R}_{j,t-s}^{b_{i,t-2}} \rangle, \qquad s = 0, 1, ..., 4, \tag{2.5}$$

where $\widetilde{R}_{j,t-s}$ denotes the realized monthly return of mutual fund j for each of the five months prior to the each disclosure date t, $\widetilde{w}_{i,t-2}$ is the value weight for stock i (disclosed at time t) two months before the disclosure date, i.e. the date on which the holdings are valid, and $\widetilde{R}_{j,t-s}^{b_{i,t-2}}$ is the month $t-s$ return of the style benchmark portfolio that is matched to stock i at the end of month $t-2$. Equation (2.5) defines the tracking error of the mutual fund relative to a DGTW-based benchmark five months before the disclosure date (three months before and two months after the snapshot date). The portfolio holdings that are valid at the end of each quarter not only serve as an indication for a fund's investments in that quarter but also convey information of the fund's intended investment strategy in the coming quarter.[9] If the portfolio disclosure is very informative of the investment style the fund has maintained, the style benchmark returns should be highly correlated with the realized fund returns and thus generate a low tracking error. High tracking errors could be driven by window dressing, portfolio pumping, intra-quarter trading as well as overall market volatility. Therefore, we argue that our measure of the disclosure representativeness is a good proxy for the accuracy of holdings in revealing a fund's true investment style.[10]

2.4 Disclosure Frequency and Copycat Fund Performance

In this section, we evaluate whether the reporting frequency of active mutual funds influences the relative success of copycat funds. We start our analysis by looking at the average copycat fund performance relative to active mutual funds. Then we examine the effect of disclosure frequency

[9] Our reporting representativeness measure differs from style consistency in Brown, Harlow and Zhang (2009) in that we impose an additional linear structure in the regression of fund returns against general style benchmark returns. We attempt to capture the extent to which an active fund deviates from its disclosed holdings in a short 5-month period. Besides, holdings-based style evaluation stands out for its higher precision and deeper classification (Chan, Chen, and Lakonishok, 2002; ter Horst, Nijman, and de Roon, 2004). ter Horst, Nijman, and de Roon (2004) evaluate various aspects of returns-based style analysis and find that factor loadings of mutual funds are in general different from the actual portfolio weights.

[10] We find a substantial dispersion in our measure of the representativeness of disclosed fund holdings. In unreported results, we calculate the distribution statistics of the representativeness measures at each disclosure date and then average them over time. The average inter-quartile range is 1.03 standard deviations, which is close to 1.35 for a normal distribution. More importantly, the average kurtosis amounts to 10.25, which indicates excessive numbers of observations in both tails of the distribution.

on the tracking performance of copycat funds by comparing the performance of copycat strategies with different rebalancing frequencies. Finally, we investigate the impact of the disclosure policy change in 2004 on copycat performance and on the information content of the reported holdings.

2.4.1 Performance Comparisons

We compare the performance of copycat funds with their primitive active funds in terms of gross returns as well as net returns. The monthly gross return (GR_t) of a mutual fund is computed by adding back expenses to the reported net return, where expenses include management fees, 12b-1 fees and other administrative expenses.[11] We follow Cohen, Coval and Pastor (2005) and divide the annual expense ratio by 12, and add the resulting number to each monthly net return (NR_t) in a given year.

Table 2.2 reports various performance measures and fund characteristics averaged across all funds year by year. To minimize any possible survival requirements, we include in our calculations each mutual fund that exists during a given month, regardless of whether that fund survives the entire year. For each month we compute the equally weighted average return across all funds existing during that month. These equally weighted monthly fund returns are then compounded into annual returns for both mutual funds and copycat strategies. The U.S. domestic active equity funds on average earn a net return of 10.33% per year, thus underperforming the CRSP value-weighted market index by 1.02%. This is consistent with previous studies showing that actively managed mutual funds on average underperform the market portfolio in net returns (Brown and Goetzmann, 1995; Carhart, 1997; Wermers, 2000). However, with an average annual expense ratio of 1.26%, mutual funds in aggregate outperform the market by 0.24%, suggesting fund managers are able to recoup at least part of their expenses. Average expense ratios increase over time, until 2003, and then start to decline. Turnover ratios show a similar pattern with a peak value of 106% appearing in 2001 and 2002.

Table 2.2 also presents the performance measures and the estimated trading costs for copycat funds. Our copycat strategies generate an average gross return of 11.44% per year, 0.09% higher than the market. However, in practice copycat fund managers cannot exactly replicate the gross performance computed from closing prices due to the reality of liquidity deficiency and price impacts (Grinblatt and Titman, 1989; Wermers, 2006). The average trading costs for copycat

[11] The net mutual fund return is before load fees. Because load fees are borne by investors, ignoring them would only render the relative success of copycat funds more difficult.

Table 2.2: **Annual Fund Performance & Characteristics**

For each month, we calculate the equally weighted average performance measures and fund characteristics across all funds in our sample. To minimize the potential survivorship bias, if any, all funds will be included in the calculation in each month regardless of whether the fund could survive past the next period. Then the equally weighted average monthly returns are compounded into annual returns. Gross copycat fund returns are the returns on the hypothetical portfolios that invest in the disclosed holdings and are rebalanced as soon as the updated holdings are available to the public. Trading costs for copycat funds are estimated using the fitted regression from Kacperczyk, Sialm and Zheng (2008). Trade size and portfolio value of copycat funds are assumed to be identical to their active targets. The estimated trading costs are averaged across all copycat funds for a given year. We assume that for all years in our sample, each copycat fund incurs expenses equal to those of the Vanguard Total Stock Market Index fund in 2002, 20 basis points. We also calculate the average expense ratios and turnover ratios for active funds at the end of each year. This table also presents the number of distinct mutual funds in our merged database each year. In CRSP MFDB, turnover ratios are missing in 1991.

		Mutual Funds				Copycat Funds		
Year	No.	CRSP VW Index Return (% per year)	Mutual Fund Return (% per year)	Expense Ratio (% per year)	Turnover Ratio (% per year)	Gross Copycat Return (% per year)	TC for Copycat Funds (% per year)	Net Copycat Return (% per year)
1985	300	31.41	27.96	1.00	79.17	29.86	0.67	28.78
1986	345	15.56	13.18	0.99	75.62	14.31	0.74	13.24
1987	394	1.83	0.39	1.06	91.84	1.60	0.84	0.64
1988	430	17.56	14.65	1.27	81.19	16.73	0.84	15.54
1989	476	28.43	25.64	1.27	76.99	27.01	0.71	25.81
1990	439	-6.08	-6.65	1.23	84.45	-5.71	0.72	-6.58
1991	533	33.64	37.44	1.02	-	39.38	0.65	38.29
1992	566	9.06	9.24	1.29	71.89	9.22	0.63	8.35
1993	744	11.58	12.82	1.26	75.10	12.66	0.64	11.70
1994	893	-0.76	-1.30	1.25	80.91	-0.42	0.65	-1.27
1995	996	35.67	31.52	1.30	88.93	32.33	0.60	31.27
1996	1088	21.16	19.12	1.29	90.77	20.15	0.59	19.21
1997	1242	30.33	24.34	1.30	87.19	25.82	0.57	24.85
1998	1388	22.28	13.84	1.30	89.11	14.93	0.57	14.00
1999	1374	25.27	25.63	1.29	89.08	24.90	0.49	24.06
2000	1530	-11.09	-0.02	1.28	99.36	0.81	0.49	0.18
2001	1602	-11.27	-10.27	1.35	105.99	-8.96	0.58	-9.63
2002	1655	-20.84	-22.65	1.40	105.91	-21.33	0.72	-22.02
2003	1707	33.14	33.56	1.46	97.23	35.48	0.67	34.34
2004	1699	13.00	12.46	1.34	89.43	13.92	0.62	12.99
2005	1705	7.33	6.97	1.34	89.87	8.59	0.59	7.76
2006	1617	16.22	12.46	1.33	87.36	14.04	0.54	13.19
2007	1602	7.30	6.26	1.30	88.29	7.13	0.48	6.40
2008	1508	-38.31	-38.61	1.28	101.98	-37.85	0.69	-38.52
1985∼2008	3046	11.35	10.33	1.26	88.57	11.44	0.64	10.52

funds amount to 0.64% per year.[12] Looking at the average net returns, we find that copycat funds are able to outperform their actively managed counterparts by 0.19% per year, which is mainly due to the lower expense ratios of copycat funds. The disadvantage of copycat funds in timely access to portfolio information is thus partly offset by their lower expenses.

Table 2.3: **Performance Comparison**

This table compares the average performance of active mutual funds and copycat funds in terms of various measures. We first calculate the equally weighted average fund returns for a given month and then compute the time-series averages. The numbers in the table are the outperformance (underperformance) of copycat funds relative to their actively managed counterparts in percentages per month. Gross copycat fund returns are the returns on the hypothetical portfolios that invest in disclosed holdings and are rebalanced as soon as the updated holdings are available to the public. Trading costs and expenses for copycat funds are defined as previously. t-statistics are reported in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Average Performance Comparison (% per month)	Gross Mutual Fund Return	Net Mutual Fund Return
Gross Copycat Fund Return	-0.01	
	(-1.19)	
Gross Copycat Fund Return after TC	-0.070***	
	(-5.54)	
Gross Copycat Fund Return after Exp		0.073***
		(6.15)
Net Copycat Fund Return		0.020*
		(1.67)

The aggregate picture is summarized in Table 2.3, which compares the gross/net monthly return measures between copycat funds and active mutual funds. The return difference between the two strategies is used as a proxy for judging the relative success of copycat funds. Before any trading costs and expenses, the copycat funds on average underperform the active funds by 1.0 basis point per month, but this difference is statistically indistinguishable from zero.[13] Taking into account transaction costs for copycat funds the return difference becomes -7.0 basis points per month (significant at the 1% level). Thus, before expenses the average active mutual fund outperforms its copycat fund. However, in terms of net returns, copycat funds outperform mutual funds by 2.0 basis points per month, although this difference is statistically significant only at the 10% level. Finally, Table 2.3 also compares the net returns before trading costs for copycat funds and the reported net returns for mutual funds. Ignoring the possible trading costs results in a statistically significant outperformance by copycat funds. The difference of 7.3 basis points

[12]The magnitude of our estimated trading costs is close to other studies. For example, Chalmers, Edelen and Kadlec (1999) estimate the average trading costs for mutual funds to be 0.75% per year. Kacperczyk, Sialm and Zheng (2008) obtain an average of 0.70% per year for trading costs. Chalmers, Edelen and Kadlec (2001), Karceski, Livingston and O'Neal (2004), Edelen, Evans and Kadlec (2006), Wermers (2000) all have estimated trading costs for U.S. mutual fund industry over different subperiods. Their estimates range from 0.75% per year to 0.96% per year. Note that copycat funds, by construction, trade less than the active mutual funds.

[13]Due to the compounding into annual returns in Table 2.2, the numbers in Table 2.3 are slightly different.

per month is larger than the finding of Frank et al. (2004), who consider only a small segment of the mutual fund industry.

The results in Tables 2.2 and 2.3 confirm that, on average, copycat funds are able to generate returns comparable to their actively managed counterparts after trading costs and expenses.[14] The relatively high expenses of mutual funds eliminate almost all the expected gains from active investments. These findings suggest that periodic portfolio disclosure provides outside investors with free-riding opportunities to generate net performance that is comparable to active funds. Outside investors are thus able to obtain the benefits of fund research and investment strategies without incurring the same level of expenses. This raises doubts over the effectiveness of the Commission's mandatory portfolio disclosure requirement that has aimed for protecting fund shareholders' interests.

2.4.2 Disclosure Frequency and Tracking Performance

More frequent access to portfolio holdings might increase the potential for free-riding activities. Nevertheless, before 2004 a substantial number of mutual funds already voluntarily disclosed their holdings more frequently than required. Frank et al. (2004) list several reasons for mutual funds to do so. It is documented, however, that these frequent reporters are not a random sample of the cross-section of mutual funds. In particular, Ge and Zheng (2006) find that funds that are more likely to have an information advantage are less likely to disclose more frequently. Parida and Teo (2010) further study the impact of portfolio disclosure frequency on fund performance and find that the SEC's mandate on more frequency disclosure has adverse effect on the performance of past winning funds. To obtain a first impression on the impact of disclosure frequency we now construct an alternative copycat strategy where we update the copycat portfolio at most two times per year. We do so by always selecting the next snapshot date (and the corresponding disclosure date) for a given fund at least 6 months from the previous one. We then implement our copycat investment strategy using the less frequently (semi-annually) available holdings data. In this case the portfolio weights can be as old as eight months. In Table 2.4 we compare the average performance of the quarterly rebalanced copycat funds (whose portfolios are updated as soon as new holdings are disclosed) and the semi-annually rebalanced copycat funds (whose portfolios are updated at least six months after the previous update). Before transaction costs, the quarterly rebalanced copycat funds outperform the semi-annually rebalanced ones on average by 0.10%

[14] In unreported results, we also compare the risk-adjusted gross and net performance between active funds and our copycat funds using the Fama-French three-factor and Carhart four-factor models, respectively. In terms of economic and statistical significance, the results are very similar.

Table 2.4: **Disclosure Frequency and Copycat Fund Performance**

For each month, we calculate the equally weighted average copycat fund performance measures across the entire database. To minimize the potential survivorship bias, if any, all funds will be included in the calculation in each month regardless of whether the fund survives past the next period. Then the equally weighted average monthly returns are compounded into annual returns. Gross copycat fund returns are the returns on the hypothetical portfolios that invest in disclosed holdings. Trading costs and expenses for copycat funds are defined as previously. Q stands for quarterly rebalancing frequency, i.e. rebalancing the copycat portfolio as soon as the new holdings are available. We also revise our copycat rebalancing algorithm by always selecting the next snapshot date (and the corresponding disclosure date) for each fund at least 6 months from the previous one (and the corresponding disclosure date). S stands for this semi-annual rebalancing frequency. In the last row, the means of performance measures and trading costs are compared between copycat strategies with different rebalancing frequencies. t-statistics are reported in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

	Gross Copycat Fund Return (% per year)		TC for Copycat Funds (% per year)		Gross Copycat Fund Return after TC (% per year)	
Year	Q	S	Q	S	Q	S
1985	29.86	29.63	0.67	0.58	29.03	28.86
1986	14.31	14.31	0.74	0.62	13.46	13.62
1987	1.60	1.43	0.84	0.71	0.85	0.78
1988	16.73	16.82	0.84	0.69	15.77	15.98
1989	27.01	26.72	0.71	0.62	26.06	25.87
1990	-5.71	-5.93	0.72	0.60	-6.39	-6.55
1991	39.38	39.34	0.65	0.55	38.56	38.70
1992	9.22	9.47	0.63	0.53	8.57	8.88
1993	12.66	12.43	0.64	0.54	11.93	11.81
1994	-0.42	-0.35	0.65	0.56	-1.08	-0.91
1995	32.33	32.12	0.60	0.53	31.53	31.45
1996	20.15	20.09	0.59	0.53	19.44	19.45
1997	25.82	25.67	0.57	0.50	25.10	25.07
1998	14.93	14.68	0.57	0.50	14.22	14.04
1999	24.90	24.09	0.49	0.42	24.30	23.61
2000	0.81	0.38	0.49	0.41	0.39	0.05
2001	-8.96	-8.77	0.58	0.49	-9.45	-9.21
2002	-21.33	-21.13	0.72	0.62	-21.86	-21.58
2003	35.48	35.47	0.67	0.55	34.60	34.73
2004	13.92	13.93	0.62	0.51	13.21	13.35
2005	8.59	8.43	0.59	0.46	7.98	7.96
2006	14.04	14.00	0.54	0.42	13.41	13.49
2007	7.13	6.98	0.48	0.39	6.61	6.57
2008	-37.85	-37.76	0.69	0.56	-38.39	-38.31
1985∼2008	11.44	11.34	0.64	0.54	10.74	10.74
Compare Means	0.11** (2.39)		0.10*** (21.48)		0.01 (0.13)	

per year. This differential is statistically significant at the 5% level. Additional analyses (not reported) indicate that the majority of this performance difference is located in the fourth month after construction of the semi-annual copycat strategy (where the quarterly portfolio is updated with more recent portfolio information), which is consistent with our expectations. However, the significantly lower transaction costs resulting from the infrequent trading make the two copycat strategies break even in terms of the average gross return after trading cost (10.74% per year). While more timely access to portfolio information facilitates the discovery of valuable investment opportunities, the additional trading costs incurred by exploiting such information appear to erode realized performance.

2.4.3 The Impact of Disclosure Policy Change on the Tracking Performance

The previous comparison provides only limited evidence for establishing the impact of imposing mandatory quarterly disclosure for all funds, as was done in 2004. First, as mentioned above, the cross-section of funds that voluntarily provides quarterly portfolio updates is a non-random sample of the entire group of mutual funds and, conceivably, is dominated by funds that potentially benefit most (or suffer less) from more frequent disclosure (cf. Wermers, 2001). Second, it ignores the potential equilibrium effects of imposing quarterly disclosure upon all mutual funds. One channel for this is that the additional information could affect investors' money flows. Third, and related to this, it could also affect the incentives for window dressing or other actions that affect the information content of portfolio disclosure.

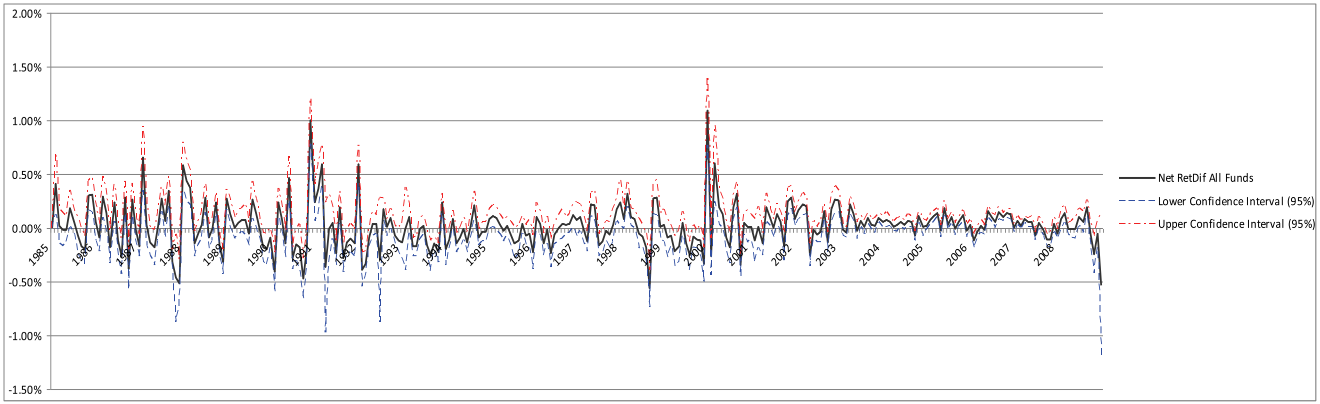
To investigate the influence of the disclosure policy change in 2004 on the average tracking performance of copycat funds, Panel A of Figure 2.1 plots the time series of monthly average net return differentials between copycat funds and active mutual funds. Around 2004 we observe a dramatic change. The fluctuations in the return differences, which were quite high in the period before the Commission mandated quarterly disclosure, flatten out after 2004. Apparently, the average copycat fund is able to track its target fund much more closely since 2004 (we will explore this issue in more detail in Table 2.5). The average level of the performance differential has also increased around 2004 and is slightly above zero in the latter part of the sample period. Besides, we also observe that the 95% confidence interval for the average net tracking performance starts to narrow down gradually after 2004.

Apart from the change in the amount of information related to the more frequent portfolio disclosure per se, it is also possible that the information content of the disclosures themselves

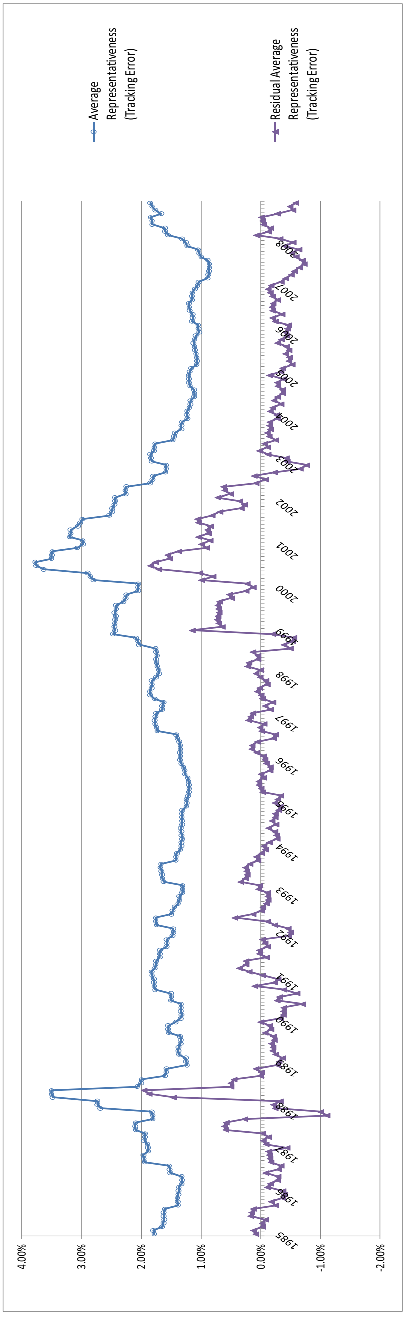
Figure 2.1: **Relative Success of Copycat Funds over Time**

Panel A of this figure depicts the dynamics of the average net return difference between the copycat funds and active funds. Trading costs and expenses for copycat funds are defined as previously. We also present the upper and lower 95% confidence interval for the net return differences in dashed lines. In Panel B, we also plot the average representativeness of the disclosed holdings over time. The representativeness is measured as the tracking error between fund returns and the returns that would have been achieved if the reported holdings are consistent with the fund's actual investment style. The lower the tracking error is, the higher the representative the disclosed holdings are of the true fund investment style. To take out the effect of market volatility, we also regress the time series of average tracking error measures against the market volatility, measured as the standard deviation of the CRSP value-weighted market returns over the same period used to compute the representativeness of holdings. Then we plot the residual representativeness (tracking errors) over time in the figure.

Panel A: Evolution of Net Return Differentials between Active Funds and Copycat Funds



Panel B: Evolution of Reporting Representativeness (Tracking Errors) of Active Mutual Funds



increased after mandatory disclosure was imposed upon all funds. In Panel B of Figure 2.1, we also present how the average representativeness of the disclosed holdings evolves over time. As explained above, portfolio representativeness is measured by the tracking error of mutual funds relative to their style benchmarks, where lower tracking error corresponds to higher representativeness. The most volatile average net return differences all appear during periods when the average representativeness is relatively low (1988, 1991-1993 and 2000-2003). This is consistent with Duong and Meschke (2009), who document a distinctive increase in portfolio pumping during the period 1998-2001, followed by a sharp decrease afterwards. Similarly, the average representativeness (which will be inversely affected by portfolio pumping) increases dramatically after the 2004 policy change. The tracking error declines and stays between 0.50% and 1.20% from 2004 to the end of 2007. To make sure that representativeness is not a simple proxy for market volatility, we also plot the residual representativeness that is orthogonalized with respect to market volatility (the standard deviation of the value-weighted CRSP index over the five months before each disclosure date). Controlling for market volatility strengthens our findings on the impact of the disclosure policy change. Accordingly, the increase in reporting representativeness after 2004 is mainly attributed to the actions on behalf of fund managers to reduce fluctuations in portfolio weights. Overall, the change in mandatory disclosure rules corresponds to much less variation in the average performance differential between copycat funds and their targets, a larger performance differential, and an increase in the representativeness of the disclosed holdings reports.

Panel A of Table 2.5 quantifies the relative success of all copycat funds over time. In terms of net returns, the outperformance of copycat funds relative to active funds increases on average by 0.02% per month after 2004. This difference is statistically insignificant. At the same time, the standard deviation of the net return differences drops substantially from 0.22% per month to only 0.07% per month, and this difference is statistically highly significant.[15] We also present the average representativeness of the disclosed holdings before and after the policy change. Clearly, disclosed holdings on average have become significantly more representative since 2004. Specifically, the average tracking error measure significantly decreases by 0.62% after the policy change. This pattern is particularly eminent if we constrain the pre-2004 period to the most recent five years.

A potentially disturbing effect is that the cross-section of mutual funds before and after 2004 is not exactly the same. New funds enter the market and a substantial number of older funds get

[15]To control for the possible effect of sample size on the standard deviation comparison, we conduct Levene's F-test to test for the homogeneity of population variances.

Table 2.5: **Disclosure Policy Change and The Relative Success of Copycat Funds**

This table reports the mean and standard deviation (in parentheses) of the gross/net return differences between copycat funds and active funds over the two subperiods dividing by the year 2004, and the tracking error of mutual funds relative to their characteristic-based benchmarks (see Equation (2.5)). Trading costs and expenses for copycat funds are defined as previously. We calculate the equally weighted cross-sectional average return differences and the time-series standard deviation. From the entire sample, we select 1601 funds that have survived past 2004 and a subset of those funds (241) that frequently disclosed their holdings before 2004. We define the frequent reporters as the funds that have average annual reporting frequency of no lower than 3.5 per year before 2004 from the surviving funds database. Threshold of 3.5 is the average number of disclosures per year across all funds existing after 2004. As a result, the selected frequently-reporting funds have been consistent in their disclosure policies. Independent sample T-tests and Levene F-tests are performed to compare means and variances respectively. All the numbers in the table are percentages per month. t-statistics are reported in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

		Panel A: All Funds			Panel B: Funds Surviving past 2004			Panel C: Frequent Reporters		
		Gross Return Difference (%/month)	Net Return Difference (%/month)	Tracking Error (%)	Gross Return Difference (%/month)	Net Return Difference (%/month)	Tracking Error (%)	Gross Return Difference (%/month)	Net Return Difference (%/month)	Tracking Error (%)
Before	Mean	-0.02	0.01	1.83	-0.04	-0.02	1.74	-0.05	-0.03	1.65
2004	StdDev	(0.22)	(0.22)	(0.58)	(0.18)	(0.19)	(0.57)	(0.25)	(0.25)	(0.64)
After	Mean	0.00	0.04	1.21	0.00	0.04	1.18	0.00	0.03	1.17
2004	StdDev	(0.07)	(0.07)	(0.26)	(0.07)	(0.08)	(0.24)	(0.10)	(0.12)	(0.22)
Compare	Difference	0.01	0.02	-0.62***	0.04***	0.05***	-0.55***	0.05***	0.06***	-0.48***
Means	T-Test	(0.71)	(1.26)	(-12.07)	(2.66)	(3.37)	(-11.25)	(2.46)	(2.74)	(-9.46)
Compare	Difference	-0.15***	-0.15***	-0.32***	-0.11***	-0.10***	-0.33***	-0.15***	-0.13***	-0.42***
StdDevs	Levene F-Test	(38.89)	(39.10)	(22.02)	(27.64)	(26.00)	(22.71)	(16.17)	(13.23)	(33.57)

liquidated at some point. Such funds may be easier or more difficult to track for a copycat fund. To control for this, we also investigate the effect of the policy change for the subset of mutual funds that experienced the disclosure policy change, and thus existed before and survived past the year 2004. This results in a sample of 1,601 funds. As can be seen from Panel B of Table 2.5, qualitatively the results do not change. Around the policy change the representativeness of the reported holdings increases, the average performance differential between copycat funds and their targets increases and becomes much less volatile. With a t-value of 3.37 the increase of 0.05% per month in the performance differential for this group of copycat funds is statistically significant.

A final subsample only considers those funds that survived the policy change but were already disclosing frequent portfolio information on a voluntary basis. We define this subgroup by the condition that the fund on average issues at least 3.5 portfolio reports per year before 2004. This reduces the sample to 241 funds, which could be expected to be least affected by the policy change. The results shown in Panel C of Table 2.5, however, are again similar. The average net return difference between copycat funds and their targets, which was -0.03% before 2004, improves significantly and becomes positive after 2004, while its volatility reduces from 0.25% to 0.12% per month. Somewhat surprisingly, the relative performance of copycat funds increases after the policy change, even within the group that already frequently disclosed portfolio information. This could be attributable, though, to the increased representativeness of the holdings disclosures. Before 2004, the holdings disclosed by frequent reporters are in general slightly more representative of their recent underlying investment styles than other funds. However, mandating quarterly portfolio disclosure in 2004 forces all funds including the frequent reporters to increase the representativeness of their disclosures to the same level regardless of their past reporting frequencies.

To summarize, mutual funds that experienced the disclosure policy change in general suffer significantly from revealing private information more frequently to the public. Copycat funds are able to remarkably improve their relative tracking performance after the policy change in 2004. The result is robust to controlling for market volatility and restricting the mimicking targets to the past frequent reporters that should be less affected by the increased mandatory disclosure frequency. In general, the policy change has led to an increase in the representativeness of portfolio holdings information, possibly by the desire of fund managers to attract investors who evaluate fund performance and manager skills based on portfolio disclosure. Only by conveying more valuable investment ideas through portfolio disclosure a mutual fund, even a past frequent reporter, can distinguish itself from others that now have the same reporting frequency. On the other hand, the access to less opaque portfolio information enables copycat funds to generate more stable tracking performance. Therefore, the results confirm our expectations that mandating more frequent portfolio disclosure expands the opportunities for potential free-riders to successfully track or even beat their active counterparts.

2.5 The Cross-Section of Copycat Fund Performance

2.5.1 Panel Regressions Explaining the Performance Differential

Our analysis so far shows that copycat strategies on average could generate marginally higher net returns than their active target funds, particularly after the disclosure policy change in 2004. We now turn to exploring the cross-section of copycat funds. To do so, we first relate the return differential between a copycat fund and its target fund to a set of fund characteristics using a panel regression. The dependent variables of the regressions are the gross return difference, the gross return difference after trading costs, and the net return difference. As the return differences can be correlated to common risk factors, we use the residuals from the Carhart (1997) four-factor model as the dependent variable.[16] As explanatory variables we include the mutual fund's expense ratio, turnover ratio, total net assets, fund age, past performance and the representativeness of reported holdings. Past performance of a mutual fund in a given month is measured by the Carhart four-factor alpha estimated over the prior 12 months. For a given copycat fund in each month we first identify the disclosure date of the holdings information used in that month. Then the 4-factor alpha over the 12 months prior to this disclosure date and the representativeness measure corresponding to this disclosure date are aligned with the other explanatory variables for that fund-month observation.

Table 2.6 summarizes the results for three different specifications. We find a significant negative relation between the past performance of active funds and the relative success of copycat funds in all specifications. Other things equal, a 1% increase in past performance of mutual funds on average leads to 0.098% per month decrease in the abnormal discrepancy in net returns between copycat funds and mutual funds. Apparently, it is much easier for a copycat fund to outperform a past loser fund than a past winner fund, even after controlling for fund size, the representativeness of the portfolio holdings and other characteristics. We come back to this issue below. The mutual fund's tracking error has a significantly negative influence on the return dif-

[16] At the beginning of each month for a given fund, we estimate factor loadings over the previous 12 months. We use these estimated coefficients to determine the predicted return differential for the subsequent month. Since the estimation of the factor loadings requires at least one year of data we lose the first year of data for each fund.

Table 2.6: **Determinants of The Relative Success of Copycat Funds**

This table presents the determinants of the outperformance/underperformance of copycat funds relative to their target active mutual funds. Trading costs and expenses for copycat funds are defined as previously. Past performance is measured here using the Carhart alpha of the fund's net returns over the 12 months before each snapshot date. The representativeness of portfolio holdings is measured by the standard deviation of the return gap between the net fund returns of its style benchmark returns over the 5 months prior to each disclosure date. The DGTW (1997) methodology is used to construct our style benchmark for each stock. We use the same portfolio weights computed on the date on which the holdings are valid for each of the 5 months. Fixed effect panel regressions are employed. Standard errors are clustered at fund level. Z-statistics are reported in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

	Abnormal Gross Return Difference	Abnormal Gross Return Difference After TC	Abnormal Net Return Difference
Expense Ratio	3.876***	8.628***	16.266***
	(6.81)	(13.25)	(24.98)
Turnover Ratio	-0.004	-0.023***	-0.023**
	(-0.64)	(-3.33)	(-3.40)
Log(TNA)	0.046***	0.051***	0.051***
	(7.92)	(8.36)	(8.29)
Fund Age	0.076***	0.080***	0.080***
	(4.94)	(4.79)	(4.99)
Past Performance	-0.089***	-0.098***	-0.098***
	(-14.17)	(-14.92)	(-14.91)
Representativeness (Tracking Error)	-1.564***	-2.019***	-1.991**
	(-3.66)	(-4.53)	(-4.47)
Time-fixed effects	Yes	Yes	Yes

ferences in all specifications. Holdings that are more representative imply a larger performance differential. We also find a significant positive relation between fund size and the return differential in all specifications. On average, a 1% increase in the TNA of an active fund results in 0.051% per month increase in the relative net performance of its copycat counterpart. The expense ratio and fund age both have a significant positive effect on the net return differences, while the effect of turnover is negative.

While the results in Table 2.6 suggest that it can be attractive for a copycat fund to target, for example, past losers or funds with more representative holdings, it is not necessarily the case that such a strategy performs well relative to other copycat strategies. To investigate this issue, we evaluate the performance of copycat funds for different subsets of mutual fund targets using univariate portfolio sorts. We focus on two dimensions: the representativeness of the periodically disclosed portfolio holdings, and past fund performance.[17] The first dimension is particularly interesting given that representativeness has been affected by the increased mandatory disclosure policy since 2004.

2.5.2 Portfolio Sorts on Representativeness of Holdings

Before moving to portfolio sorts, we first analyze the determinants of the representativeness of disclosed holdings. At each snapshot date, we collect TNAs, new money growth over a three-month period prior to the snapshot date, expense ratios, fund net turnover, fund age, past performance measured by the Carhart four-factor alphas over the previous 12 months, and market volatility. Table 2.7 summarizes our main findings. We add the squared past performance in the second specification because both skilled and unskilled funds could have incentives to camouflage their portfolios. For instance, past losers may be reluctant to disclose their true investment positions because they try to avoid exposing their excessive risk taking or style drifting behavior to investors. On the other hand, past winners may tend to do so hoping to protect their valuable private information derived from costly research. In both specifications, time dummies are included. The results show a significantly positive (and nonlinear) relation between the past performance of mutual funds and the tracking error measure. This is consistent with Meier and Schaumburg (2006) who report that funds with poor recent performance are more likely to report misleading holdings. Portfolio turnover, fund expenses and market return volatility are all significantly and positively associated with the tracking error measure. Intuitively, frequent and

[17] We believe these two dimensions, namely, information validity and fund performance, are the primary concerns for an ordinary outside investor. Results using sorts based on other fund characteristics are not reported and available upon request.

dramatic changes in fund portfolio weights and stock returns will make it harder for copycat funds to track their active targets. Furthermore, younger funds and funds with capital outflows are found to disclose holdings less representative of their true investment styles. Intuitively, more experienced managers tend to manipulate their portfolio disclosures while the fund managers facing shrinking assets would likely paint a different picture of their investment strategy hoping to attract more investor money.

Table 2.7: **Determinants of Representativeness of Portfolio Disclosures**
This table presents the determinants of window dressing which leads to variation in how representative the disclosed holdings of a mutual fund are of its true investment style. The representativeness measure is defined as previously and is aligned with other variables at each snapshot date for each mutual fund. Past performance is measured here using the Carhart alpha for the fund's net returns over the 12 months before each snapshot date. New money growth is defined as the relative change in TNA over the 3 months before each snapshot date given the net return and the assumption that all inflows happen at the end of the period. Market volatility is the standard deviation of the value-weighted CRSP index over the five months before each disclosure date. Fixed effect panel regressions are employed. Standard errors are clustered at fund level. Z-statistics are reported in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

	Representativeness of Portfolio Disclosure (Tracking Error)	
Past Performance	0.07***	0.06***
	(4.66)	(4.46)
Past Performance^2		4.05**
		(2.13)
Turnover Ratio	0.00**	0.00***
	(2.74)	(2.65)
Expense Ratio	0.06***	0.05***
	(5.52)	(4.60)
Log(TNA)	0.00	0.00
	(1.52)	(1.53)
Fund Age	0.00***	-0.00***
	(-3.85)	(-3.44)
New Money Growth	-0.00***	-0.00***
	(-100.67)	(-98.02)
Market Volatility	0.07***	0.07***
	(19.25)	(19.06)
Time-Fixed Effects	Yes	Yes
R^2 (in %)	24.48	20.49
F-value	122.35***	121.58***

We next analyze the performance of copycat strategies focused at particular levels of representativeness. To do so we first sort all funds into decile portfolios, at the end of each February, May, August and November[18], and then calculate the equally weighted post-ranking portfolio returns across all active and copycat funds for the subsequent three months. If any disclosure

[18]Although some mutual funds have snapshot dates that do not coincide with calendar quarter ends, the vast majority of mutual funds file their holdings in these months.

happens for a mutual fund between the portfolio rebalancing dates, we adjust the copycat replicating strategy for that fund and wait until the next portfolio rebalancing date to re-rank all mutual funds.[19] Next, we link the post-ranking portfolio returns across disclosure periods to generate full time series of post-ranking returns. Table 2.8 reports the cross-sectional variation in copycat fund performance sorted on our representativeness measure, where decile 10 contains the funds whose reported holdings are the least representative of their true investment strategies in the recent past (highest tracking error). Panel A presents the time-series average return differences across decile portfolios, panel B provides similar measures after controlling for exposure to the three Fama-French factors, and panel C presents four-factor Carhart (1997) alphas. The post-ranking average returns for active funds in decile 10 and the returns for the corresponding copycat funds tend to be significantly lower than those for the other decile portfolios in both panels. The discrepancies in gross/net copycat fund returns between the two extreme deciles are all negative and in many cases statistically significant.

Before trading costs, no clear pattern is found in the gross return differences between the copycat funds and their targets (panel A). Moreover, the majority of these gross return differences are all insignificantly different from zero. When we take trading costs into consideration, the average relative gross performance of copycat funds decreases monotonically from -0.02% per month (significant at 10% level) in decile 1 to -0.15% per month (significant at 1% level) in decile 10. The difference between these two extreme deciles is -0.13% per month, which is significant at 1% level. The monotonic pattern is mainly attributed to the increasing trading costs for copycat funds across deciles (from 0.03% to 0.12%). In unreported results, the increasing trading costs for copycat funds are closely related to increasing net turnover of the active funds. The last column of Panel A in Table 2.8 presents the net return differences between the copycat funds and the active funds. The net return differences still decrease (though not strictly monotonically) from the low tracking error decile (1) to the high tracking error decile (10). The difference in average returns between the two extreme deciles equals -0.08% per month, which is significant at the 1% level. Interestingly, copycat funds in decile 1 significantly outperform their active targets that disclose highly representative holdings.

The evidence of the relative success of copycat funds is robust to alternative ways of risk adjustment, as shown in Panels B and C of Table 2.8. Using the four-factor alpha of net re-

[19]For instance, if a mutual fund has disclosure dates in February and March we rebalance the copycat strategy at the end of March based on the newly released holdings information. Thus after the sorting procedure at the end of February the post-ranking returns for the decile portfolio to which this fund belongs will be influenced by the holdings disclosed in March. However, this does not influence our sorting procedure because we wait until May to rebalance the decile portfolios.

Table 2.8: **The Representativeness of Portfolio Disclosures and The Relative Success of Copycat Strategies**

At the end of February, May, August and November, all mutual funds are sorted into decile portfolios based on the extent of representativeness of holdings. The performance of mutual funds and their corresponding copycat funds in the subsequent 3 months are kept. Equally weighted average portfolio returns are then calculated for each of the 3 months. At the end these portfolio returns/return differences are linked across quarters to generate 10 time series of returns. We next calculate for each decile portfolio the average return (Panel A), the Fama-French three-factor alpha (panel B) and the Carhart four-factor alpha (Panel C) for various performance measures shown below. Gross copycat fund returns are the returns on the hypothetical portfolios that replicate disclosed holdings. The return difference measures the relative outperformance or underperformance of copycat funds compared to their mimicking targets. The representativeness of portfolio disclosure and the trading costs and expenses for copycat funds are defined as previously. All numbers are monthly returns in percentages; t-statistics are reported in parentheses. * significant at 10% level, * at 5% level, ** at 1% level.

Panel A: Average Return								
	Gross MF Return	Net MF Return	Gross Copycat Return	Copycat Return after TC	Net Copycat Return	Gross RetDif	Gross RetDif after TC	Net RetDif
Decile 1	1.03	0.94	1.04	1.01	0.99	0.01	-0.02*	0.05***
	(4.47)	(4.10)	(4.48)	(4.36)	(4.29)	(1.17)	(-1.65)	(5.46)
Decile 2	1.07	0.98	1.05	1.02	1.01	-0.01	-0.04***	0.03**
	(4.48)	(4.10)	(4.38)	(4.24)	(4.17)	(-0.97)	(-3.58)	(2.33)
Decile 3	1.06	0.97	1.06	1.02	1.00	0.00	-0.04***	0.04***
	(4.44)	(4.05)	(4.39)	(4.23)	(4.16)	(-0.24)	(-4.02)	(3.63)
Decile 4	1.07	0.98	1.08	1.04	1.02	0.00	-0.04***	0.04***
	(4.46)	(4.06)	(4.38)	(4.22)	(4.15)	(0.11)	(-2.87)	(3.02)
Decile 5	1.05	0.95	1.03	0.98	0.96	-0.02	-0.07***	0.01
	(4.24)	(3.84)	(4.04)	(3.87)	(3.80)	(-1.32)	(-3.70)	(0.69)
Decile 6	1.07	0.97	1.06	1.01	0.99	-0.02	-0.07***	0.02
	(4.25)	(3.85)	(4.13)	(3.93)	(3.86)	(-1.19)	(-4.87)	(1.41)
Decile 7	1.04	0.93	1.02	0.97	0.95	-0.01	-0.07***	0.02
	(3.99)	(3.58)	(3.79)	(3.57)	(3.51)	(-0.62)	(-3.77)	(1.03)
Decile 8	1.07	0.96	1.05	0.98	0.96	-0.02	-0.09***	0.00
	(3.87)	(3.47)	(3.73)	(3.49)	(3.43)	(-1.23)	(-5.20)	(0.23)
Decile 9	1.09	0.97	1.08	0.99	0.97	-0.01	-0.10***	0.00
	(3.48)	(3.11)	(3.34)	(3.08)	(3.02)	(-0.46)	(-4.10)	(0.16)
Decile 10	0.96	0.82	0.93	0.81	0.80	-0.03	-0.15***	-0.03
	(2.48)	(2.13)	(2.36)	(2.07)	(2.02)	(-0.86)	(-4.09)	(-0.72)
D10 - D1	-0.07	-0.12	-0.11	-0.20	-0.20	-0.04	-0.13***	-0.08***
	(-0.31)	(-0.54)	(-0.50)	(-0.90)	(-0.90)	(-1.30)	(-3.99)	(-2.40)

	Panel B: Fama-French Alpha							
	Gross MF Return	Net MF Return	Gross Copycat Return	Copycat Return after TC	Net Copycat Return	Gross RetDif	Gross RetDif after TC	Net RetDif
Decile 1	0.02	-0.07	0.02	-0.01	-0.02	0.00	-0.02***	0.04***
	(0.51)	(-2.21)	(0.59)	(-0.25)	(-0.76)	(0.35)	(-2.57)	(4.73)
Decile 2	0.05	-0.04	0.03	-0.01	-0.02	-0.02	-0.05***	0.02
	(1.32)	(-1.17)	(0.71)	(-0.16)	(-0.61)	(-1.61)	(-3.99)	(1.43)
Decile 3	0.04	-0.06	0.02	-0.02	-0.03	-0.01	-0.05***	0.02**
	(0.99)	(-1.50)	(0.57)	(-0.40)	(-0.83)	(-1.46)	(-5.21)	(2.27)
Decile 4	0.04	-0.06	0.02	-0.02	-0.04	-0.02	-0.06***	0.02
	(0.95)	(-1.35)	(0.49)	(-0.45)	(-0.84)	(-1.42)	(-4.50)	(1.53)
Decile 5	0.01	-0.09	-0.04	-0.09	-0.10	-0.05**	-0.09***	-0.01
	(0.20)	(-2.10)	(-0.88)	(-1.85)	(-2.21)	(-2.41)	(-4.54)	(-0.57)
Decile 6	0.04	-0.06	0.01	-0.04	-0.06	-0.03**	-0.08***	0.00
	(0.88)	(-1.43)	(0.19)	(-0.95)	(-1.33)	(-2.30)	(-6.13)	(0.33)
Decile 7	0.00	-0.10	-0.03	-0.09	-0.10	-0.03*	-0.09***	0.00
	(0.11)	(-2.18)	(-0.57)	(-1.82)	(-2.18)	(-1.87)	(-5.35)	(-0.08)
Decile 8	0.04	-0.07	0.00	-0.07	-0.08	-0.03**	-0.10***	-0.01
	(0.71)	(-1.46)	(0.03)	(-1.33)	(-1.67)	(-2.07)	(-6.18)	(-0.57)
Decile 9	0.07	-0.04	0.06	-0.03	-0.05	-0.02	-0.10***	0.00
	(1.06)	(-0.62)	(0.73)	(-0.39)	(-0.62)	(-0.68)	(-4.14)	(-0.14)
Decile 10	-0.04	-0.18	-0.09	-0.21	-0.23	-0.05	-0.17***	-0.05
	(-0.40)	(-1.80)	(-1.03)	(-2.30)	(-2.49)	(-1.47)	(-4.66)	(-1.37)
D10 - D1	-0.06	-0.11	-0.11	-0.20**	-0.20**	-0.06*	-0.15***	-0.09***
	(-0.51)	(-0.99)	(-1.14)	(-2.03)	(-2.03)	(-1.69)	(-4.29)	(-2.78)

	Panel C: Carhart Alpha							
	Gross MF Return	Net MF Return	Gross Copycat Return	Copycat Return after TC	Net Copycat Return	Gross RetDif	Gross RetDif after TC	Net RetDif
Decile 1	0.03	-0.06	0.03	0.00	-0.01	0.00	-0.02**	0.05***
	(0.77)	(-1.60)	(0.83)	(0.12)	(-0.30)	(0.48)	(-2.28)	(4.59)
Decile 2	0.06	-0.03	0.04	0.00	-0.01	-0.03*	-0.06***	0.02
	(1.42)	(-0.63)	(0.79)	(0.09)	(-0.26)	(-1.85)	(-4.17)	(1.09)
Decile 3	0.05	-0.04	0.03	-0.01	-0.03	-0.02**	-0.06***	0.02
	(1.10)	(-0.93)	(0.58)	(-0.22)	(-0.57)	(-2.07)	(-5.57)	(1.37)
Decile 4	0.06	-0.04	0.03	-0.01	-0.03	-0.03**	-0.07***	0.01
	(1.28)	(-0.78)	(0.54)	(-0.27)	(-0.61)	(-2.39)	(-5.36)	(0.44)
Decile 5	0.03	-0.07	-0.02	-0.07	-0.08	-0.06***	-0.10***	-0.02
	(0.72)	(-1.42)	(-0.43)	(-1.25)	(-1.56)	(-2.64)	(-4.68)	(-0.88)
Decile 6	0.05	-0.05	0.02	-0.03	-0.05	-0.04***	-0.09***	0.00
	(1.13)	(-1)	(0.35)	(-0.68)	(-1.02)	(-2.57)	(-6.08)	(-0.15)
Decile 7	0.00	-0.10	-0.04	-0.10	-0.11	-0.04***	-0.10***	-0.01
	(0.03)	(-1.95)	(-0.71)	(-1.80)	(-2.11)	(-2.54)	(-6.28)	(-0.59)
Decile 8	0.02	-0.09	-0.01	-0.08	-0.10	-0.03*	-0.10***	-0.01
	(0.39)	(-1.67)	(-0.21)	(-1.49)	(-1.80)	(-1.88)	(-5.84)	(-0.45)
Decile 9	0.01	-0.11	0.00	-0.09	-0.10	0.00	-0.09***	0.01
	(0.07)	(-1.44)	0.00	(-1.06)	(-1.26)	(-0.20)	(-3.68)	(0.35)
Decile 10	-0.10	-0.23	-0.12	-0.24	-0.26	-0.03	-0.14***	-0.02
	(-0.92)	(-2.22)	(-1.24)	(-2.41)	(-2.57)	(-0.70)	(-3.73)	(-0.60)
D10 - D1	-0.12	-0.18	-0.16	-0.24**	-0.24**	-0.03	-0.12***	-0.07*
	(-1.12)	(-1.59)	(-1.50)	(-2.35)	(-2.35)	(-0.87)	(-3.30)	(-1.89)

turns, we find that copycat funds significantly outperform their active counterparts on average by 0.05% per month in decile 1, but underperform by 0.02% per month in decile 10. Funds in the lower deciles report the most representative holdings and copycatting them results in a net return of around 1% per month, which exceeds the net return of mutual funds in each decile. Therefore, by identifying the active funds whose reported holdings are highly representative of their true investment styles, investors are able to outperform these target funds as well as the majority of the fund universe by simply replicating their portfolios. Thus, the use of representative reported holdings for copycat strategies helps achieve superior performance net of trading costs and expenses at both relative and absolute levels.

To consider the evolution of the relative net return difference across deciles, we plot the net return difference for the two extreme deciles sorted on reporting representativeness against time in Figure 2.2. We observe that the funds that disclose the most representative holdings information are much easier for the potential copycat funds to track. The tracking volatility using the most representative holdings is significantly smaller than using the most opaque information. Moreover, the influence of the 2004 policy change appears to be important mainly for funds that used to engage in activities of camouflaging their portfolio disclosures. When we compare the average net return difference (between copycat funds and their active targets) before and after the 2004 policy change, the results show a significant increase in the net return difference for funds in decile 10 that disclose the least representative holdings versus an insignificant change for funds in decile 1.

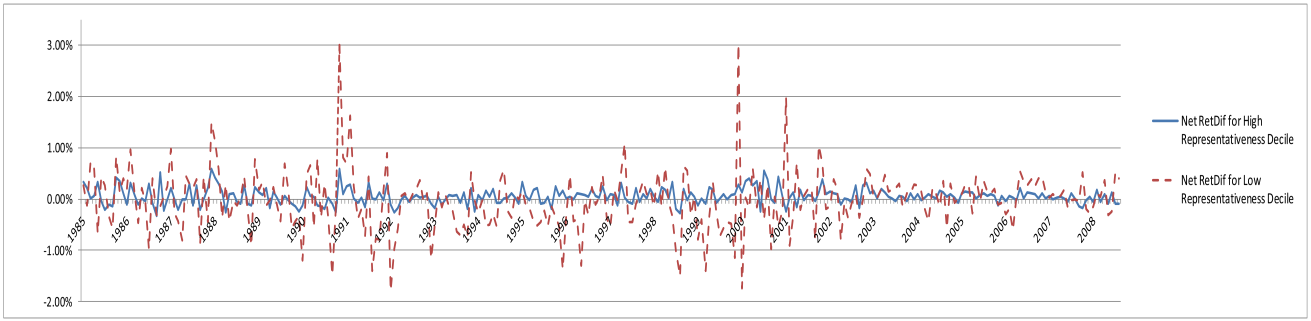
2.5.3 Portfolio Sorts on Past Performance

We conclude our analysis by investigating the performance of copycat strategies focusing upon winning or losing mutual funds. Table 2.9 presents the results when we construct decile portfolios based on the average fund returns over the previous year. Sorting funds using their past four-factor alpha produces very similar results. In Panel A, we present the gross and net performance of the mutual funds in these portfolios, the gross and net performance of the copycat funds and their differences, all in terms of raw returns. Panels B and C present the results after risk adjustment using the Fama-French three-factor and the Carhart four-factor models. The results in the table confirm the findings of relative performance persistence of Carhart (1997), with a net return spread of 0.56% between winner and loser funds. As shown in panel C, this relative performance persistence is mainly attributable to the stock momentum documented by Jegadeesh and Titman (1993).

In Panel A of Table 2.9, we see that copycat funds tracking past losers in decile 1 on average

Figure 2.2: **Reporting Representativeness and Relative Success of Copycat Funds over Years**

At the end of February, May, August and November, all mutual funds are sorted into decile portfolios based on the representativeness of disclosed holdings. The representativeness is measured as the tracking error between fund returns and the returns that would have been achieved if the reported holdings are consistent with the fund's actual investment style. The performance of mutual funds and their corresponding copycat funds in the subsequent 3 months are kept. Equally weighted portfolio returns are then calculated for each of the 3 months. At the end these portfolio returns are linked across quarters to generate 10 time series of returns. We next calculate the average mutual fund net returns and the average copycat fund returns respectively for each decile portfolio. Trading costs and expenses for copycat funds are defined as previously. This figure depicts the evolution of the average net return differences between the active and copycat funds for both top and bottom deciles.



significantly outperform their actively managed counterparts by 0.06% per month before trading costs and expenses. In contrast, the copycat funds mimicking past winner funds significantly underperform their mimicking targets by 0.12% per month. The gross return difference between these two extreme deciles is -0.18% per month (significant at 1% level), which confirms our earlier findings that past performance of active funds is negatively related to the relative success of copycat funds. If past performance is an appropriate proxy for fund manager skills, skilled managers seem to be better at protecting their private information while the unskilled funds can be easily outperformed by a simple copycat strategy. Alternatively, the unobserved interim trading by past skilled managers enhances their performance, while that of unskilled managers deteriorates their (already bad) performance.

Deducting trading costs for copycat funds does not change the decreasing trend of the gross return differences across deciles but now almost all of them become significantly negative. This is in line with our previous result that copycat funds on average significantly underperform the active funds in gross returns after trading costs. The last column of Panel A in Table 2.9 shows the variation in net return differences after trading costs and expenses. Tracking past losers results in an average outperformance of 0.09% per month in net returns while mimicking past winners leads to an underperformance of 0.11% per month. Both differences are statistically significant at the 1% level. The 0.20% per month difference between the two extreme deciles is also significant. Correcting for exposure to the four Carhart factors results in an even bigger return difference. In Panel C, we find a net Carhart alpha difference of -0.13% per month for decile 10 and 0.09% per month for decile 1. The discrepancy between the two extreme deciles is 0.23% per month. All numbers are significant at the 1% level. The copycat funds' advantages in lower expenses explain their significant outperformance when tracking past losing funds. However, this advantage is not large enough to offset the significant underperformance in gross returns after trading costs when tracking past winners. It is noteworthy that the trading costs for copycat funds and the expense ratios for active funds are comparable in magnitude and both show a U-shaped pattern across deciles. This is exactly why the pattern of net return differences is similar to that of the gross return differences.

Overall, we see a significant cross-sectional variation in the relative success of copycat funds when the mimicking targets differ in their past performance. Despite underperforming their active counterparts, copycat funds mimicking past winners can still generate an average net return of 1.02% per month that beats nine out of ten decile portfolios formed on past fund performance. Given that the performance persistence for mutual funds can be mainly attributed to momentum, duplicating the holdings of past winning funds provides investors with a cheap momentum strat-

Table 2.9: **Past Mutual Fund Performance and The Relative Success of Copycat Strategies**

At the end of February, May, August and November, all funds in our sample are sorted into decile portfolios based on the average market-adjusted fund returns over the previous 12 months. The performance of mutual funds and their corresponding copycat funds in the subsequent 3 months are kept. Equally weighted average portfolio returns are then calculated for each of the 3 months. At the end these portfolio returns are linked across quarters to generate 10 time series of returns. We next calculate for each decile portfolio the average return (Panel A), the Fama-French three-factor alpha (panel B) and the Carhart four-factor alpha (Panel C) for various performance measures shown below. The return difference measures the relative outperformance or underperformance of copycat funds relative to their mimicking targets. Gross copycat fund returns are the returns on the hypothetical portfolios that replicate disclosed holdings. Trading costs and expenses for copycat funds are defined as previously. All numbers are monthly returns in percentages; t-statistics are reported in parentheses. * significant at 10% level, * at 5% level, ** at 1% level.

Panel A: Average Return								
	Gross MF Return	Net MF Return	Gross Copycat Return	Copycat Return after TC	Net Copycat Return	Gross RetDif	Gross RetDif after TC	Net RetDif
Decile 1	0.69	0.56	0.75	0.67	0.66	0.06**	-0.02	0.09***
	(2.17)	(1.77)	(2.29)	(2.04)	(1.99)	(2.23)	(-0.62)	(3.23)
Decile 2	0.78	0.67	0.78	0.72	0.71	0.00	-0.06***	0.04
	(2.69)	(2.31)	(2.62)	(2.42)	(2.36)	(0.13)	(-2.48)	(1.55)
Decile 3	0.79	0.69	0.83	0.78	0.76	0.04**	-0.01	0.07***
	(2.81)	(2.45)	(2.91)	(2.73)	(2.67)	(2.18)	(-0.72)	(4.18)
Decile 4	0.86	0.77	0.86	0.81	0.80	-0.01	-0.05***	0.03**
	(3.10)	(2.75)	(3.03)	(2.87)	(2.81)	(-0.37)	(-3.62)	(2.20)
Decile 5	0.91	0.81	0.89	0.85	0.83	-0.02	-0.07***	0.01
	(3.31)	(2.96)	(3.14)	(2.98)	(2.93)	(-1.39)	(-3.97)	(0.82)
Decile 6	0.89	0.80	0.87	0.82	0.80	-0.03*	-0.07***	0.01
	(3.17)	(2.82)	(3.02)	(2.85)	(2.79)	(-1.70)	(-4.68)	(0.43)
Decile 7	0.97	0.87	0.96	0.91	0.90	-0.01	-0.05***	0.03*
	(3.41)	(3.07)	(3.36)	(3.19)	(3.14)	(-0.44)	(-3.48)	(1.68)
Decile 8	0.99	0.89	0.97	0.92	0.90	-0.02	-0.07***	0.01
	(3.38)	(3.05)	(3.31)	(3.13)	(3.07)	(-1.20)	(-4.3)	(0.65)
Decile 9	1.05	0.95	1.02	0.96	0.94	-0.03*	-0.09***	-0.01
	(3.34)	(3.02)	(3.21)	(3.02)	(2.97)	(-1.77)	(-4.91)	(-0.34)
Decile 10	1.23	1.12	1.12	1.03	1.02	-0.12***	-0.20***	-0.11***
	(3.34)	(3.04)	(2.97)	(2.74)	(2.70)	(-4.24)	(-7.03)	(-3.79)
D10 - D1	0.54*	0.56*	0.36	0.36	0.36	-0.18***	-0.18***	-0.20***
	(2.11)	(2.18)	(1.36)	(1.36)	(1.36)	(-4.8)	(-4.74)	(-5.21)

Panel B: Fama-French Alpha								
	Gross MF Return	Net MF Return	Gross Copycat Return	Copycat Return after TC	Net Copycat Return	Gross RetDif	Gross RetDif after TC	Net RetDif
Decile 1	-0.24	-0.37	-0.20	-0.28	-0.30	0.04	-0.04	0.07***
	(-1.88)	(-2.86)	(-1.47)	(-2.08)	(-2.20)	(1.57)	(-1.38)	(2.56)
Decile 2	-0.13	-0.24	-0.16	-0.22	-0.23	-0.02	-0.08***	0.01
	(-1.51)	(-2.73)	(-1.72)	(-2.38)	(-2.56)	(-0.80)	(-3.01)	(0.39)
Decile 3	-0.11	-0.21	-0.08	-0.14	-0.15	0.03	-0.02	0.06***
	(-1.66)	(-3.15)	(-1.17)	(-1.87)	(-2.10)	(1.50)	(-1.29)	(3.35)
Decile 4	-0.04	-0.14	-0.05	-0.10	-0.12	-0.01	-0.06***	0.02
	(-0.73)	(-2.50)	(-0.94)	(-1.74)	(-2.03)	(-0.90)	(-4.11)	(1.57)
Decile 5	0.02	-0.08	-0.02	-0.06	-0.08	-0.03**	-0.08***	0.00
	(0.39)	(-1.72)	(-0.38)	(-1.37)	(-1.74)	(-2.35)	(-5.28)	(0.09)
Decile 6	-0.01	-0.10	-0.04	-0.08	-0.10	-0.03**	-0.08***	0.00
	(-0.13)	(-2.64)	(-1.02)	(-2.29)	(-2.74)	(-2.02)	(-4.88)	(-0.02)
Decile 7	0.08	-0.01	0.07	0.02	0.00	-0.01	-0.06***	0.02
	(2.30)	(-0.42)	(1.67)	(0.53)	(0.12)	(-0.78)	(-3.66)	(1.21)
Decile 8	0.12	0.02	0.09	0.04	0.02	-0.03	-0.08***	0.00
	(2.37)	(0.39)	(1.73)	(0.76)	(0.44)	(-1.52)	(-4.49)	(0.21)
Decile 9	0.20	0.10	0.16	0.11	0.09	-0.03	-0.09***	-0.01
	(2.47)	(1.21)	(2.03)	(1.31)	(1.10)	(-1.53)	(-4.20)	(-0.36)
Decile 10	0.41	0.30	0.28	0.20	0.19	-0.13***	-0.21***	-0.12***
	(3.20)	(2.35)	(2.13)	(1.51)	(1.39)	(-4.69)	(-7.61)	(-4.29)
D10 - D1	0.66***	0.68***	0.48**	0.49*	0.49*	-0.17***	-0.17***	-0.19***
	(2.80)	(2.88)	(1.97)	(1.97)	(1.97)	(-4.37)	(-4.32)	(-4.75)

Panel C: Carhart Alpha								
	Gross MF Return	Net MF Return	Gross Copycat Return	Copycat Return after TC	Net Copycat Return	Gross RetDif	Gross RetDif after TC	Net RetDif
Decile 1	0.05	-0.07	0.12	0.04	0.02	0.06**	-0.02	0.09***
	(0.47)	(-0.63)	(0.99)	(0.30)	(0.17)	(2.19)	(-0.60)	(3.13)
Decile 2	0.05	-0.06	0.03	-0.03	-0.05	-0.02	-0.08	0.01
	(0.52)	(-0.70)	(0.29)	(-0.34)	(-0.52)	(-0.62)	(-2.54)	(0.41)
Decile 3	0.01	-0.09	0.04	-0.01	-0.03	0.03*	-0.02	0.07***
	(0.12)	(-1.29)	(0.56)	(-0.11)	(-0.33)	(1.85)	(-0.95)	(3.73)
Decile 4	0.04	-0.06	0.02	-0.02	-0.04	-0.02	-0.06***	0.02
	(0.66)	(-1.03)	(0.34)	(-0.40)	(-0.66)	(-1.06)	(-3.96)	(1.17)
Decile 5	0.05	-0.04	0.02	-0.03	-0.05	-0.04**	-0.08***	0.00
	(0.99)	(-0.77)	(0.29)	(-0.54)	(-0.86)	(-2.42)	(-5.10)	(-0.20)
Decile 6	-0.01	-0.10	-0.05	-0.10	-0.11	-0.04***	-0.09***	-0.01
	(-0.17)	(-2.37)	(-1.12)	(-2.20)	(-2.59)	(-2.89)	(-6.12)	(-0.61)
Decile 7	0.02	-0.08	0.00	-0.05	-0.06	-0.02	-0.06***	0.02
	(0.44)	(-2.14)	(0.02)	(-1.07)	(-1.45)	(-0.97)	(-3.96)	(1.06)
Decile 8	-0.01	-0.11	-0.04	-0.09	-0.11	-0.03*	-0.08***	0.00
	(-0.29)	(-2.52)	(-0.92)	(-2.08)	(-2.46)	(-1.66)	(-4.71)	(0.08)
Decile 9	-0.01	-0.11	-0.05	-0.10	-0.12	-0.03	-0.09***	-0.01
	(-0.24)	(-2.11)	(-0.77)	(-1.73)	(-2.01)	(-1.35)	(-3.71)	(-0.33)
Decile 10	0.07	-0.04	-0.07	-0.15	-0.17	-0.14***	-0.23***	-0.13***
	(0.78)	(-0.43)	(-0.77)	(-1.64)	(-1.82)	(-5.09)	(-8.01)	(-4.75)
D10 - D1	0.02	0.03	-0.19	-0.19	-0.19	-0.21***	-0.21***	-0.23***
	(0.10)	(0.20)	(-1.09)	(-1.09)	(-1.09)	(-5.14)	(-5.11)	(-5.54)

egy as found by Wermers (2003). This could also explain why such superior performance of copycat funds relative to the majority of active funds vanishes when adjusting for the momentum factor. Parida and Teo (2010) also document a significant performance decrease for winning funds in recent years after the SEC mandates more frequent portfolio disclosure. It appears that past winners are more exposed to the exploitation of reported holdings by outsiders, especially after the disclosure policy change.

2.6 Conclusion

Portfolio disclosure can be costly to actively managed mutual funds because it enables competitors to construct portfolios that mimic, with a lag, the primitive fund's holdings. Using a large database of active mutual fund holdings, we show that, on average, copycat funds can produce returns that are close to their target funds, taking into account transaction costs and expenses. After extensive discussion and deliberation, the SEC increased the mandatory reporting frequency of mutual fund holdings from semi-annually to quarterly in 2004. Our results show that this policy change leads to an increase in the return differential between copycat funds and their targets, and a strong reduction in the volatility of the return differentials. This implies that since 2004 it is easier for outside investors to free-ride on disclosed fund holdings, which might contradict the Commission's original intention to protect fund shareholders' interests. At the same time, the policy change has increased the representativeness of the reported holdings, which could indicate that window dressing and other ways of camouflaging the true fund's holdings have reduced in the situation where all funds are mandated to quarterly disclose their holdings.

This paper also characterizes certain subgroups of mutual funds whose disclosed holdings are most valuable for free-riding investors. The significant cross-sectional dispersion in the relative success of copycat funds helps the potential free-riders to better understand the way in which holdings information can be used. We show that past fund performance and the representativeness of reported holdings are important determinants of the relative success of copycat funds. It appears that the smartest copycat strategy would be to mimic the portfolios of funds that disclose representative holdings and exhibit good recent performance. Finally, our findings provide some insights into the hidden cost of frequent portfolio disclosure for active funds. Policymakers will also have to consider the benefits of portfolio disclosure such as increased transparency to strike a balance for an optimal disclosure policy design.

2.A Database Construction and Sample Selection

We select all U.S. open-ended mutual funds from both CRSP MFDB and TFN/CDA databases spanning the period January 1985 – December 2008. When a mutual fund offers multiple share classes we select the share class having the longest history of data; if there is no difference by this measure, we select the fund with the lowest CRSP fund identifier (in our sample more than 90% of funds have more than one share class).[20] During the majority of the sample period U.S. mutual funds are required to file their holdings to the SEC on a semi-annual basis (according to section 30 of ICA 1940). At the same time, the CDA data team also managed to obtain more frequent holdings data for funds that provide voluntary quarterly portfolio disclosures to their shareholders, large institutional clients or fund-tracking firms such as Morningstar Inc. To focus on U.S. equity funds, we follow a procedure similar to Pastor and Stambaugh (2002).[21] We use the CRSP investment objective codes provided by Lipper (L), Wiesenberger (OBJ) and Strategic Insight (SI) to select all growth funds, income funds and capital gains funds. In particular, we require all mutual funds to have at least one of the following investment objective classifications or missing:

Lipper(L):'EI', 'EIEI', 'EMN', 'G', 'GI', 'I', 'LCCE', 'LCGE', 'LCVE', 'LSE', 'MC', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', 'SESE', 'SG'.

Wiesenberger (OBJ): 'SCG', 'AGG', 'G', 'G-S', 'S-G', 'GRO', 'LTG', 'I', 'I-S', 'IEQ', 'ING', 'GCI', 'G-I', 'G-I-S', 'G-S-I', 'I-G', 'I-G-S', 'I-S-G', 'S-G-I', 'S-I-G', 'GRI', 'MCG'.

Strategic Insight (SI): 'SCG', 'GRO', 'AGG', 'ING', 'GRI', 'GMC'.

Furthermore, we also require that the investment objective code reported by TFN/CDA Spectrum is aggressive growth, growth, growth and income, balanced, unclassified or missing. We then look at the percentage of stocks in the portfolio as reported by CRSP and select the funds on average hold more than 80% and less than 105% in common stocks. All these criteria together most notably exclude any bond funds, asset allocation funds, international funds, precious metal funds and sector funds because these funds generally hold and trade minimal quantities of domestic equities (Wermers, 2000). Finally, we eliminate index funds if fund names contain the following keywords: 'INDEX', 'INDE', 'INDX', 'INX', 'IDX', 'S&P', 'ISHARES', 'DOW JONES' and 'MSCI'. To avoid any abbreviation and misspelling errors, we manually inspect the data and filter out remaining international funds, sector funds, tax-managed funds, fixed-income

[20] Our method here is similar to that of Cohen, Coval and Pastor (2005). In particular, we select the share class with the greatest number of months of valid data throughout the whole sample period instead of restricting this filter to each given year. We believe this would render our data more consistent over time.

[21] According to the March 2008 quarterly updated guide for the CRSP Survivor-Bias-Free U.S. Mutual Fund Database, ICDI codes have been removed and new Lipper codes have been added to the style table.

funds, balanced funds, real estate funds and annuities.

We use the MFLINKS database provided by WRDS to assign a unique Wharton Financial Institution Center Number (WFICN) to each fund in both CRSP MFDB and TFN CDA/Spectrum data sets. As MFLINKS concentrates on U.S. domestic equity funds, we further exclude some non-equity mutual funds if any by assigning the WFICN identifiers. Approximately 92% of the target universe, which was derived by using objective codes and stock holding percentages in CRSP MFDB, has been linked successfully. MFLINKS also resolves several issues including re-used fund identifiers and arbitrary changes in fund identifiers in the TFN CDA/Spectrum database.

The CDA/Spectrum data set provides two dates for holdings information, RDATE and FDATE. RDATEs represent the dates on which the holdings are valid (i.e. actually held by fund managers). FDATEs ('vintage dates' at quarter ends) signify a particular vintage of data and serve as a primary key to join multiple tables in CDA/Spectrum S12 master files. We only keep a distinct series of snapshot dates (RDATE) for our analysis.[22]

[22]Further details on Thomson Financial CDA/Spectrum database are available in 'M. Boldin, & B. Ding, 2008, User's Guide to Thomson Reuters Mutual Fund and Investment Company Common Stock Holdings Databases on WRDS.' and Wermers (1999, 2000). These data are free of survival bias as noted by Daniel et al. (1997).

Chapter 3

Information Content when Mutual Funds Deviate from Benchmarks*

3.1 Introduction

The mutual fund industry is becoming increasingly important in financial markets. At the end of 2009, total assets managed by U.S. mutual funds reached more than \$11 trillion, growing by more than 80 times from the \$135 billion they managed at the end of 1980 (Investment Company Institute, 2010). As a result of this dramatic expansion, 21% of U.S. households' financial assets are managed by mutual funds.

Despite the increasing importance though, the role that mutual funds play in determining security prices remains insufficiently understood. Considering the dominance of actively managed mutual funds in this industry and the resulting vast amount of resources they spend on security analysis and research,[1] we might expect active funds to be good candidates as informed investors, whose costly acquisition and implementation of information help impound information into asset prices (Grossman and Stiglitz, 1980). Prior literature on the performance of actively managed mutual funds, however, has painted a picture of active funds generally failing to outperform

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[1] In 2009, active equity funds manage approximately 87% of total U.S. equity mutual fund net assets, pushing the average expense ratio for stock funds to be 0.99% (2010 Investment Company Fact Book, p. 33 and p. 64). French (2008) argues that the annual cost of active investing is 0.67% of the aggregate market value.

passive benchmarks, without creating value from active investing.[2] This disheartening image appears to contradict the view of active mutual funds as informed investors in financial markets.

In this study, we provide strong evidence of the informational role of actively managed mutual funds in the determination of stock prices. We deviate from prior research by studying the information content of the deviations of active funds from their performance benchmarks. As the performance of an active fund is typically evaluated against a performance benchmark, the manager often invests a substantial portion of fund assets in the benchmark (Cremers and Petajisto, 2009). Therefore, focusing on the performance of the active portion of fund investments, that is, the deviations from the benchmark, should grant us more power to identify active funds' informational advantages.

To assess the information content of active funds' deviations from benchmarks, we create a stock-level measure that seeks to aggregate various pieces of information scattered among active fund managers, as revealed through their over- and underweighting decisions. Specifically, for each stock in our sample, we first compute the difference between the stock's weight in each individual fund portfolio and its weight in the stock index against which that fund is benchmarked. We average this difference in portfolio weights across active funds whose investment universe includes this stock,[3] thereby creating a stock-level measure of mutual funds' deviations from benchmarks, DFB.

This measure of mutual funds' deviations from benchmarks strongly predicts future stock returns. In univariate portfolio sorts, for example, stocks in the decile portfolio with the highest DFB, which are those most heavily overweighted by active funds, perform substantially better than those with the lowest DFB. Over the period 1980–2008, the average equal-weighted return on the top decile of stocks with the highest DFB was higher than that on the bottom decile of stocks, or those with the lowest DFB, by 0.74% per month, and this return difference was highly statistically significant with a t-statistic of 4.38. The superior performance of the stocks that active funds overweight relative to those that they underweight does not simply reflect the high risk propensity of active funds. As we show, the risk-adjusted returns on the spread portfolio between high and low DFB stocks are 0.66%, 0.72%, 0.58%, and 0.61% per month, as calculated by the Capital Asset Pricing Model (CAPM), the Fama and French's (1993) three-factor model, a four-factor model that includes momentum (Jegadeesh and Titman, 1993), and a five-factor model that

[2]Analyses of mutual fund returns generally report disappointing fund performance (e.g., Jensen, 1968, Malkiel, 1995, Carhart, 1997, Fama and French, 2010). Studies based on fund portfolio holdings suggest better but still moderate fund performance before expenses and trading costs (e.g., Grinblatt and Titman, 1989 and 1993, Daniel, Grinblatt, Titman, and Wermers, 1997, Wermers, 2000).

[3]A stock enters a mutual fund's investment universe if it is held by the mutual fund or it is a member of the fund's benchmark index.

also includes Pastor and Stambaugh's (2003) liquidity factor, respectively. The statistical significance of the returns on the spread portfolio remains high even after these risk adjustments. These results also are robust to the various specifications of Fama and MacBeth's (1973) cross-sectional regressions with common stock return predictors, to the Daniel, Grinblatt, Titman, and Wermers (1997) characteristic-adjustment procedure, for different weighting schemes, and across various subperiods. They suggest that actively managed mutual funds possess value-relevant information that is not fully reflected in stock prices.

Although interesting, these results also may be subject to alternative interpretations. For example, the higher returns on stocks with higher DFB may be a result of mutual funds' demand pressure, which pushes stock prices above equilibrium levels and thus generates higher in-sample returns. This interpretation is possible because there is evidence that mutual funds tend to herd (Wermers, 1999; Sias, 2004) and that they may continue to buy the stocks they have overweighted. To differentiate this alternative interpretation based on price pressure from our story of informed fund managers, we conduct a number of tests, which uniformly support our information-based story.

First, we explore the distinct implications of informed managers and price pressure hypotheses for the dynamics of changes in mutual funds' deviations from benchmarks. Specifically, suppose that, in the world with informed fund managers, a risk-averse manager receives a positive signal about a stock in period t and decides to increase his portfolio weight in this stock relative to his benchmark, which results in an increase in DFB from $t-1$ to t. In the next period $t+1$, as his positive private information transmits into the stock price, the risk-averse manager has incentives to at least partially unwind the position that he has built up to capture the gains to his information. This position reversal takes place because the manager desires to reduce the long-run risk of future price changes arising from future events he cannot predict. In this scenario, a large increase in DFB in one period should predict a subsequent decline in DFB. In the world dominated by mutual fund herds, however, a large increase in the excess weight of a stock in an average fund's portfolio attracts further demand from the herd, which leads to increases in the stock price. According to this interpretation, a large increase in DFB in one period should forecast a further increase in DFB. Our tests show that an increase in DFB in one quarter reliably predicts a decline in DFB in the subsequent quarter, which concurs with the story of informed fund managers but contradicts the price pressure-based interpretation.

Second, a simple approach to examine the influence of demand pressure on our findings is to test the return forecasting power of our measure of deviations from benchmarks after we control for realized future demand shocks. If active funds' deviations from benchmarks can forecast future returns mainly through the channel of future demand shocks, the return predictive power should cease to exist once the association between future returns and future demand shocks is controlled for. We find, however, that the return forecasting power of active funds' deviations from benchmarks remains intact after we control for future demand shocks.

Third, we examine the persistence of the performance of stocks overweighted by mutual funds: If the high returns on stocks with high DFB arise mainly from demand pressure, these returns subsequently should reverse. If, however, the high returns come mostly from value-relevant information possessed by fund managers and the market reacts properly to that information, we expect to observe no subsequent return reversal. Our tests show that the positive association between DFB and future excess returns concentrates for the most proximate quarter. This positive association shows no tendency to reverse for the subsequent two to four quarters. Thus, DFB appears to forecast returns due primarily to the value-relevant information that DFB aggregates from diverse mutual fund managers, as revealed through their investment decisions.

To further increase our confidence in this information-based story, we conduct a series of tests based on stock and fund attributes. First, we examine the return forecasting power of DFB across size groups. The idea is that very large firms tend to be more transparent, with better disclosure policy. They also tend to be more closely followed and researched by market participants. It is therefore more difficult for mutual funds to gain information advantages on those firms. On the other hand, returns to analyzing tiny firms appear to be small relative to the costs of information acquisition. These considerations prompt us to conjecture that mid-cap stocks could be the fields where information miners or stock pickers have the greatest information advantage. Consistent with this conjecture, we find that the return forecasting power of DFB concentrates among mid-cap stocks. Along a similar vein of thinking, if mutual funds have informational advantages about individual stocks, we expect their advantages to be greater among stocks with more firm-specific information. Also, we expect the funds' informational advantages to be more valuable when the funds have fewer competitors. Consistent with these predictions, we find that the return forecasting power of DFB is stronger among firms that have higher idiosyncratic volatilities and those that attract fewer mutual fund investors.

Second, our measure of DFB reflects the investment decisions of all active mutual funds in our sample. Prior literature shows heterogeneous levels of skills or alphas across mutual funds (e.g., Fama and French, 2010). If fund managers with a higher level of alphas have better informational advantages, a DFB measure constructed from the universe of those high-performing funds could be a better return predictor than that from the universe of the low-performing funds with a lower level of alphas. We find that, indeed, a strategy that buys high DFB stocks and sells low DFB stocks based on the portfolio decisions of high-performing funds generates a monthly four-factor alpha of 0.54% (t=5.42), which is more than twice as large as the four-factor alpha of 0.25% (t=2.64) on a similar strategy based on the portfolio decisions of low-performing funds. Interestingly, the higher returns on the DFB strategy implemented on higher-alpha managers come from both the higher returns on stocks that they overweight and the lower returns on stocks they underweight. We also find that a DFB strategy based on the portfolio selection of growth funds generates significant returns whereas a similar strategy based on the investment decisions of income funds generates insignificant returns.

To explore the nature of the information content captured by DFB, we examine the relation between DFB and firms' future earnings surprises. We find that stocks with high DFB tend to experience large and positive earnings surprises during the following four quarters, and the effect, strongest for the most proximate quarter, decays substantially through time. Even after we adjust for the possibility that active funds might trade on earnings momentum, we still find reliably positive earning surprises in the most proximate quarter for stocks they overweight. We also find that a significant portion of the return premiums on the stocks with high DFB occurs around corporate earnings announcements. These results suggest that part of active funds' superior information relates to firms' fundamental prospects.

Finally, how can we reconcile evidence that points to strong informational advantages of mutual funds in stock markets with the overall lackluster performance of mutual funds reported by prior literature? We find that in aggregate, mutual funds invest less than 10% of their assets in high DFB stocks but approximately 34% in low DFB stocks. Therefore, a large four-factor alpha of 6–7% per year on high DFB stocks translates into a small mutual fund alpha of less than 1% per year. After we take into account trading costs and fees, little, if any, alpha remains for mutual fund investors to capture. These results are consistent with the predictions of Berk and Green (2004) on the equilibrium behavior of mutual fund managers.

Our paper joins a small but growing body of literature that connects mutual fund investing to asset prices. Coval and Moskowitz (2001) use geography to identify a link between mutual fund investments and stock prices. They find that the holdings of geographically proximate firms by local fund managers perform better than their holdings of distant firms, which suggests fund managers have better access to local information and that their investments facilitate the transfer of information into the prices of local stocks. Cohen, Frazzini, and Malloy (2008) exploit educational background to establish a social link between corporate managers and fund managers that in turn influences stock prices.[4] Unlike these two studies, which use a priori links between

[4]In a similar vein, Tang (2009) examines the information advantages of portfolio managers for firms they previ-

firms and funds, we track the investment decisions of mutual fund managers and extract and aggregate the information that is scattered among these managers from their portfolio decisions. We also provide strong evidence that this measure of aggregated information predicts future stock returns, which is particularly useful for a better understanding of the informational role played by mutual funds in stock markets.

Our paper also relates to Chen, Jegadeesh, and Wermers (2000), who assess the value of active portfolio management by examining the association between mutual fund trades and future stock returns (see, also, Grinblatt and Titman, 1993). The trading decisions of mutual funds, however, could reflect not only informational motives but also other motivations such as flow-driven liquidity needs (e.g., Alexander, Cici, and Gibson, 2007). Our measure of deviations from benchmarks is less subject to the influence of fund flows, because fund managers can simply scale up or down fund assets in response to flows, without having to substantially alter the composition of their active portfolios. Therefore, our measure could have more power to detect active funds' information advantages. Empirically, we are able to show that our measure of deviations from benchmarks dominates the trade-based measure used by Chen, Jegadeesh, and Wermers.[5]

In some recent study, Cohen, Polk, and Silli (2010) document the superior performance of fund managers' best idea stocks. Their analysis focuses on the top holdings in each manager's portfolio; we are interested instead in whether a measure that aggregates information dispersed among fund managers captures their informational advantages as an investor group. Our analysis of the entire portfolio composition of mutual funds enables us to detect the negative abnormal returns on stocks that active funds choose to underweight. Moreover, our results are insensitive to the exclusion of each manager's best ideas in computing DFB. Shumway, Szefler, and Yuan (2009) propose a novel technique to elicit fund managers' beliefs about expected stock returns from their portfolio holdings. They apply their method to rank these fund managers and find that skilled managers possess superior information relative to their unskilled peers. Our primary interest, however, is in whether an average mutual fund has informational advantages in stock markets.

To pursue these interests, we organize the rest of this chapter as follows: In Section 3.2, we introduce our measure of mutual funds' deviations from benchmarks, DFB, and in Section 3.3, we describe our sample selection and summary statistics. With Section 3.4, we explore the information content of mutual funds that deviate from benchmarks, then provide several robustness checks in Section 3.5. Section 3.6 concludes our paper.

ously served as financial analysts.

[5]In Appendix D, we compare our measure of active funds' deviations from benchmarks with the Chen, Jegadeesh, and Wermers (2000) trade measure.

3.2 Measuring Mutual Funds' Deviations from Benchmarks, DFB

We measure a mutual fund j's deviation from its benchmark for stock i in quarter t as the difference between this stock's weight in the fund portfolio, $w_{i,t}^{j}$, and its weight in the stock index against which the fund's performance is benchmarked, $w_{i,t}^{b}$. Our primary interest is in whether mutual funds, as an investor group, have informational advantages for individual stocks in their investment universe; therefore, we create a stock-level measure of mutual funds' deviations from benchmarks, DFB, by averaging the difference in portfolio weights across all mutual funds whose investment universe comprises this stock. A stock enters a mutual fund's investment universe if it (1) is held by the mutual fund or (2) is a member of the fund's benchmark index. We thus can define a measure of mutual funds' deviations from benchmarks for stock i as:

$$DFB_{i,t} = \sum_{j=1}^{N_i} (w_{i,t}^{j} - w_{i,t}^{b})/N_i, \tag{3.1}$$

where N_i is the number of funds whose investment universe includes stock i. Our simple measure of mutual funds' deviations from benchmarks equally reflects each fund's distance from its performance benchmark and therefore captures a typical fund's deviation from its benchmark. Other ways to aggregate information across mutual funds include weighting each fund's distance from a benchmark based on net fund assets, which captures funds' deviations from benchmarks for every invested dollar, or weighting each fund's distance from a benchmark based on how active the funds are. Our results remain robust when we use such weighting schemes, but we present our main results using the simple equal-weighting scheme, which also is economically intuitive.

If fund managers deviate from their benchmarks for informational reasons, DFB can aggregate diverse pieces of information about the future value of individual stocks scattered among fund managers. If not yet has this aggregated information been fully reflected in current market prices (i.e., mutual funds as an investor group possess private information), DFB should predict future stock returns relatively well. A stock with a higher value for DFB, ceteris paribus, should have higher future returns. If mutual funds do not possess value-relevant private information or deviate from performance benchmarks for other considerations,[6] we expect DFB to be unrelated, or even negatively related, to future stock returns. In Appendix A, we show that with

[6] A growing literature analyzes the incentives of mutual fund managers, which suggests that they may deviate from their performance benchmarks for agency considerations, beyond the objective of return maximization or portfolio diversification (e.g., Brown, Harlow, and Starks, 1996, Chevalier and Ellison, 1997).

certain assumptions, DFB linearly relates to expected future excess returns, conditional on fund managers' information set.

3.3 Sample and Summary Statistics

In this section, we describe our data set and sample selection criteria, as well as our methods for selecting funds' performance benchmarks, followed by summary statistics for the mutual fund sample and the characteristics of stocks with large mutual funds' deviations from benchmarks, DFB.

3.3.1 Data and Sample Selection

To construct our mutual fund database, we combined the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database (MFDB) with the CDA/Spectrum Mutual Fund Holdings Database from Thomson Financial.[7] Because we wish to examine the informational advantages of mutual funds in stock markets, we only include active mutual funds that invest primarily in U.S. common stocks; we eliminate balanced, bond, money market, international, index funds, and sector funds, as well as funds not invested primarily in equity securities (for details on our selection, see Appendix B). Our sample covers the period from 1980 to 2008.

Data on the monthly returns, prices, and market values of equity for common stocks traded on the NYSE, AMEX, and NASDAQ come from the CRSP. Consistent with previous literature, we exclude closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, primes, and scores (we keep only shares with codes of 10 or 11). To mitigate the concern that our stock return tests might be influenced by return outliers, we eliminate stocks with prices below $5 as of the portfolio formation date (typically the end of the previous quarter).

3.3.2 Benchmark Index Holdings

We next must compute the weights of each fund's holdings against its performance benchmark; the crucial step is selecting the stock index that the fund seeks to outperform. We use two methods to identify each fund's performance benchmark index. First, because there might be a discrepancy between a mutual fund's self-declared performance benchmark and the actual benchmark the fund follows (Sensoy, 2009), we adopt Cremers and Petajisto's (2009) method

[7] Our merging procedure uses the MFLINKS data set maintained by Russ Wermers and the Wharton Research Data Services (WRDS).

and select 19 benchmark indexes commonly used by practitioners: the S&P 500, S&P 400, S&P 600, S&P 500/Barra Value, S&P 500/Barra Growth, Russell 1000, Russell 2000, Russell 3000, Russell Midcap, the value and growth variants of the four Russell indexes, Wilshire 5000, and Wilshire 4500. For each fund in each quarter, we select from the 19 indexes the one that minimizes the average distance between the fund portfolio weights and the benchmark index weights. Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are from Compustat. For the remaining indexes and time periods, we use the holdings of index funds to approximate the index holdings.[8] In Appendix C, we describe in detail our selection of benchmark indexes.

Second, for each individual fund, we tailor a performance benchmark by constructing a value-weighted portfolio of all stocks the fund actually holds.[9] Since these two approaches generate qualitatively similar results, we report our main results based on the first approach.

3.3.3 Summary Statistics for the Mutual Fund Sample

Table 3.1 reports the summary statistics for our mutual fund sample, which includes 2,691 distinct U.S. active equity funds. During 1980–2008, the industry of active equity mutual funds experienced dramatic expansion: The number of actively managed funds increased from 201 in 1980 to 1397 in 2008, with total assets under their management increasing from $26.55 to $953.91 billion. On average, these funds invested 93% of their assets in common stocks, which suggests that our sample effectively represents the universe of U.S. active funds with an investment focus on domestic equity. Throughout our sample period, the expansion of mutual funds outpaced the growth of stock markets, which led them to become increasingly important shareholders of common equity. In particular, mutual funds' ownership of U.S. stocks in the CRSP database increased from approximately 2% to around 10%.

3.3.4 Characteristics of Stocks with Extreme DFB

What are the characteristics of stocks with heavy mutual fund bets? In this subsection, we examine the characteristics of stocks with large mutual fund over- and underweighting. We present univariate results based on the decile portfolios in Table 3.2. Specifically, at the end of

[8] We obtain qualitatively similar results if we use index fund holdings throughout our sample period.

[9] A mutual fund might respond to negative information about a firm by avoiding holding its shares, so we also use a value-weighted benchmark consisting of all stocks that the fund held during the previous five years. The results are qualitatively similar.

Table 3.1: **Stock Holdings of Active Mutual Funds**

Each year-end from 1980 to 2008, we calculate the number of distinct actively managed equity mutual funds in our sample (see Appendix B for details on sample selection) and compute the average proportion of fund assets invested in common stocks. We also report the total number and dollar amount of common stocks held by those mutual funds and their proportion in the CRSP stock database. The calculations exclude stocks with prices lower than $5 at the year-end.

Year	No. of Distinct Funds	% of Fund Assets Invested in Common Equity	No. of Distinct Stocks Held by Funds	% of CRSP Stocks (Number)	Total Mutual Funds Assets ($ Billions)	% of CRSP Stocks ($)
1980	196	88.01	1900	39.52	26.81	2.04
1981	197	83.05	1865	35.87	18.25	1.49
1982	202	86.4	2055	39.85	27.69	1.97
1983	225	87.22	2934	51.01	43.28	2.49
1984	237	85.59	3059	52.01	45.47	2.71
1985	261	86.35	3353	56.98	66.59	3.19
1986	300	85.61	3547	57.06	74.99	3.19
1987	339	85.19	3454	53.49	88.5	3.83
1988	358	84.86	3572	57.52	85.6	3.41
1989	392	86.02	3558	59.51	104.8	3.43
1990	421	84.72	3289	56.42	101.14	3.68
1991	450	86.95	3461	58.78	142.29	3.83
1992	552	86.28	3737	62.08	211.73	5.14
1993	681	87.7	4879	74.47	232.21	4.97
1994	793	90.83	5123	74.54	267.72	5.78
1995	907	90.95	5545	78.09	403.14	6.38
1996	1013	92.2	5953	78.72	575.74	7.47
1997	1126	93.25	5997	78.95	823.27	8.22
1998	1218	93.59	5671	78.99	1073.73	8.69
1999	1358	93.06	5633	82.27	1270.82	8.05
2000	1490	92.24	5458	83.25	1283.24	8.96
2001	1541	93.46	4933	84.53	998.35	7.89
2002	1607	94.03	4266	78.84	938.53	9.52
2003	1630	95.29	4481	88.28	1307.75	10.18
2004	1641	94.26	4479	89.99	1684.5	11.8
2005	1617	96.4	4156	84.99	1691.34	11.43
2006	1580	96.83	4188	87.05	2053.51	12.48
2007	1587	96.28	4286	91.46	2004.32	12.15
2008	1510	95.92	3997	90.84	1024.99	10.26
Average	877	90.09	4098	69.15	643.8	6.37

each quarter, we sort stocks into deciles according to their DFB, calculate the cross-sectional averages of the characteristics, and report their time-series averages.

The results show that stocks heavily overweighted by mutual funds tend to have low portfolio weights in benchmark indexes, whereas stocks heavily underweighted by mutual funds tend to have high portfolio weights in benchmark indexes. A typical stock in Decile 10 with the highest DFB has an average portfolio weight of only 3 basis points in its benchmark index, which is substantially lower than the average portfolio weight of 29 basis points in the benchmark for a typical stock in Decile 1 with the lowest DFB. We also find that most stocks in Decile 10 remain outside of mutual funds' performance benchmarks. On average, approximately two thirds of the stocks in Decile 10 are outside of benchmark indexes, whereas no stocks in Decile 1 are outside of benchmark indexes.

Furthermore, the results show that stocks in Decile 10 tend to be the least popular among mutual funds; they reside in the investment universe of only 34 funds. On the contrary, stocks in Decile 1 appear in the investment universe of 213 funds. On average, only 16 mutual funds hold stocks in Decile 10, compared with 36 funds holding stocks in Decile 1. These results indicate that stocks with high active fund bets do not pertain just to a few "hot" or popular names among money managers.

Finally, we find that stocks heavily overweighted by mutual funds tend to be relatively small with an average decile rank value of 3.3, based on NYSE market-cap decile breakpoints in ascending order. They also have a slight tendency to be winners in the previous year and have higher idiosyncratic volatilities. There exists no apparent relation between DFB and the book-to-market ratio. We note that the high excess weights of Decile 10 stocks in mutual fund portfolios should not result mechanically from their high past returns: Large increases in the relative prices of those stocks increase their weights not only in the mutual fund portfolio but also in the benchmark index.

3.4 Information Content of DFB

In this section, we explore whether our measure of mutual funds' deviations from benchmarks contains information relevant for future stock returns. We start by looking at the relation between DFB and future stock returns using both univariate portfolio sorts and the Fama and MacBeth (1973) cross-sectional regressions. Then we examine and find evidence contradicting an alternative interpretation of the return forecasting power of DFB, namely, the demand pressure from mutual funds. We provide further evidence regarding the information content of DFB by inves-

Table 3.2: **Summary of the Data: Decile Portfolios**

At the end of each quarter, we compute for each stock a measure of mutual funds' deviations from benchmarks, DFB, which is the simple average of the stock's weight in a mutual fund portfolio in excess of its weight in the fund's benchmark index, across all mutual funds in the stock-fund cohort. We then sort stocks into deciles in ascending order based on DFB, and calculate the stock characteristics for each decile portfolio. A mutual fund belongs to a stock-fund cohort if the stock appears in the mutual fund portfolio or is a member of the index against which the fund is benchmarked. For each mutual fund in each quarter, we select from 19 stock indexes one benchmark index that minimizes the average distance between the fund portfolio weights and the benchmark index weights. Our set of characteristic variables includes the average deviations from benchmarks DFB, the average benchmark weight, the average number of funds in the stock-fund cohort, the average number of funds that hold the stocks, the average proportion of stocks outside the benchmarks, the average proportion of funds in the stock-fund cohort for which the stock is not held by funds but in their benchmarks, the market cap, the book-to-market ratio, past one year return (skipping the most recent month), and the residual return volatility in the past quarter. The market cap of a stock is computed by multiplying the stock price with the number of outstanding shares at each quarter end (in millions). The book-to-market ratio is determined for each stock at the end of last calendar year using the book value of the stock at the end of last fiscal year and the market value of the stock at the end of last calendar year. We regress the daily stock returns against daily Fama French factors in a given quarter and use the standard deviation of the residuals as the residual volatility of the stock for that quarter (at least 40 daily observations of stock returns must be available). To facilitate comparison across deciles, we score for each quarter the size, book-to-market, and past returns from 1 to 10, with 10 representing the deciles with the largest market cap (based on NYSE break-points), highest book-to-market, and highest past one-year return. Stocks with prices lower than $5 at the quarter end are excluded.

Decile	DFB (%)	Benchmark Weights (%)	No. of Funds in the Stock-Fund Cohort	No. of Funds Holding the Stock	Proportion of Stocks Outside of Benchmarks (%)	Market Cap Score (1-10)	BM Score (1-10)	Pr1Yr Score (1-10)	Residual Volatility (%)
1	-0.15	0.29	213	36	0	6.75	4.6	5.95	1.94
2	-0.03	0.08	167	19	0.9	4.49	4.88	5.45	2.4
3	0	0.05	144	16	8.15	3.57	4.96	5.37	2.61
4	0.04	0.03	99	11	23.15	2.8	5.28	5.27	2.74
5	0.09	0.04	106	14	31.65	3.12	5.27	5.38	2.69
6	0.14	0.04	121	18	27.34	3.6	5.12	5.58	2.57
7	0.2	0.05	117	21	27.24	3.83	5.06	5.82	2.52
8	0.29	0.05	99	22	30.78	3.95	4.94	6.11	2.52
9	0.44	0.05	74	22	40.91	3.87	4.79	6.28	2.59
10	1.01	0.03	34	16	67.34	3.28	4.7	6.74	2.76
D10 - D1	1.17	-0.27	-180	-20	67.34	-3.47	0.1	0.79	0.82

tigating the association between DFB and stock returns for different subgroups of stocks and funds, as well as the relation between DFB and corporate earnings surprises. We conclude this section by relating DFB to mutual fund performance.

3.4.1 Return Forecasting Power of DFB

To test for the return forecasting power of DFB, we first sort stocks into deciles based on DFB and examine the subsequent performance of these decile portfolios. As we update DFB each quarter, the portfolios accordingly get rebalanced. Fama and French (2008) point out that equal-weight portfolio returns may be driven by tiny stocks that are numerous in number but small in economic significance, whereas value-weight portfolio returns may be driven by a few very large caps. To assess whether our results may be representative, we present both equal-weight and value-weight returns on the decile portfolios in Table 3.3.

The first columns in Panels A (equal-weight returns) and B (value-weight returns) of Table 3.3 show that DFB strongly predicts future returns. A portfolio that buys stocks in Decile 10 and sells short stocks in Decile 1 generates average returns of 0.74% and 0.56% per month on an equal- and value-weight basis. These returns are statistically significant, with t-statistics of 4.38 and 2.48, respectively. To examine whether the high returns on stocks heavily overweighted by mutual funds simply reflect fund managers' propensity to take high risks, we employ standard risk-adjustment models to examine the abnormal returns. The specific risk-adjustment models include the Capital Asset Pricing Model (CAPM), the Fama and French three-factor model, a four-factor model including momentum, and a five-factor model that also includes Pastor and Stambaugh's (2003) liquidity factor.[10] In addition to linear factor models, we employ a characteristic-adjustment procedure, as proposed by Daniel, Grinblatt, Titman, and Wermers (hereafter, DGTW, 1997).

Columns 2–6 in Panels A and B provide the results. The high returns on stocks heavily overweighted by mutual funds, in excess of the returns on their underweighted counterparts, remains large and statistically significant after those adjustment procedures. For example, the spread portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 earns equal-weighted abnormal returns of 0.66%, 0.72%, 0.58%, 0.61%, and 0.56% per month after the adjustments according to the CAPM, three-factor model, four-factor model, five-factor model, and DGTW adjustment procedure, respectively. All five versions of the alphas are highly statistically significant, with t-statistics ranging between 4 and 7. We note that a portfolio characterized by

[10] We obtain qualitatively similar results if we use a six-factor model that also includes a volatility factor (Ang, Hodrick, Xing, and Zhang, 2006).

Table 3.3: DFB **and Future Stock Returns: Decile Portfolios**

This table presents the performance of decile portfolios formed on the basis of mutual funds' deviations from benchmarks, DFB. At the end of each quarter from 1980Q3 to 2008Q3, we sort stocks into deciles in ascending order based on DFB and compute the average monthly equal-weight (Panel A) and value-weight (Panel B) portfolio returns in the subsequent quarter. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Finally, we present the portfolio performance using the DGTW (1997) characteristic adjustment. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

	Panel A: Equal-Weight Post-Ranking Portfolio Return (%/month)						Panel B: Value-Weight Post-Ranking Portfolio Return (%/month)					
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return
1	0.67	-0.21	-0.31	-0.29	-0.30	-0.17	0.77	-0.08	0.00	-0.01	-0.01	-0.10
	(2.50)	(-2.88)	(-5.45)	(-4.72)	(-4.87)	(-3.62)	(3.25)	(-1.15)	(0.02)	(-0.24)	(-0.2)	(-3.16)
2	0.71	-0.19	-0.38	-0.22	-0.22	-0.14	0.93	0.05	-0.08	0.01	0.01	0.04
	(2.32)	(-1.57)	(-5.6)	(-3.23)	(-3.14)	(-2.78)	(3.44)	(0.66)	(-1.26)	(0.08)	(0.11)	(0.61)
3	0.77	-0.16	-0.35	-0.15	-0.13	-0.09	0.95	0.04	-0.08	0.01	0.03	0.07
	(2.35)	(-1.11)	(-4.51)	(-2.08)	(-1.87)	(-1.4)	(3.36)	(0.47)	(-0.9)	(0.17)	(0.41)	(1.19)
4	0.82	-0.07	-0.23	-0.09	-0.07	-0.09	0.91	0.02	-0.09	0.02	0.03	-0.04
	(2.60)	(-0.45)	(-2.21)	(-0.92)	(-0.74)	(-1.08)	(3.19)	(0.22)	(-1.16)	(0.24)	(0.37)	(-0.53)
5	0.89	-0.01	-0.18	-0.06	-0.04	-0.05	0.95	0.02	-0.10	0.04	0.04	0.02
	(2.81)	(-0.05)	(-2.29)	(-0.72)	(-0.53)	(-0.79)	(3.21)	(0.19)	(-1.09)	(0.43)	(0.36)	(0.29)
6	0.99	0.07	-0.12	0.00	0.03	0.06	0.95	0.02	-0.10	-0.03	-0.01	0.02
	(3.08)	(0.45)	(-1.49)	(0.04)	(0.35)	(1.12)	(3.28)	(0.18)	(-1.45)	(-0.33)	(-0.13)	(0.36)
7	1.10	0.17	0.00	0.09	0.13	0.13	1.01	0.09	0.03	0.08	0.11	0.06
	(3.40)	(1.16)	(0.06)	(1.21)	(1.79)	(2.12)	(3.58)	(1.27)	(0.40)	(1.16)	(1.67)	(1.16)
8	1.04	0.09	-0.02	-0.03	0.01	0.05	0.93	-0.01	-0.03	-0.08	-0.07	0.00
	(3.12)	(0.60)	(-0.25)	(-0.41)	(0.12)	(0.80)	(3.10)	(-0.13)	(-0.38)	(-0.86)	(-0.78)	(-0.02)
9	1.23	0.28	0.23	0.14	0.16	0.20	1.28	0.31	0.43	0.22	0.23	0.29
	(3.60)	(1.74)	(3.13)	(2.05)	(2.33)	(3.01)	(3.84)	(2.17)	(3.38)	(1.83)	(1.88)	(2.92)
10	1.40	0.45	0.41	0.29	0.31	0.39	1.33	0.36	0.57	0.28	0.30	0.31
	(3.93)	(2.48)	(4.39)	(3.28)	(3.49)	(5.58)	(3.73)	(2.10)	(3.54)	(2.11)	(2.29)	(2.20)
D10-D1	0.74***	0.66***	0.72***	0.58***	0.61***	0.56***	0.56**	0.44**	0.57***	0.29*	0.31**	0.41***
	(4.38)	(4.07)	(6.44)	(5.28)	(5.53)	(5.99)	(2.48)	(2.20)	(3.26)	(1.94)	(2.11)	(2.73)
D9-D2	0.51***	0.48***	0.61***	0.36***	0.38***	0.34***	0.35*	0.26	0.51***	0.21	0.22	0.25**
	(4.31)	(4.02)	(6.04)	(3.77)	(3.80)	(4.13)	(1.93)	(1.50)	(3.31)	(1.51)	(1.54)	(2.01)

long stocks in Decile 9 and short stocks in Decile 2 also delivers superior performance on an equal-weighted basis. Consistent with stocks highly overweighted by mutual funds tending to be relatively small, as shown in Section 3.3.4, the value-weighted return on a long-short portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 is smaller but still economically meaningful and statistically significant.

To examine the return predictive power of DFB in the presence of other return predictors, we employ the Fama and MacBeth cross-sectional regressions. To examine large overweights and underweights separately, we discretize DFB into two dummy variables: $D1$ that represents the membership in the decile of stocks with the lowest DFB and $D10$ that represents the membership in the decile with the highest DFB. The slope coefficient for the dummy variables in the Fama and MacBeth regressions can be interpreted as the difference in quarterly returns between stocks in each respective decile and all stocks in other deciles, while controlling for stock characteristics.

Specifically, at the end of each quarter from 1980Q3 to 2008Q3, we perform cross-sectional regressions specified as follows:

$$R_{i,t+1} = \alpha + \beta D1_{i,t} + \gamma D10_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}, \tag{3.2}$$

where $R_{i,t+1}$is the return on stock i in quarter t in excess of the market return in quarter t, and $X_{i,t}$ includes a bunch of stock characteristics such as firm size, the book-to-market ratio, past one-year (skipping the most recent month) returns, idiosyncratic volatilities, turnover, and past one-month (month t) return. Following Fama and MacBeth (1973), we conduct statistical inference based on the time-series variation of the coefficients.

The results in columns 1 and 2 of Panel A in Table 3.4 show that stocks in Decile 1 significantly underperform other stocks and stocks in Decile 10 significantly outperform other stocks, even after we control for the influence of other firm characteristics such as firm size, the book-to-market ratio, past one-year returns, idiosyncratic volatilities, turnover, and past one-month return.

Chen, Jegadeesh, and Wermers (2000) argue that a trade-based measure of changes in the fraction of shares owned by mutual funds ($\triangle MFO$) is a significant predictor of future stock returns. Chen, Hong, and Stein (2002) argue that changes in the number of mutual funds that hold the stock, $\triangle Breadth$, correlate with future stock returns. Wermers, Yao, and Zhao (2007) find that investment strategies based on portfolio holdings, weighted by past fund performance (WWA), generate superior abnormal returns. Cohen, Polk, and Silli (2010) examine the performance of stocks that represent fund managers' $BestIdeas$ and find that the stock that active managers display the most conviction towards ex-ante, outperforms the market. Motivated by these prior studies, we include these variables in our cross-sectional regressions to stress-test the return forecasting power of our measure of deviations from benchmarks. The results in columns 3 and 4 of Panel A indicate that these variables leave the return forecasting power of DFB intact.

In summary, we find strong evidence that a stock-level measure that aggregates mutual funds' deviations from benchmarks, DFB, strongly and positively forecasts the cross-sectional variation in future returns. The superior (inferior) performance of stocks heavily overweighted (underweighted) by mutual funds is consistent with the notion that actively managed mutual funds behave as informed investors in stock markets. In the next subsection, we investigate an alternative interpretation of the return forecasting power of DFB, that is, mutual funds' demand pressure.

Table 3.4: **DFB and Future Stock Returns: Fama and MacBeth (1973) Cross-Sectional Regressions**

This table uses the Fama and MacBeth (1973) cross-sectional regressions to examine the relation between mutual funds' deviations from benchmarks, DFB, at each quarter end and the cumulative market-adjusted returns in the subsequent (up to 4) quarters. R_{t+1} denotes market adjusted return in quarter $t+1$, $R_{t+1,t+2}$ denotes market-adjusted return over quarters $t+1$ and $t+2$, and so forth. To make the results comparable with the portfolio analysis, we discretize DFB into two dummy variables, D10 (overweight) that equals one if the stock is in Decile 10 with the highest DFB and 0 otherwise, and D1 (underweight) that equals one if the stock is in Decile 1 with the lowest DFB and 0 otherwise. Market cap, book-to-market ratio, residual volatility, and turnover ratio are defined as previously. Pr1Yr is the past one year return skipping the most recent month and Pr1Mt is the past one month return. $\triangle MFO$ is the change in the fraction of shares held by mutual funds (Chen, Jegadeesh, and Wermers, 2000), and $\triangle Breadth$ is the change in the number of mutual funds that hold the stock scaled by the total number of mutual funds that exist at the beginning of a given quarter, as in Chen, Hong, and Stein (2002). WWA is the weighted average fund alpha estimator as defined by Wermers, Yao, Zhao (2007), in which the forecasted alpha for a given stock is the weighted average of past fund alphas, where weights are proportional to current fund portfolio weights on the stock. $BestIdeas$ is a dummy variable which equals unity when the stock is among fund managers' best ideas and zero otherwise. We identify the best idea of a manager as the stock with the highest tilt in his portfolio. Stocks with prices lower than \$5 at the quarter end are excluded. As the cumulative returns overlap, we compute the t-statistics based on the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at the 10% level.

	R_{t+1}					$R_{t+1,t+2}$		$R_{t+1,t+3}$		$R_{t+1,t+4}$	
	1	2	3	4	5	6	7	8	9	10	11
$D1_t$	-0.0102**	-0.0073***	-0.0089*	-0.0056**	-0.0063**	-0.0058	-0.0082**	-0.0064	-0.0097	-0.0058	-0.0111
	(-2.09)	(-2.64)	(-1.91)	(-2.04)	(-2.44)	(-1.37)	(-2.13)	(-0.98)	(-1.62)	(-0.68)	(-1.46)
$D10_t$	0.0197***	0.0159***	0.0170***	0.0136***	0.0141***	0.0229***	0.0242***	0.0289***	0.0319***	0.0295***	0.0350***
	(5.30)	(5.39)	(5.36)	(5.08)	(5.56)	(4.43)	(5.09)	(3.83)	(4.52)	(3.06)	(3.97)
$MarketCap_t$		-0.0032**		-0.0037***	-0.0035***	-0.0061**	-0.0054*	-0.0083*	-0.0076*	-0.0097	-0.0089
		(-2.17)		(-2.70)	(-2.63)	(-2.08)	(-1.97)	(-1.72)	(-1.68)	(-1.46)	(-1.46)
BM_t		0.0038*		0.0038*	0.0039*	0.0079*	0.0080**	0.0117**	0.0115**	0.0153**	0.0152**
		(1.70)		(1.74)	(1.81)	(1.93)	(2.05)	(2.04)	(2.13)	(2.07)	(2.23)
$Pr1Yr_t$		0.0276***		0.0262***	0.0237***	0.0406***	0.0349***	0.0448***	0.0373***	0.0453***	0.0372***
		(5.83)		(5.67)	(5.08)	(5.59)	(4.77)	(4.56)	(3.71)	(3.79)	(3.01)
$ResidualVol$		-0.6942***		-0.6862***	-0.6466**	-1.0486**	-0.9726**	-1.3478**	-1.1884*	-1.5075*	-1.3079
		(-2.68)		(-2.68)	(-2.54)	(-2.21)	(-2.07)	(-2.00)	(-1.78)	(-1.84)	(-1.65)
$Turnover_t$		-0.0107*		-0.0104	-0.0105	-0.0282**	-0.0268**	-0.0428**	-0.0386*	-0.0564**	-0.0499**
		(-1.69)		(-1.60)	(-1.65)	(-2.11)	(-2.00)	(-2.24)	(-1.98)	(-2.35)	(-2.06)
$Pr1M_t$		-0.0173		-0.0217	-0.0337**	0.0182	-0.0123	0.0574*	0.0078	0.0947**	0.0315
		(-1.20)		(-1.56)	(-2.44)	(0.74)	(-0.53)	(1.70)	(0.25)	(2.27)	(0.81)
$\triangle MFO$			0.0574	-0.0093	0.0207	0.0389	0.1746**	0.0396	0.2957***	0.0485	0.4920***
			(0.89)	(-0.18)	(0.43)	(0.52)	(2.24)	(0.42)	(2.63)	(0.44)	(3.42)
$\triangle Breadth$			0.2430*	0.1175	0.0669	0.2814*	0.1712	0.4885**	0.3614*	0.5106*	0.3584
			(1.90)	(1.33)	(0.75)	(1.82)	(1.06)	(2.52)	(1.87)	(1.98)	(1.46)
WWA			1.1294***	0.8710***	0.7730***	1.5163***	1.2071***	1.8519***	1.3280**	1.9881***	1.2466**
			(3.54)	(4.09)	(3.80)	(3.79)	(3.30)	(3.11)	(2.49)	(2.90)	(2.02)
$BestIdeas$			0.0206***	0.0210***	0.0228***	0.0242***	0.0309***	0.0307***	0.0444***	0.0359***	0.0567***
			(4.71)	(5.87)	(6.19)	(4.83)	(5.68)	(4.73)	(5.45)	(4.39)	(4.93)
$\triangle MFO_{t+1}$					1.1278***						
					(10.21)						
$\triangle MFO_{t+1,t+2}$							1.6964***				
							(10.02)				
$\triangle MFO_{t+1,t+3}$									2.2510***		
									(9.89)		
$\triangle MFO_{t+1,t+4}$											2.7712***
											(9.34)
Intercept	0.0026	0.0322**	0.0017	0.0336**	0.0302**	0.0549*	0.0451*	0.0746*	0.0588	0.0882	0.0658
	(0.50)	(2.28)	(0.29)	(2.49)	(2.30)	(1.97)	(1.69)	(1.73)	(1.44)	(1.52)	(1.22)
$AvgAdj-R^2$	0.60%	6.87%	1.46%	7.19%	8.41%	7.03%	9.42%	6.86%	10.44%	6.66%	11.16%

3.4.2 Informed Fund Managers or Mutual Fund Herding?

Although consistent with the notion that mutual funds possess value-relevant information that is not fully reflected in stock prices, the higher returns on stocks with higher DFB may have alternative interpretations as well. For example, Gompers and Metrick (2001) argue that the expansion of institutional investors in U.S. stock markets impacted stock prices, driving up the prices of the stocks they preferred to hold beyond equilibrium levels and thus increasing the in-sample returns on those stocks. Does a demand pressure story explain the higher future returns on stocks with large active mutual fund bets? In the context of mutual funds, there is evidence that mutual funds tend to herd (Wermers, 1999, and Sias, 2004). If funds continue to buy stocks they previously overweighted, their demand pressure may push up stock prices, leading to positive returns.

To differentiate this alternative interpretation based on price pressure from our story of informed fund managers, we conduct a number of tests, which uniformly support the information-based interpretation for our finding. First, we explore their distinct implications for the dynamics of changes in mutual funds' deviations from benchmarks. Specifically, suppose that, in the world with informed fund managers, a risk-averse manager receives a positive signal about a stock in period t and decides to increase his portfolio weight in this stock relative to his benchmark, which results in an increase in DFB from $t-1$ to t. In the next period $t+1$, as his positive private information transmits into the stock price, the risk-averse manager has incentives to at least partially unwind the position that he has built up to capture the gains to his information. This position reversal takes place because the manager desires to reduce the long-term risk of future price movements arising from future events he cannot predict. In this scenario, a large increase in DFB in one period should predict a subsequent decline in DFB. In the world dominated by mutual fund herds, however, a large increase in the excess weight of a stock in an average fund's portfolio attracts further demand from the herd, which leads to increases in the stock price. According to this interpretation, a large increase in DFB in one period should forecast a further increase in DFB.

To test these different predictions, for each quarter from 1981Q1 to 2008Q3, we perform cross-sectional regressions of changes in DFB on the lagged changes in DFB and the lagged level of DFB. We use the Fama-MacBeth (1973) procedure with the Newey-West (1987) adjustment for serial correlation to conduct statistical significance. Panel A of Table 3.5 shows that an increase in DFB in one quarter reliably predicts a decline in DFB in the subsequent quarter, which concurs with the story of informed fund managers but contradicts the price pressure-based interpretation. In Panels B, C, and, D of Table 3.5, we perform similar analyses for subperiods in our sample. The results consistently show that an increase in DFB in one quarter reliably predicts a decline in DFB in the subsequent quarter.[11]

Second, a simple approach to examine the influence of demand pressure on our findings is to test the return forecasting power of our measure of deviations from benchmarks in the presence of realized future demand shocks. If active funds' deviations from benchmarks can forecast future returns due mainly to their correlation with future demand shocks, the return predictive power should cease to exist once the association between future returns and future demand shocks is controlled for. We conduct this test in column 5 of Panel A in Table 3.4. The results indicate that the return forecasting power of active funds' deviations from benchmarks remains intact after we control for future changes in mutual fund demand.

Last, we examine the persistence of the performance of stocks overweighted by mutual funds: If the high returns on stocks with high DFB arise mainly from demand pressure, these returns subsequently should reverse. If, however, the high returns come mostly from value-relevant information possessed by fund managers and the market reacts properly to that information, we expect to observe no subsequent return reversal.[12] In Panels B, C, and D of Table 3.4, we perform regressions similar to Equation (3.2) with the cumulative market-adjusted returns in the subsequent quarters as dependent variables. The results show that the positive association between DFB and future excess returns concentrates for the most proximate quarter, and this positive association shows no tendency to reverse for the subsequent two to four quarters. Thus, DFB appears to forecast returns due primarily to the value-relevant information that DFB aggregates from diverse mutual fund managers, as revealed through their investment decisions.

[11] The regulatory environment for mutual funds to disclose their portfolio compositions has varied over our sample period. For example, in 1985 the U.S. Securities and Exchange Commission (SEC) reduced the mandatory portfolio disclosure frequency from every quarter to every six months; effective May 2004, the SEC increased the required portfolio disclosure frequency from every six months to every quarter. To consider the potential influence of regulatory changes on our results, we split our sample into three subperiods, 1981-1984 (Panel B of Table 3.5), 1985-2004 (Panel C), and 2005-2008 (Panel D).

[12] One caveat about this prediction on long-term performance is that as managers unwind the positions they have overweighted relative to their benchmark, other market participants might continue to buy those shares, which could influence future price movements.

Table 3.5: **Dynamics of Changes in DFB, $\triangle DFB$**

This table presents the dynamic relation between consecutive changes in DFB. Specifically, at the end of each quarter from 1981Q1 to 2008Q3, we regress changes in a stock's DFB, $\triangle DFB_{t+1}$, on the lagged changes in DFB, $\triangle DFB_t$, the lagged level of DFB, DFB_t, and a bunch of stock characteristics. The t-statistics are computed using the Fama and MacBeth (1973) procedure with the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

$\triangle DFB_{t+1}$	Panel A: 1980-2008			Panel B: 1980-1984			Panel C: 1985-2004			Panel D: 2005-2008		
	1	2	3	1	2	3	1	2	3	1	2	3
Intercept	-0.0001	0.0002**	0.0011**	-0.0004	0.0007***	0.0035***	0.0000	0.0001***	0.0007***	0.0000	0.0000*	0.0002***
	(-0.97)	(2.52)	(2.61)	(-1.13)	(3.93)	(3.97)	(0.19)	(8.06)	(7.34)	(-1.53)	(2.05)	(3.85)
$\triangle DFB_t$	-0.3644***	-0.2739***	-0.2703***	-0.2422***	-0.1698***	-0.1711***	-0.3942***	-0.2950***	-0.2903***	-0.3519***	-0.2972***	-0.2963***
	(-14.28)	(-12.50)	(-12.79)	(-7.20)	(-6.27)	(-6.33)	(-18.96)	(-14.94)	(-15.20)	(-6.74)	(-6.01)	(-6.03)
DFB_t		-0.1583***	-0.1728***		-0.1751***	-0.1881***		-0.1661***	-0.1826***		-0.0856***	-0.0886***
		(-10.69)	(-11.20)		(-3.96)	(-4.30)		(-10.84)	(-12.01)		(-4.92)	(-5.24)
$MktCap_t$			-0.0001***			-0.0004***			-0.0001***			-0.0000***
			(-3.09)			(-3.94)			(-7.85)			(-3.77)
BM_t			0.0000			-0.0002***			0.0000***			0.0000***
			(-0.30)			(-3.11)			(3.47)			(3.41)
$Pr1Yr_t$			0.0000			0.0001			0.0000			-0.0001*
			(0.98)			(0.54)			(1.38)			(-2.13)
$ResVol_t$			-0.0036			-0.0245***			0.0001			0.0013
			(-1.13)			(-3.36)			(0.21)			(1.30)
$Turnover_t$			0.0002			0.0012*			0.0000			-0.0000**
			(1.24)			(1.87)			(0.10)			(-2.59)
$Adj-R^2$	17.31%	25.18%	26.56%	9.36%	20.65%	22.20%	19.75%	27.45%	28.79%	13.82%	18.53%	19.86%

3.4.3 Stock Characteristics

To increase our confidence in this information-based story, we conduct a series of tests based on stock attributes. First, we examine the return forecasting power of DFB across size groups. The idea is that very large firms tend to be more transparent, with better disclosure policy. They also tend to be more closely followed and researched by market participants. It is therefore more difficult for mutual funds to gain information advantages on those firms. On the other hand, returns to analyzing tiny firms appear to be small relative to the costs of information acquisition. These considerations prompt us to conjecture that mid-cap stocks could be the fields where information miners or stock pickers have the greatest information advantage. Second, along a similar vein of thinking, if mutual funds have informational advantages about individual stocks, we expect their advantages to be greater among stocks with more firm-specific information. Third, we expect the funds' informational advantages to be more valuable when the funds have fewer competitors. To examine these conjectures, we perform two-way sorts of stocks independently on DFB and firm size as well as proxies for the amount of firm-specific information and the number of mutual funds competing for private information. We use the idiosyncratic volatility, computed as the standard deviation of residuals from regressions of daily excess stock returns on the Fama and French factors in the past quarter, to proxy for the amount of firm-specific information, and the number of mutual funds that hold the stock at each quarter end to proxy for the number of investors competing for private information.

Specifically, along one dimension we sort stocks into quartiles based on DFB, and in the other dimension we sort stocks into quartiles based on their stock attributes such as size, idiosyncratic volatilities or the number of mutual fund holders. Sixteen portfolios thus emerge from the intersection of the two-way sorts. We hypothesize that a strategy that buys high DFB stocks and sells low DFB stocks generates higher abnormal returns among mid-caps and stocks with higher idiosyncratic volatilities and a lower number of mutual fund investors.

Table 3.6 presents the results. To conserve space, we only present equal- and value-weight four-factor alphas, but the results are qualitatively similar if we use other specifications of asset pricing models. Panel A of Table 3.6 shows that a strategy that buys high DFB and shorts low DFB stocks generates insignificant four-factor alpha among very large firms (Quartile 4) and tiny firms (Quartile 1) but produces large and significant four-factor alphas for mid-cap stocks in Quartiles 2 and 3, ranging between 0.45 and 0.60% per month on both equal- and value-weight basis. These results support our conjecture based on the economics of information acquisition.

Panel B of Table 3.6 shows that a strategy that is long high DFB and short low DFB stocks for stocks with high idiosyncratic volatilities yields average monthly four-factor alphas of 0.80%

Table 3.6: **Return-Predictive Power of DFB and Stock Characteristics**

This table presents the relation between the return-predictive power of DFB and stock characteristics. Specifically, at the end of each quarter from 1980Q3 to 2008Q3, we sort stocks independently based on their characteristics and DFB into quartiles. Sixteen portfolios thus form from these double sorts, with portfolio (1,1) containing stocks with the lowest value of the sorting variables and vice versa. The characteristics include market cap (Panel A), residual volatilities (Panel B), and the number of funds that hold the stock (Panel C). Then we calculate the average monthly equal-weight and value-weight returns for each of 16 portfolios for the subsequent quarter. We also report the Carhart 4-factor alpha differences between the extreme portfolios. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

	Equal-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)					Value-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)				
Ranking Variable	*DFB*					*DFB*				
Panel A: Stock Size	1	2	3	4	Q4-Q1	1	2	3	4	Q4-Q1
1	-0.13	-0.16	0.05	0.16	0.29	-0.20	-0.18	0.06	0.21	0.41*
	(-0.67)	(-1.15)	(0.38)	(1.29)	(1.22)	(-0.98)	(-1.4)	(0.45)	(1.66)	(1.69)
2	-0.19	-0.14	0.03	0.26	0.45***	-0.15	-0.13	0.03	0.31	0.46***
	(-1.86)	(-1.43)	(0.31)	(2.72)	(3.44)	(-1.53)	(-1.28)	(0.36)	(3.26)	(3.56)
3	-0.30	-0.07	0.02	0.27	0.57***	-0.31	-0.05	0.03	0.28	0.58***
	(-3.62)	(-0.84)	(0.24)	(2.06)	(3.40)	(-3.94)	(-0.6)	(0.31)	(2.10)	(3.43)
4	-0.14	-0.03	0.01	0.09	0.23	0.00	0.01	-0.04	0.14	0.14
	(-2.88)	(-0.35)	(0.09)	(0.61)	(1.53)	(0.10)	(0.17)	(-0.55)	(1.28)	(1.07)
Q4-Q1	-0.01	0.14	-0.04	-0.07	-0.06	0.21	0.19	-0.09	-0.06	-0.27
	(-0.05)	(0.84)	(-0.29)	(-0.32)	(-0.21)	(1.04)	(1.35)	(-0.66)	(-0.33)	(-0.98)
Panel B: Residual Vol	1	2	3	4	Q4-Q1	1	2	3	4	Q4-Q1
1	0.03	0.23	0.24	0.25	0.23***	-0.01	0.20	0.04	0.16	0.17
	(0.29)	(2.16)	(2.55)	(2.49)	(3.44)	(-0.1)	(2.07)	(0.37)	(1.54)	(1.45)
2	-0.16	0.10	0.17	0.22	0.38***	-0.23	-0.26	0.01	0.36	0.59***
	(-1.82)	(0.95)	(1.63)	(2.08)	(3.99)	(-2.25)	(-1.88)	(0.14)	(2.47)	(3.27)
3	-0.22	-0.01	0.05	0.28	0.50***	-0.19	-0.11	-0.09	0.34	0.53**
	(-2.9)	(-0.17)	(0.59)	(2.67)	(3.95)	(-1.07)	(-0.85)	(-0.72)	(1.89)	(2.20)
4	-0.97	-0.52	-0.33	-0.17	0.80***	-1.00	-0.62	-0.38	-0.12	0.88***
	(-6.74)	(-3.82)	(-2.75)	(-1.31)	(4.74)	(-5.41)	(-3.13)	(-1.72)	(-0.41)	(3.55)
Q4-Q1	-0.99***	-0.75***	-0.58***	-0.42**	0.57***	-1.00***	-0.82***	-0.42	-0.28	0.72***
	(-4.82)	(-3.88)	(-3.18)	(-2.25)	(3.28)	(-4.45)	(-3.25)	(-1.6)	(-0.91)	(2.80)
Panel C: # of Funds	1	2	3	4	Q4-Q1	1	2	3	4	Q4-Q1
1	-0.42	-0.16	0.02	0.12	0.55***	-0.66	-0.13	0.01	0.07	0.75***
	(-3.66)	(-1.16)	(0.17)	(1.04)	(3.81)	(-5.18)	(-1.01)	(0.09)	(0.55)	(4.11)
2	-0.26	-0.16	0.06	0.14	0.40***	-0.31	-0.12	0.07	0.13	0.44***
	(-2.93)	(-1.49)	(0.66)	(1.50)	(2.94)	(-2.99)	(-1.2)	(0.72)	(1.07)	(2.94)
3	-0.19	-0.08	0.07	0.28	0.47***	-0.20	-0.05	0.09	0.48	0.68***
	(-1.99)	(-0.75)	(0.80)	(2.51)	(3.08)	(-2.23)	(-0.58)	(1.05)	(2.69)	(3.37)
4	-0.10	-0.11	-0.03	0.14	0.24*	0.02	0.00	-0.05	0.12	0.10
	(-1.46)	(-1.1)	(-0.27)	(1.22)	(1.94)	(0.47)	(0.01)	(-0.58)	(1.15)	(0.80)
Q4-Q1	0.32**	0.04	-0.06	0.03	-0.29	0.68***	0.13	-0.06	0.05	-0.63***
	(2.27)	(0.24)	(-0.39)	(0.16)	(-1.62)	(5.33)	(0.80)	(-0.35)	(0.32)	(-3.34)

(t=4.74) on the equal-weight basis and 0.88% (t=3.55) on the value-weight basis. A similar strategy invested among stocks with low idiosyncratic volatilities generates average monthly four-factor alphas of only 0.23% (t=3.44) on the equal-weight basis and only 0.17% (t=1.45) on the value-weight basis. The difference in abnormal returns between these two strategies is large and statistically significant for both equal- and value-weighting. These results support our conjecture that informed mutual funds could have better information advantages in stocks with more firm-specific information.

The results in Panel C of Table 3.6 also support the information-based story. A strategy that buys high DFB stocks and sells low DFB stocks generates a value-weight monthly four-factor alpha of 0.75% (t=4.11) when implemented among stocks with a low number of mutual fund investors; the same strategy when implemented among stocks with a high number of mutual fund investors produces a value-weight monthly four-factor alpha of only 0.10% (t=0.80). This difference in abnormal returns also is large and statistically significant.

3.4.4 Fund Characteristics

The preceding results are devoted to a measure of DFB that reflects the investment decisions of all active mutual funds in our sample. In this subsection, we consider how different fund characteristics might influence the return forecasting power of DFB. Prior literature shows heterogeneous levels of skills or alphas across mutual funds (e.g., Fama and French, 2010). If fund managers with a higher level of alphas have better informational advantages, a DFB measure constructed from the universe of those funds could be a better return predictor than that from the universe of all active funds. To examine this conjecture, we partition funds into three groups based on their past performance, construct the measure of DFB using the portfolio compositions for each group of funds, and test for the forecasting power of DFB. If past performance relates to the level of skills of managers and thus to their informational advantages, a strategy that buys high DFB stocks and sells low DFB stocks should generate higher abnormal returns based on the portfolio decisions of funds with higher past performance. We measure fund performance using the Carhart (1997) four-factor alpha from rolling-window regressions of monthly fund returns during the past 24 or 36 months. We use both alphas and the precision-adjusted alphas, the t-statistics. As the results are qualitatively similar, we report those based on alphas estimated in the past 24 months.

Panel A of Table 3.7 shows the results. We find that a strategy that buys high DFB stocks and sells low DFB stocks based on the portfolio decisions of mutual funds with high past two-year alphas generates a equal-weight monthly four-factor alpha of 0.54% (t=5.42), which is more than twice as large as the four-factor alpha of 0.25% (t=2.64) on a similar strategy based on the portfolio decisions of low-performing funds. This difference in returns is large and statistically significant. These results support the notion that higher alpha fund managers have better informational advantages.

One concern with these results is that mutual fund flows tend to chase past fund performance (e.g., Sirri and Tufano, 1998; Chevalier and Ellison, 1997). If high inflows into top-performing funds induce fund managers to purchase the stocks they have overweighted, their buying pressure may lead to higher returns on these stocks. A similar story can be told for bottom-performing managers driven by fund outflows to sell the stocks they have underweighted. Contradicting these stories, we find that the higher returns on the DFB strategy implemented for higher-alpha managers come from both the higher returns on stocks that they overweight and the lower returns on stock they underweight. These results cast doubt on the flow-based explanation but lend further credit to the story of skilled managers.

We also consider whether funds with different investment styles could have different information advantages. For example, growth-oriented mutual funds tend to have better performance than income funds (e.g., Grinblatt and Titman, 1993). Da, Gao, and Jagannathan (2010) argue that income funds tend to provide liquidity, whereas growth funds, likely driven by their superior information, tend to engage in informed trading. Based on these considerations, we conjecture that a DFB strategy based on the portfolio selection of growth funds could generate higher performance than does a similar strategy based on the investment decisions of income funds. Panel B of Table 3.7 provides evidence that concurs with our conjecture.

3.4.5 DFB and Corporate Earnings News

If mutual funds have informational advantages about the stocks they overweight relative to their benchmarks, we expect those stocks to perform particularly well around the days their positive information gets released to the market. In stock markets, one of the most important corporate news events is the release of corporate earnings.

To explore the nature of the information content captured by DFB, we start by examining the relation between DFB and firms' future earnings surprises. We use two proxies for earnings surprises: the difference between actual earnings and the consensus analyst earnings forecasts from the Institutional Brokers' Estimate System (I/B/E/S) divided by the absolute value of actual earnings and that divided by the stock price at the end of the previous quarter. For each quintile portfolio based on DFB, we calculate the earnings surprises for the median firm in the following four quarters and report their time-series averages. Panels A and B of Table 3.8 show that stocks

Table 3.7: **Return Predictive Power of DFB and Fund Characteristics**

This table presents the return forecasting power of DFB constructed using the portfolio holdings of mutual funds grouped on the basis of fund characteristics. Panel A uses past fund alphas, estimated as intercepts from rolling-window regressions of excess net fund returns on the market, size, value, and momentum factors in the past two years. Specifically, at the end of each quarter from 1983Q4 to 2008Q3, we divide all mutual funds by their characteristics into terciles based on fund alphas. Within each tercile, we compute mutual funds' deviations from benchmarks, DFB, as the simple average of the stock's weight in a mutual fund portfolio in excess of its weight in the fund's benchmark index across all mutual funds. We sort stocks into quintiles in ascending order based on DFB for each tercile of funds and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter. We also present the risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Panel B groups funds based on their investment objectives. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Grouping Funds into Terciles Based on Past Two-Year Alpha

Sorting Variable		Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Past alpha	DFB	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
Low	1	0.80	-0.09	-0.21	-0.16	-0.16	0.78	-0.06	0.02	0.01	0.01
		(2.81)	(-1.08)	(-3.89)	(-2.67)	(-2.61)	(3.17)	(-1.05)	(0.40)	(0.16)	(0.16)
	5	1.15	0.21	0.14	0.09	0.12	1.09	0.17	0.25	0.11	0.12
		(3.34)	(1.34)	(1.82)	(1.19)	(1.55)	(3.63)	(1.94)	(3.33)	(1.40)	(1.50)
	Q5-Q1	0.36***	0.30**	0.36***	0.25***	0.27***	0.31**	0.23*	0.23**	0.10	0.11
		(2.74)	(2.34)	(3.70)	(2.64)	(2.79)	(2.36)	(1.87)	(2.54)	(1.05)	(1.15)
Medium	1	0.73	-0.16	-0.28	-0.24	-0.23	0.77	-0.07	0.00	0.00	0.00
		(2.51)	(-1.82)	(-5.2)	(-3.91)	(-3.82)	(3.13)	(-1.25)	(-0.11)	(-0.11)	(-0.05)
	5	1.26	0.34	0.24	0.20	0.22	1.19	0.29	0.35	0.22	0.23
		(3.79)	(2.25)	(3.23)	(2.81)	(3.21)	(4.00)	(3.09)	(4.05)	(2.77)	(2.95)
	Q5-Q1	0.53***	0.50***	0.52***	0.44***	0.46***	0.42***	0.36***	0.35***	0.22**	0.23**
		(4.96)	(4.64)	(6.05)	(5.14)	(5.36)	(3.13)	(2.80)	(3.39)	(2.16)	(2.31)
High	1	0.68	-0.19	-0.34	-0.28	-0.28	0.77	-0.06	-0.02	-0.02	-0.02
		(2.48)	(-2.25)	(-6.12)	(-4.54)	(-4.48)	(3.26)	(-1.11)	(-0.58)	(-0.5)	(-0.43)
	5	1.34	0.39	0.38	0.26	0.28	1.26	0.30	0.49	0.26	0.26
		(3.74)	(2.29)	(4.74)	(3.53)	(3.80)	(3.63)	(2.26)	(4.05)	(2.35)	(2.39)
	Q5-Q1	0.66***	0.58***	0.72***	0.54***	0.56***	0.49**	0.35**	0.51***	0.28**	0.28**
		(4.20)	(3.88)	(7.12)	(5.42)	(5.48)	(2.57)	(2.19)	(3.58)	(2.04)	(2.06)
High-Low	1	-0.11***	-0.10**	-0.13***	-0.12***	-0.12**	-0.01	0.00	-0.04	-0.03	-0.02
		(-2.7)	(-2.26)	(-2.84)	(-2.6)	(-2.58)	(-0.27)	(0.08)	(-1.44)	(-0.92)	(-0.81)
	5	0.19**	0.18**	0.23***	0.17***	0.17***	0.16	0.13	0.24**	0.15	0.14
		(2.55)	(2.30)	(3.30)	(2.71)	(2.67)	(1.55)	(1.25)	(2.19)	(1.47)	(1.43)
	Q5-Q1	0.30***	0.27**	0.36***	0.29***	0.29***	0.17	0.13	0.28**	0.17	0.17
		(2.96)	(2.57)	(3.60)	(3.10)	(3.05)	(1.35)	(1.03)	(2.16)	(1.44)	(1.38)

Panel B: Grouping Funds into Terciles Based on Investment Objectives

Sorting Variable		Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Investment Objectives	DFB	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
Aggressive Growth	1	0.86	-0.01	-0.19	-0.11	-0.12	0.83	-0.01	0.00	0.01	0.01
		(3.28)	(-0.16)	(-3.84)	(-2.16)	(-2.27)	(3.58)	(-0.29)	(-0.12)	(0.30)	(0.36)
	5	1.23	0.23	0.23	0.15	0.20	1.04	0.06	0.17	0.07	0.10
		(3.41)	(1.49)	(2.70)	(1.79)	(2.48)	(3.20)	(0.61)	(2.12)	(0.81)	(1.22)
	Q5-Q1	0.36**	0.24*	0.42***	0.26***	0.32***	0.21	0.07	0.18*	0.06	0.09
		(2.25)	(1.68)	(4.28)	(2.70)	(3.38)	(1.36)	(0.57)	(1.74)	(0.54)	(0.83)
Growth	1	0.69	-0.21	-0.36	-0.28	-0.27	0.79	-0.06	-0.02	-0.02	-0.01
		(2.43)	(-2.19)	(-6.58)	(-4.63)	(-4.48)	(3.35)	(-1.09)	(-0.46)	(-0.47)	(-0.31)
	5	1.28	0.34	0.29	0.19	0.21	1.21	0.24	0.41	0.19	0.20
		(3.77)	(2.08)	(3.96)	(2.83)	(3.02)	(3.67)	(2.04)	(3.87)	(2.13)	(2.25)
	Q5-Q1	0.59***	0.54***	0.64***	0.47***	0.47***	0.42**	0.30**	0.42***	0.21*	0.22**
		(4.70)	(4.39)	(7.20)	(5.41)	(5.28)	(2.43)	(2.02)	(3.41)	(1.89)	(1.97)
Growth & Income	1	1.01	0.08	-0.02	-0.06	-0.04	0.81	-0.07	0.03	0.02	0.01
		(3.39)	(0.76)	(-0.25)	(-0.79)	(-0.62)	(3.18)	(-1.18)	(0.67)	(0.38)	(0.30)
	5	1.09	0.19	-0.01	0.02	0.04	0.99	0.11	0.08	-0.01	0.02
		(3.74)	(1.56)	(-0.1)	(0.34)	(0.58)	(3.91)	(1.58)	(1.15)	(-0.08)	(0.22)
	Q5-Q1	0.08	0.10	0.01	0.08	0.08	0.18	0.19*	0.05	-0.02	0.00
		(0.92)	(1.26)	(0.11)	(1.02)	(1.08)	(1.65)	(1.67)	(0.57)	(-0.22)	(0.03)
Growth & Income - Aggressive Growth	1	0.14*	0.09	0.17***	0.06	0.08	-0.02	-0.06	0.03	0.00	0.00
		(1.74)	(1.19)	(2.76)	(0.88)	(1.22)	(-0.45)	(-1.25)	(0.77)	(0.12)	(-0.01)
	5	-0.14	-0.04	-0.23***	-0.13*	-0.16**	-0.05	0.06	-0.09	-0.07	-0.09
		(-1.1)	(-0.39)	(-3.07)	(-1.7)	(-2.19)	(-0.42)	(0.55)	(-1.05)	(-0.82)	(-0.93)
	Q5-Q1	-0.28	-0.14	-0.41***	-0.18	-0.24**	-0.03	0.11	-0.12	-0.08	-0.08
		(-1.45)	(-0.79)	(-3.4)	(-1.55)	(-2.05)	(-0.18)	(0.81)	(-1.03)	(-0.65)	(-0.69)

with high DFB tend to experience large and positive earnings surprises for up to the next four quarters, and the effect, strongest for the most proximate quarter, decays substantially through time. There is evidence of earnings momentum (e.g., Chan, Jegadeesh, and Lakonishok, 1996). If active mutual funds trade on earnings momentum, we could observe a positive association between DFB and subsequent earnings surprises. To examine this conjecture, we first group stocks into terciles based on the current quarter's earnings surprises and then divide the stocks within each tercile into five quintiles based on DFB. We average the difference in earnings surprises between high and low DFB stocks across the three terciles and report this averaged difference as momentum-adjusted earnings surprises. Our results show that this adjustment eliminates the higher earnings surprises in the next two to four quarters for stocks active funds overweight, but for the most proximate quarter, stocks with higher DFB remain to experience significantly higher earnings surprises.

We also examine the three-day abnormal returns surrounding earnings announcements for each portfolio of stocks sorted on the basis of DFB. Panel C of Table 3.8 shows that an average stock in the top quintile of stocks heavily overweighted by mutual funds earns, in the time around earnings announcements in the following quarter, a three-day cumulative abnormal return of approximately 30 basis points, which is statistically significant. In contrast, an average stock in the bottom quintile heavily underweighted by mutual funds generates a three-day cumulative abnormal return of only 3 basis points, or 90% lower. Even after adjustments for earnings momentum, the difference in three-day abnormal returns around earnings announcements is 24 basis points and statistically significant. These results suggest that a significant portion of the return premiums on the stocks mutual funds heavily overweight occurs around corporate earnings releases, which in turn implies that part of active funds' superior information relates to firms' fundamental prospects.[13]

3.4.6 DFB and Mutual Fund Performance

How can we reconcile our evidence that points to strong informational advantages of mutual funds in stock markets with the overall lackluster performance of mutual funds identified by

[13] Our evidence is consistent with Baker, Litov, Wachter, and Wurgler (2010), who argue that fund managers actively trade stocks prior to earnings announcements to exploit their informational advantages. We recognize that the magnitude of the abnormal performance of stocks heavily overweighted by mutual funds around earnings announcement dates may be insufficient to explain the superior performance of those stocks; the sign of the abnormal performance of stocks heavily underweighted by mutual funds around earnings announcement dates differs from the overall performance of those stocks. Our evidence therefore suggests some aspects of informational advantages for mutual funds, other than their ability to forecast near-term earnings news. We leave the further identification of specific informational advantages of mutual funds to future research.

Table 3.8: DFB **and Future Earnings News**

This table presents the forecasting power of DFB for subsequent earnings surprises. At the end of each quarter from 1980Q3 to 2008Q3, we sort stocks into quintiles, based on DFB, in ascending order and compute the average quarterly earnings surprise and the cumulative abnormal returns around the earnings announcement in the four quarters following the portfolio formation date. The earnings surprise is the difference between actual earnings and consensus analyst forecast, divided by the absolute value of actual earnings or stock price. The earnings announcement cumulative abnormal return is calculated for the three days around the earnings announcement date. Earnings data and earnings announcement dates come from I/B/E/S. To adjust for earnings momentum, we first group stocks into terciles based on the current quarter's earnings surprises and then divide the stocks within each tercile into five quintiles based on DFB. We average the difference in earnings surprises for subsequent quarters between high and low DFB stocks across the three terciles and report the averaged difference as momentum-adjusted earnings surprises. Stocks with prices lower than \$5 at the quarter end are excluded. The t-statistics are computed using the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

	Quarters			
	t+1	t+2	t+3	t+4
A: Earnings Surprise Scaled by Actual Earnings (%)				
Q1	0.159	0.393	0.462	0.453
	(0.32)	(1.05)	(1.26)	(1.19)
Q5	2.470	1.840	1.262	0.858
	(5.62)	(4.35)	(2.81)	(1.85)
Q5-Q1	2.353***	1.447***	0.800***	0.405**
	(6.03)	(9.05)	(5.69)	(2.22)
Q5-Q1 (Momentum-Adj)	1.384***	0.474	0.468	0.467
	(5.31)	(0.93)	(1.38)	(1.12)
B: Earnings Surprise Scaled by Price (%)				
Q1	-0.004	0.002	0.003	0.003
	(-0.39)	(0.30)	(0.44)	(0.42)
Q5	0.033	0.025	0.015	0.010
	(5.60)	(4.27)	(2.44)	(1.46)
Q5-Q1	0.038***	0.023***	0.012***	0.007**
	(4.06)	(6.93)	(6.36)	(2.10)
Q5-Q1 (Momentum-Adj)	0.024***	-0.010	0.004*	0.062
	(4.23)	(-0.74)	(1.70)	(1.02)
C: CARs around Earnings Announcement (%)				
Q1	0.034	0.086	0.075	0.063
	(1.20)	(3.13)	(3.01)	(2.47)
Q5	0.298	0.163	0.157	0.140
	(5.06)	(3.25)	(3.18)	(2.88)
Q5-Q1	0.260***	0.077	0.082*	0.076*
	(4.32)	(1.46)	(1.97)	(1.93)
Q5-Q1 (Momentum-Adj)	0.243***	-0.005	0.017	0.053
	(3.13)	(-0.15)	(0.35)	(1.18)

prior literature? To understand the contribution of stocks with large active fund bets to the overall performance of active funds, for each decile of stocks sorted on the basis of DFB we calculate the fund investments-weighted portfolio returns and report the fraction of total mutual fund assets invested in each decile portfolio. The results in Table 3.9 indicate that stocks in Decile 10 heavily overweighted by active funds generate high abnormal returns with a four-factor alpha of 6% per year. But active funds in aggregate invest less than 10% of their assets in those stocks. On the other hand, although stocks in Decile 1 heavily underweighted by active funds generate a four-factor alpha close to zero, they receive approximately 34% of total active fund assets. In other words, a large four-factor alpha of 6% per year on high DFB stocks translates into a small mutual fund alpha of less than 1% per year before fees and expenses.

Up to this point, we have found evidence consistent with the notion that mutual funds deviate from their benchmarks to exploit their informational advantages and that their deviations generate superior performance. Yet we have left unexplained whether funds make optimal portfolio decisions. For example, could a fund manager have performed better by constructing a more aggressive portfolio with larger tilts away from its benchmark?

In the model economy outlined in Appendix A, a manager's portfolio choice is governed by the desire to maximize the portfolio's performance relative to its benchmark and an aversion to taking active risks associated with deviating from that benchmark. The manager's optimal decision therefore is jointly determined by three factors: degree of risk aversion, expected returns of securities conditional on the manager's information set, and risks of securities. We lack accurate estimates of these three variables, so we cannot to provide a definitive answer to the question. The results in Table 3.2 show that the stocks with high DFB tend to be relatively small and frequently float outside the stock indexes against which mutual funds are benchmarked; on the contrary, the stocks with low DFB tend to be large and the majority of them appear in the indexes against which active funds are benchmarked. These observations lead us to conjecture that aversion to taking large active risks could have an important role in shaping the activeness of fund managers' portfolios.

In the real world, fund managers seek to maximize their compensation for the portfolio management services they provide to fund investors. Conventional industry practice rewards mutual fund managers mainly on the basis of the size of the assets under their management. Accordingly, they have incentives to grow their assets. Berk and Green (2004) thus tell an interesting story: For skilled fund managers to capitalize on their informational advantages, they combine an active portfolio that consists of stocks that generate alphas and a passive portfolio that is invested primarily in a benchmark index. In equilibrium, these skilled fund managers capture economic

Table 3.9: DFB **and Mutual Fund Performance**

This table presents the contribution of portfolios sorted on the basis of DFB to the aggregate mutual fund performance. At the end of each quarter from 1980Q3 to 2008Q3, we sort stocks into deciles, based on DFB, in ascending order and compute the aggregate fund dollar holdings for each decile. We calculate the average monthly holdings-weighted portfolio returns in the subsequent quarter, and also present the risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with the Pastor and Stambaugh (2003) liquidity factor. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

		Holdings-Weighted Post-Ranking Portfolio Return (%/month)				
Decile	% of Aggregate Fund Investments	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.34	0.80	-0.08	0.00	-0.02	-0.02
		(3.16)	(-1.23)	(0.09)	(-0.4)	(-0.4)
2	0.07	1.08	0.18	0.05	0.14	0.14
		(3.81)	(1.88)	(0.54)	(1.49)	(1.43)
3	0.05	1.03	0.10	-0.03	0.05	0.07
		(3.49)	(0.86)	(-0.24)	(0.55)	(0.68)
4	0.03	0.97	0.05	-0.06	0.04	0.05
		(3.06)	(0.45)	(-0.56)	(0.33)	(0.42)
5	0.05	1.02	0.07	-0.06	0.10	0.11
		(3.29)	(0.51)	(-0.53)	(0.84)	(0.84)
6	0.07	1.03	0.07	-0.07	0.05	0.06
		(3.31)	(0.62)	(-0.69)	(0.44)	(0.59)
7	0.09	1.12	0.17	0.11	0.17	0.20
		(3.67)	(1.77)	(1.25)	(1.83)	(2.31)
8	0.10	1.04	0.08	0.05	0.02	0.04
		(3.30)	(0.68)	(0.52)	(0.16)	(0.38)
9	0.11	1.38	0.40	0.49	0.32	0.35
		(4.20)	(2.95)	(4.32)	(2.95)	(3.36)
10	0.09	1.57	0.56	0.81	0.50	0.55
		(3.95)	(2.61)	(3.81)	(2.98)	(3.34)
D10-D1		0.77***	0.64***	0.80***	0.52***	0.57***
		(2.92)	(2.68)	(3.64)	(2.82)	(3.17)
D9-D2		0.30*	0.22	0.44***	0.18	0.22
		(1.81)	(1.34)	(3.20)	(1.33)	(1.62)

rents by managing a large portfolio so that investors, who have no comparative advantages in competitive capital markets, earn a return that is close to the benchmark. Although our study is not a direct test of Berk and Green's model, our evidence is consistent with their predictions about the behavior of fund managers.

3.5 Robustness Checks

We perform several robustness checks. First, we compute DFB based on an alternative benchmark index: the value-weighted portfolio of stocks that a fund actually holds. Second, we consider results based on changes in DFB. Third, we examine the performance of portfolios sorted by DFB through different subperiods. Four, we consider conditional performance evaluation. Finally, we consider the influence of mutual funds' potential preferential access to IPO allocations.

3.5.1 Alternative Measures of DFB

We have included 19 stock indexes widely used by practitioners as our primary universe of performance benchmarks, and for each fund, we selected for each quarter one index that minimizes the distance between stocks' weights in the fund and those in the index. In this subsection, we consider an alternative way to construct a benchmark index for a specific fund, namely, by forming market cap-weighted portfolios that consist of stocks actually held by each fund.[14]

Panel A of Table 3.10 reports the performance of DFB when we use these specifically tailored benchmark indexes. Consistent with the results in Table 3.3, mutual funds' deviations from benchmarks captured by this new measure of DFB strongly and positively forecast future stock returns. For example, Panel A of Table 3.10 shows that stocks heavily overweighted by mutual funds in Decile 10 generate a monthly equal-weight four-factor alpha of 0.56%, whereas stocks heavily overweighted by mutual funds in Decile 1 earn a negative four-factor alpha of -0.37% per month. Therefore, a portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 earns a four-factor alpha of 0.93% per month, 3.10 is statistically significant. This positive association between DFB and future returns is robust to different risk adjustments and reliable for both equal-weighting and value-weighting.

We also consider a variation of the DFB measure by discretizing the distance between a

[14]Because a mutual fund might respond to negative information about a firm by avoiding holding its shares, we also consider a value-weighted benchmark consisting of all stocks that the fund has held during the past five years. The results are qualitatively similar.

stock's weight in a fund's portfolio and the benchmark portfolio into two categories: over- and underweighting. In particular, we construct an indicator variable that equals one if the stock is overweighted by the fund and zero otherwise. Then we average this indicator variable for all funds whose investment comprises that stock, as in Equation (3.2). This new measure, DFB^{alt}, captures the fraction of funds that overweight the stock. It also can be viewed as polling each fund manager to vote for stocks that they perceive as future winners based on their portfolio weighting decisions. A stock receives a strong buy recommendation if the majority of the funds polled are bullish about the stock; it receives a strong sell if the majority of the funds are bearish about it.

$$DFB_{i,t}^{alt} = \sum_{j=1}^{N_i} Indicator(w_{i,t}^{j} - w_{i,t}^{b} > 0)/N_i, \tag{3.3}$$

Panel B of Table 3.10 presents the average returns and factor alphas on decile portfolios formed according to DFB^{alt}. The results indicate that stocks with high DFB^{alt} strongly outperform stocks with low DFB^{alt} and that this outperformance is robust to equal- and value-weighting and remains strong after various risk adjustments. These results reinforce the existence of informational advantages of mutual funds in stock markets.

We finally consider the influence of the best ideas that Cohen, Polk and Silli (2010) consider on our results. We find that our results remain virtually unchanged after we exclude each manger's best one to three ideas from the computation of DFB. To summarize, the return forecasting power of DFB is insensitive to different ways of forming benchmark portfolios and robust to the exclusion of fund managers' best ideas.

3.5.2 Changes in DFB

Our results have shown that DFB captures information relevant for future returns and that the value of the information tends to dissipate after one quarter. If fund managers respond to new information by efficiently adjusting their portfolio weights, a measure based on their portfolio adjustments should relate to future returns. In this subsection, we examine this conjecture by relating changes in DFB and stock returns. The changes in DFB contain two components: changes in a stock's weights in the mutual fund portfolio and in the benchmark index. If passive managers who track the performance of their benchmarks adjust their portfolio weights according to changes in the benchmark weights, changes in DFB should capture the active trades made by active managers.

Table 3.10: **Alternative Measure of DFB and Future Stock Returns**

This table presents the performance of decile portfolios formed on the basis of alternative measures of DFB. Panel A uses an alternative set of benchmark index. At the end of each quarter from 1980Q3 to 2008Q3, we select for each mutual fund a benchmark portfolio containing stocks that are held by the fund. We construct the benchmark as the market-capitalization-weighted portfolio of these stocks. Panel B uses an alternative measure DFB^{alt} based on the fraction of funds that overweight the stock, as defined in Equation (3.3). We sort stocks into deciles, based on these alternative measures of mutual funds' deviations from benchmarks in ascending order and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

Panel A: Alternative Benchmark Index

	Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.53	-0.46	-0.50	-0.37	-0.40	0.83	-0.11	-0.02	0.00	0.00
	(1.73)	(-5.03)	(-6.43)	(-5.17)	(-5.45)	(3.30)	(-1.75)	(-0.6)	(-0.05)	(-0.05)
2	0.74	-0.20	-0.38	-0.27	-0.26	0.72	-0.27	-0.35	-0.12	-0.12
	(2.27)	(-1.21)	(-4.23)	(-2.88)	(-2.65)	(2.42)	(-2.76)	(-3.38)	(-1.13)	(-1.1)
3	0.80	-0.12	-0.32	-0.17	-0.14	0.75	-0.23	-0.31	-0.13	-0.14
	(2.50)	(-0.7)	(-3.23)	(-1.85)	(-1.54)	(2.58)	(-2.21)	(-3.37)	(-1.58)	(-1.62)
4	0.94	-0.04	-0.25	-0.08	-0.06	0.95	-0.03	-0.16	-0.04	-0.03
	(2.90)	(-0.27)	(-3.19)	(-1.08)	(-0.83)	(3.35)	(-0.37)	(-2.14)	(-0.55)	(-0.44)
5	0.93	-0.06	-0.26	-0.07	-0.06	0.91	-0.05	-0.18	-0.13	-0.13
	(2.93)	(-0.39)	(-3.63)	(-1.02)	(-0.85)	(3.38)	(-0.63)	(-2.33)	(-1.69)	(-1.62)
6	1.03	0.03	-0.17	-0.05	-0.03	1.08	0.11	-0.01	0.02	0.02
	(3.18)	(0.21)	(-2.33)	(-0.72)	(-0.45)	(3.93)	(1.30)	(-0.21)	(0.24)	(0.29)
7	1.13	0.13	-0.03	0.02	0.04	1.12	0.16	0.06	0.06	0.07
	(3.50)	(0.96)	(-0.45)	(0.30)	(0.58)	(4.14)	(1.90)	(0.75)	(0.78)	(0.82)
8	1.17	0.18	0.04	0.04	0.07	1.24	0.28	0.19	0.10	0.12
	(3.75)	(1.36)	(0.57)	(0.53)	(0.98)	(4.61)	(3.31)	(2.71)	(1.44)	(1.67)
9	1.36	0.35	0.25	0.16	0.20	1.39	0.42	0.37	0.17	0.19
	(4.22)	(2.58)	(3.36)	(2.07)	(2.69)	(4.94)	(4.34)	(4.50)	(2.29)	(2.69)
10	1.86	0.82	0.77	0.56	0.60	1.90	0.89	0.95	0.60	0.62
	(5.22)	(4.83)	(8.31)	(6.32)	(7.06)	(5.50)	(5.62)	(6.10)	(4.50)	(4.77)
D10-D1	1.32***	1.28***	1.27***	0.94***	1.00***	1.08***	1.00***	0.97***	0.60***	0.62***
	(8.34)	(7.72)	(9.01)	(7.38)	(8.24)	(5.15)	(5.10)	(5.62)	(3.89)	(4.09)
D9-D2	0.62***	0.55***	0.63***	0.43***	0.46***	0.67***	0.69***	0.73***	0.29**	0.31**
	(5.83)	(4.77)	(5.25)	(3.30)	(3.44)	(5.26)	(5.34)	(4.70)	(2.00)	(2.23)

Panel B: DFB^{alt} based on the Fraction of Active Funds that Overweight the Stock

	Equal-Weight Post-Ranking Portfolio Return (%/month)						Value-Weight Post-Ranking Portfolio Return (%/month)					
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return
1	0.49	-0.41	-0.58	-0.39	-0.40	-0.35	0.56	-0.29	-0.49	-0.34	-0.35	-0.27
	(1.53)	(-2.9)	(-5.73)	(-3.91)	(-4.2)	(-4.08)	(2.06)	(-2.7)	(-5.78)	(-3.99)	(-4.1)	(-4.28)
2	0.79	-0.13	-0.34	-0.13	-0.13	-0.09	0.86	0.00	-0.18	-0.08	-0.09	-0.05
	(2.56)	(-1)	(-4.14)	(-1.65)	(-1.71)	(-1.45)	(3.44)	(0.03)	(-2.25)	(-1.05)	(-1.27)	(-0.81)
3	0.93	-0.02	-0.20	-0.05	-0.04	0.03	0.93	0.03	-0.09	-0.04	-0.05	0.00
	(2.96)	(-0.19)	(-2.81)	(-0.63)	(-0.47)	(0.58)	(3.53)	(0.32)	(-1.19)	(-0.52)	(-0.65)	(-0.06)
4	0.95	0.04	-0.09	0.04	0.05	0.03	0.95	0.10	0.01	0.02	0.02	-0.01
	(2.89)	(0.31)	(-1.07)	(0.59)	(0.61)	(0.45)	(3.45)	(1.38)	(0.17)	(0.26)	(0.22)	(-0.16)
5	0.95	0.04	-0.08	0.03	0.04	0.07	0.87	0.02	-0.04	-0.03	-0.05	0.01
	(2.92)	(0.27)	(-1.13)	(0.39)	(0.49)	(1.21)	(3.21)	(0.28)	(-0.66)	(-0.54)	(-0.95)	(0.12)
6	0.94	0.05	-0.02	0.03	0.05	0.11	0.86	0.03	0.05	0.00	0.01	0.02
	(2.88)	(0.41)	(-0.29)	(0.46)	(0.76)	(2.03)	(3.15)	(0.37)	(0.68)	(0.03)	(0.11)	(0.42)
7	1.16	0.20	0.09	0.10	0.13	0.15	1.11	0.18	0.20	0.19	0.20	0.11
	(3.59)	(1.47)	(1.48)	(1.58)	(2.07)	(3.09)	(3.77)	(2.27)	(2.48)	(2.39)	(2.52)	(1.32)
8	1.00	0.23	0.14	0.02	0.04	0.20	0.51	-0.23	-0.13	-0.31	-0.30	-0.05
	(2.42)	(1.08)	(0.85)	(0.14)	(0.20)	(0.99)	(1.46)	(-1.53)	(-0.79)	(-1.69)	(-1.54)	(-0.5)
9	1.07	0.18	0.17	0.14	0.15	0.02	0.97	0.07	0.30	0.00	0.03	0.05
	(2.96)	(0.85)	(1.37)	(1.10)	(1.21)	(0.17)	(2.55)	(0.27)	(1.40)	(0.02)	(0.15)	(0.43)
10	1.19	0.46	0.29	0.22	0.24	0.23	1.25	0.52	0.42	0.34	0.39	0.27
	(2.96)	(1.85)	(1.84)	(1.35)	(1.43)	(1.78)	(3.38)	(2.18)	(1.95)	(1.51)	(1.74)	(1.69)
D10-D1	0.75***	0.84***	0.81***	0.64***	0.67***	0.63***	0.71***	0.76***	0.79***	0.63***	0.69***	0.55***
	(3.77)	(4.29)	(4.44)	(3.55)	(3.67)	(4.31)	(3.23)	(3.38)	(3.45)	(2.67)	(2.96)	(3.56)
D9-D2	0.40**	0.39**	0.51***	0.26*	0.28*	0.15	0.17	0.08	0.46*	0.04	0.08	0.12
	(2.48)	(2.43)	(3.60)	(1.83)	(1.89)	(1.35)	(0.56)	(0.27)	(1.79)	(0.19)	(0.38)	(0.84)

Table 3.11 presents the performance of portfolios sorted according to changes in DFB. Consistent with our conjecture, changes in DFB contain strong return-forecasting power. Panel A of Table 3.11, for example, shows that stocks with the largest increases in DFB outperform, in the subsequent quarter, stocks with the largest decreases in DFB by 1.15% per month on the equal-weighted basis. This difference is highly statistically significant, with a t-statistic of 7.79. Standard risk adjustments have virtually no effect on this return differential. Panel B further shows that value-weighted returns yield a similar pattern both qualitatively and quantitatively. These results lend further support to mutual funds' informational advantages for the stocks for which they display the most conviction.

3.5.3 Subperiod Analysis

The information environment of corporations in United States has changed over time.[15] Does this change influence mutual funds' informational advantages as an investor group? To address this question, we divide our sample into four subperiods (1980–1987, 1988–1994, 1995–2001, and 2002–2008) and consider the performance of DFB through time.

Table 3.12 presents the performance of decile portfolios that is formed on the basis of DFB over four subperiods. Except for the first subperiod, from 1980 to 1987,[16] the return forecasting power of DFB remains strong across time. Therefore, despite the changing information environment, active mutual funds appear to maintain a consistent edge in acquiring relevant and costly information. This evidence is consistent with the idea that mutual funds gain their informational advantages from their superior skills.

3.5.4 Conditional Performance Evaluation

Jiang, Yao, and Yu (2007) argue that mutual funds have superior market-timing ability, which translates into superior fund performance.[17] Could the higher returns on stocks heavily overweighed by mutual funds reflect their managers' correct assessment of future market returns,

[15] For example, the U.S. Securities and Exchange Commission (SEC) instated the Regulation Fair Disclosure (Reg FD) in October 2000 to eliminate selective disclosure by firms to a subset of market participants. In the SEC release about Reg FD, its stated goal was to eliminate situations in which "a privileged few gain an informational edge – and the ability to use that edge to profit – from their superior access to corporate insiders, rather than from their skill, acumen, or diligence."

[16] The mutual fund industry was relatively small during the early part of our sample. During 1980–1987, 200 to 360 funds reported their holdings that accounted for less than 4% of the CRSP sample based on market cap. Moreover, few benchmark indexes were available during this period, which could be another reason for the weak results.

[17] Taliaferro (2009) and Beron-Drish and Sagi (2009) provide recent but less optimistic evidence on the timing ability of mutual funds.

Table 3.11: **Changes in DFB and Future Stock Returns**

This table presents the performance of decile portfolios formed on the basis of the changes in DFB between adjacent quarters. At the end of each quarter from 1980Q4 to 2008Q3, we sort stocks into deciles in ascending order based on the changes in DFB over the quarter and compute the average monthly equal-weight (Panel A) and value-weight (Panel B) portfolio returns in the subsequent quarter. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

	Panel A: Equal-Weight Post-Ranking Portfolio Return (%/month)					Panel B: Value-Weight Post-Ranking Portfolio Return (%/month)				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.48	-0.49	-0.56	-0.53	-0.51	0.44	-0.48	-0.35	-0.51	-0.50
	(1.32)	(-3.15)	(-4.99)	(-4.65)	(-4.24)	(1.42)	(-4.2)	(-2.85)	(-3.93)	(-3.89)
2	0.57	-0.37	-0.50	-0.42	-0.39	0.47	-0.44	-0.42	-0.43	-0.43
	(1.70)	(-2.76)	(-6.16)	(-5.2)	(-4.78)	(1.62)	(-4.75)	(-4.64)	(-4.7)	(-4.58)
3	0.65	-0.27	-0.45	-0.36	-0.34	0.72	-0.18	-0.23	-0.22	-0.21
	(2.03)	(-2.23)	(-6.23)	(-4.74)	(-4.41)	(2.63)	(-2.19)	(-2.87)	(-2.4)	(-2.29)
4	0.68	-0.22	-0.42	-0.32	-0.31	0.89	0.01	-0.05	-0.04	-0.05
	(2.20)	(-1.71)	(-6.18)	(-5.09)	(-4.99)	(3.32)	(0.13)	(-0.61)	(-0.51)	(-0.58)
5	0.82	-0.04	-0.25	-0.16	-0.16	0.94	0.07	-0.07	0.03	0.03
	(2.76)	(-0.26)	(-3.02)	(-2.15)	(-2.27)	(3.57)	(0.77)	(-0.86)	(0.39)	(0.34)
6	0.98	0.11	-0.06	0.07	0.08	0.99	0.11	-0.01	0.05	0.05
	(3.41)	(0.83)	(-0.73)	(0.77)	(0.95)	(3.94)	(1.30)	(-0.11)	(0.59)	(0.51)
7	1.06	0.15	-0.03	0.13	0.15	1.07	0.19	0.09	0.17	0.16
	(3.53)	(1.09)	(-0.44)	(1.52)	(1.76)	(4.05)	(2.43)	(1.15)	(2.42)	(2.13)
8	1.25	0.33	0.17	0.27	0.30	1.18	0.30	0.23	0.28	0.29
	(3.96)	(2.34)	(2.23)	(3.58)	(4.10)	(4.71)	(3.35)	(2.65)	(3.17)	(3.28)
9	1.47	0.53	0.46	0.46	0.50	1.42	0.54	0.54	0.60	0.61
	(4.58)	(3.51)	(5.54)	(5.69)	(6.28)	(5.57)	(5.86)	(6.23)	(6.62)	(6.75)
10	1.63	0.67	0.69	0.53	0.54	1.49	0.57	0.80	0.72	0.75
	(4.55)	(3.42)	(7.04)	(5.81)	(5.99)	(4.97)	(3.40)	(5.19)	(4.67)	(4.70)
D10-D1	1.15***	1.16***	1.25***	1.06***	1.05***	1.05***	1.05***	1.15***	1.23***	1.25***
	(7.79)	(7.58)	(8.14)	(6.96)	(6.76)	(5.19)	(5.00)	(5.18)	(5.28)	(5.37)
D9-D2	0.90***	0.90***	0.95***	0.88***	0.88***	0.95***	0.98***	0.96***	1.03***	1.04***
	(8.49)	(8.26)	(8.60)	(7.72)	(7.44)	(6.35)	(6.50)	(6.74)	(7.04)	(7.01)

Table 3.12: **Return Predictive Power of DFB across Subperiods**

This table presents the performance of decile portfolios formed on DFB over four periods: 1980-1987, 1988-1994, 1995-2001, and 2002-2008. At the end of each quarter from 1980Q3 to 2008Q3, we sort stocks into deciles in ascending order based on DFB and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter for the four subperiods. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Stocks with prices lower than \$5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

Panel A: 1980-C1987

	Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	1.12	-0.03	-0.22	-0.18	-0.20	1.22	0.08	0.03	0.00	-0.01
	(2.02)	(-0.26)	(-1.8)	(-1.32)	(-1.5)	(2.35)	(0.89)	(0.43)	(-0.05)	(-0.23)
2	1.25	0.09	-0.10	0.00	-0.02	1.33	0.16	0.00	0.08	0.07
	(1.93)	(0.38)	(-0.94)	(-0.02)	(-0.17)	(2.20)	(1.09)	(-0.01)	(0.60)	(0.55)
9	1.35	0.12	0.31	0.31	0.32	1.18	-0.06	0.18	0.15	0.17
	(1.88)	(0.54)	(2.56)	(2.66)	(2.60)	(1.79)	(-0.5)	(1.46)	(1.15)	(1.15)
10	1.35	0.10	0.31	0.24	0.23	1.16	-0.09	0.26	0.09	0.08
	(1.81)	(0.47)	(2.44)	(1.95)	(1.87)	(1.62)	(-0.53)	(1.63)	(0.56)	(0.46)
D10-D1	0.23	0.14	0.52***	0.42**	0.42**	-0.06	-0.17	0.23	0.10	0.09
	(0.84)	(0.61)	(3.12)	(2.34)	(2.39)	(-0.21)	(-0.81)	(1.32)	(0.48)	(0.44)
D9-D2	0.10	0.03	0.42**	0.31*	0.34*	-0.15	-0.22	0.19	0.08	0.09
	(0.52)	(0.18)	(2.53)	(1.81)	(1.82)	(-0.77)	(-1.15)	(0.98)	(0.40)	(0.44)

Panel B: 1988-C1994

	Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.93	-0.07	-0.13	-0.11	-0.12	1.01	0.03	0.04	0.05	0.04
	(2.26)	(-0.5)	(-1.36)	(-1.04)	(-1.17)	(3.48)	(0.27)	(0.70)	(0.83)	(0.62)
2	0.93	-0.14	-0.20	-0.15	-0.17	1.07	0.01	-0.05	0.02	0.00
	(1.79)	(-0.59)	(-2.59)	(-1.72)	(-2.06)	(2.48)	(0.09)	(-0.64)	(0.17)	(-0.05)
9	1.29	0.12	0.20	0.16	0.19	1.19	0.03	0.12	0.00	0.05
	(2.26)	(0.49)	(2.19)	(1.63)	(1.82)	(2.53)	(0.15)	(0.97)	(0.01)	(0.47)
10	1.48	0.27	0.36	0.28	0.31	1.62	0.35	0.49	0.36	0.42
	(2.32)	(0.87)	(2.93)	(2.22)	(2.44)	(2.83)	(1.75)	(3.33)	(2.12)	(2.29)
D10-D1	0.55*	0.34	0.49***	0.39**	0.43**	0.61*	0.32	0.45***	0.32	0.39*
	(1.68)	(1.20)	(3.25)	(2.32)	(2.46)	(1.67)	(1.22)	(2.65)	(1.57)	(1.83)
D9-D2	0.36**	0.27	0.40***	0.31**	0.36***	0.13	0.02	0.18	-0.02	0.06
	(2.10)	(1.56)	(3.29)	(2.25)	(2.68)	(0.58)	(0.07)	(1.14)	(-0.11)	(0.37)

Panel C: 1995-C2001

Decile	EW Post-Ranking Portfolio Return					VW Post-Ranking Portfolio Return				
	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.75	-0.50	-0.58	-0.53	-0.52	1.09	-0.13	0.01	-0.04	-0.03
	(1.42)	(-2.58)	(-4.09)	(-3.25)	(-3.14)	(2.07)	(-0.71)	(0.13)	(-0.33)	(-0.24)
2	0.77	-0.52	-0.71	-0.36	-0.37	1.13	-0.05	-0.30	-0.11	-0.13
	(1.30)	(-1.62)	(-4.41)	(-2.41)	(-2.42)	(2.23)	(-0.22)	(-1.83)	(-0.66)	(-0.8)
9	1.61	0.30	0.26	0.10	0.13	2.48	1.00	1.20	0.72	0.73
	(2.28)	(0.58)	(1.19)	(0.55)	(0.69)	(3.15)	(2.05)	(3.08)	(1.97)	(1.95)
10	1.96	0.62	0.58	0.47	0.50	2.03	0.51	0.86	0.29	0.29
	(2.66)	(1.14)	(2.42)	(2.10)	(2.17)	(2.24)	(0.95)	(1.87)	(0.88)	(0.91)
D10-D1	1.21***	1.12**	1.16***	1.00***	1.01***	0.94	0.63	0.85*	0.33	0.31
	(2.84)	(2.51)	(3.89)	(3.27)	(3.27)	(1.33)	(1.05)	(1.71)	(0.89)	(0.91)
D9-D2	0.84**	0.81**	0.97***	0.46**	0.50**	1.36**	1.05*	1.50***	0.83**	0.86**
	(2.38)	(2.28)	(3.44)	(2.13)	(2.20)	(2.29)	(1.85)	(3.58)	(2.24)	(2.27)

Panel D: 2002-C2008

Decile	EW Post-Ranking Portfolio Return					VW Post-Ranking Portfolio Return				
	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	-0.15	-0.23	-0.43	-0.44	-0.46	-0.24	-0.34	-0.20	-0.16	-0.12
	(-0.26)	(-1.86)	(-4.58)	(-4.02)	(-4.37)	(-0.49)	(-2.96)	(-1.89)	(-1.77)	(-1.32)
2	-0.12	-0.18	-0.53	-0.49	-0.43	0.19	0.11	0.01	0.02	0.05
	(-0.18)	(-0.87)	(-4.8)	(-4.24)	(-3.83)	(0.32)	(0.91)	(0.08)	(0.26)	(0.50)
9	0.66	0.60	0.23	0.21	0.18	0.26	0.20	0.16	0.11	0.08
	(0.91)	(2.41)	(2.16)	(1.81)	(1.50)	(0.42)	(1.46)	(1.14)	(0.80)	(0.61)
10	0.82	0.75	0.41	0.31	0.30	0.51	0.43	0.44	0.36	0.36
	(1.13)	(2.70)	(2.68)	(2.16)	(1.97)	(0.87)	(2.04)	(1.73)	(1.62)	(1.67)
D10-D1	0.97***	0.98***	0.84***	0.76***	0.76***	0.75***	0.76***	0.63*	0.52*	0.47*
	(3.88)	(4.09)	(4.21)	(3.68)	(3.71)	(2.77)	(2.87)	(1.92)	(1.88)	(1.79)
D9-D2	0.78***	0.78***	0.77***	0.69***	0.61***	0.08	0.09	0.15	0.08	0.04
	(4.53)	(4.56)	(5.04)	(4.72)	(3.78)	(0.45)	(0.53)	(0.95)	(0.57)	(0.24)

instead of their firm-specific information? In other words, could fund managers make portfolio decisions in a way such that high DFB stocks tend to exhibit higher loadings on the market or other risk factors in periods with higher expected returns and lower loadings on the risk factors in periods with lower expected returns?

To address this question, we need to take into account the time variation in those stocks' loadings on the market or other risk factors. Thus, we employ Ferson and Schadt's (1996) conditional performance evaluation approach to allow for time-varying betas. Specifically, we augment the traditional CAPM and Cahart four-factor model with five conditioning variables: the lagged level of the one-month Treasury bill yield, the lagged dividend yield of the CRSP value-weighted stock index, the lagged measure of the slope of the term structure (a constant-maturity 10-year Treasury bond yield less the 3-month Treasury bill yield), the lagged quality spread in the corporate bond market (corporate bond default yield spread as Moody's BAA-rated corporate bond yield less the AAA-rated corporate bond yield), and a dummy variable for the month of January. Untabulated results show that the return premium on high DFB stocks remains large and significant after the adjustments for time-varying betas.

3.5.5 Preferential allocations of IPOs

Gaspar, Massa, and Matos (2005) and Reuter (2006) argue that preferential access to IPOs could lead to boosted mutual fund performance. To assess the extent to which such preferential allocations of IPOs might influence our results, we exclude all stocks whose return history in CRSP falls below six months from our sample, and repeat our portfolio analysis based on mutual funds' deviations from benchmarks. We find that the exclusion of those stocks results in negligible influence on our results.

3.6 Conclusion

We find strong evidence that supports the informational role of actively managed mutual funds in determining security prices. Using a sample of U.S. equity mutual funds during the period 1980–2008, we find that stocks heavily overweighted by active mutual funds relative to benchmarks strongly outperform their underweighted counterparts. The return premium on stocks heavily overweighted by mutual funds, relative to their underweighted counterparts, reaches more than 7% per year even after adjustments for their loadings on the market, size, value, momentum, and liquidity factors. A significant portion of this premium occurs around corporate earnings announcements. These results point to an informational link between mutual fund investing and asset prices.

Our research suggests interesting avenues for further research. First, the results indicate that mutual funds acquire information that is not fully reflected in prices for those stocks about which they display the most conviction, according to their over- and underweighting decisions. But it is unclear which potential channels might enable them to gain this superior information. Recent studies by Coval and Moskowitz (2001) and Cohen, Frazzini, and Malloy (2008) make some initial progress by suggesting that geographic proximity and shared educational experiences between corporate and fund managers provide important channels for mutual fund managers to access private information. It would be interesting to connect the our findings to these two informational channels and explore additional networks of information flow to gain a better understanding of how information finds its way into asset prices.

Second, other types of institutions, such as pension funds, banks, and insurance companies spend enormous resources in security analysis. These types of institutions might have important impact on the discovery of stock prices. It would be interesting to explore whether portfolio decisions made by these institutions similarly contain information relevant for the behavior of future asset returns.

3.A An Illustrative Interpretation of DFB

In this appendix, we provide an illustrative interpretation of active funds' deviations from benchmark, DFB, following the intuition in Roll (1992). Suppose there are J fund managers investing in N risky assets. Each manager is attempting to beat the performance benchmark B. Denote the returns on risky assets in excess of the risk-free rate as $\tilde{R} = [\tilde{R}_1, \tilde{R}_2, ..., \tilde{R}_N]'$. Each manager forms conditional expectations about future returns on risky assets in the investment universe based on his information set I. In addition, Σ is the variance-covariance matrix of the risky assets, which is assumed to be known and agreed upon by all managers; $w_j^B = [w_1^b, w_2^b, ..., w_N^b]'$ refers to the portfolio weights for fund manager j's benchmark B_j. Note that certain elements in w_j^B could be equal to 0, depending on the composition of the particular index. Fund manager j makes portfolio choice $w_j = [w_1^j, w_2^j, ..., w_N^j]'$ to maximize the benchmark-adjusted, active return on his portfolio while minimizing the active risk or the tracking error variance of his portfolio.[18]

We can write manager j's objective function as:

$$\underset{w_j}{Max}\{\underbrace{(w_j - w_j^B)'E[\tilde{R}|I_j]}_{Active\ Return} - \frac{\lambda_j}{2}\underbrace{(w_j - w_j^B)'\Sigma(w_j - w_j^B)}_{Active\ Risk}\},$$

where $E[\tilde{R}|I_j]$ is the expected excess returns on risky assets conditional on the information set of manager j, and λ_j is the manager's risk-aversion coefficient. We can easily show that the optimal portfolio solution for manager j is

$$w_j - w_j^B = \frac{1}{\lambda_j}\Sigma^{-1}E[\tilde{R}|I_j].$$

If we further assume that the risk-aversion coefficient is a constant λ across fund managers and Σ is a diagonal matrix, it is apparent that the distance of an asset i's weight in the manager's portfolio from its weight in the benchmark index $w_{i,j} - w_{i,j}^B$ is proportional to the expected excess return of the asset, conditional on manager j's information set. If we further make a simplifying assumption that Σ is an identity matrix, then $w_j - w_j^B = \frac{1}{\lambda}E[\tilde{R}|I_j]$. In other words, for any risky asset i in manager j's investment universe, $w_{i,j} - w_{i,j}^B = \frac{1}{\lambda}E[\tilde{R}_i|I_j]$. Our measure $DFB_i = \sum_{j=1}^{N_i}(w_{i,j} - w_{i,j}^B)/N_i = \frac{1}{\lambda}\sum_{j=1}^{N_i}E[\tilde{R}_i|I_j]/N_i$, where N_i is the number of funds whose investment universe comprises asset i. Therefore, DFB_i aggregates information about the future excess return of asset i scattered among fund managers.[19]

[18]Consistent with our empirical approach, we only consider funds' investments in risky assets and ignore their cash holdings.

[19]These assumptions are certainly restrictive. To the extent that they introduce noise into our measure of mutual funds' DFB, we expect to observe a weaker relation between DFB and future returns. Empirically though, we find strong evidence that DFB forecasts future stock returns.

3.B Sample Selection

We start with all U.S. equity mutual funds from the intersection between the CRSP mutual fund database and the TFN/CDA Spectrum mutual fund holdings database. We use the MFLINKS data set available from the WRDS to link the two databases. As our benchmark holdings data start from September 1980, our final sample of stock holdings spans the period from September 1980 through September 2008.

Because we wish to capture active mutual funds that invest primarily in U.S. equities, we follow Pastor and Stambaugh (2002) and Kacperczyk, Sialm and Zheng (2008), by eliminating balanced, bond, money market, sector, and international funds as well as funds that do not primarily invest in U.S. common equity. In particular, we use the following steps in sample selection. We select funds with the following Lipper class codes, provided by the CRSP: EIEI, G, I, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If a fund does not have any of these Lipper class codes, we select funds with the following strategic Insight objectives: SCG, GRO, AGG, ING, GRI, or GMC. If both codes are missing for a fund, we pick funds with the following Wiesenberger objectives: SCG, AGG, G, G-S, S-G, GRO, LTG, I, I-S, IEQ, ING, GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI, or MCG. If none of the objective codes are available, we require that a fund have a CS policy code.

We eliminate funds with any of the following investment objectives as provided by TFN/CDA Spectrum: International, Municipal Bonds, Bond and Preferred, and Balanced. Furthermore, we use the portfolio composition data provided by CRSP to exclude funds that invest less than 80% or more than 105%, on average, in common equity. To address the incubation bias documented by Elton, Gruber and Blake (2001) and Evans (2010), we exclude observations prior to the reported fund inception date, those for which the names of the funds are missing in the CRSP database, and funds whose net assets fall below $5 million. To prevent outliers from driving our measure of mutual funds' deviations from benchmarks, we also require that a fund have at least 10 stock holdings to be eligible for consideration in our analysis.

To ensure that we capture active mutual funds, we eliminate index funds whose names contained the following keywords: INDEX, INDE, INDX, INX, IDX, DOW JONES, ISHARE, S&P, S &P, S& P, S & P, 500, WILSHIRE, RUSSELL, RUSS, or MSCI. To lessen errors due to abbreviation and misspelling, we manually inspected fund names and filtered out remaining international funds, sector funds, tax-managed funds, fixed-income funds, balanced funds, real estate funds and annuities.

3.C Benchmark Holdings

Our main method of selecting benchmark indexes for individual mutual funds follows Cremers and Petajisto (2009). In particular, the universe of benchmark indexes includes the 19 stock indexes widely used by practitioners: S&P 500, S&P 400, S&P 600, S&P 500/Barra Value, S&P 500/Barra Growth, Russell 1000, Russell 2000, Russell 3000, Russell Midcap, the value and growth variants of the four Russell indexes, Wilshire 5000, and Wilshire 4500. Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are from Compustat. For the remaining indexes and time periods, we use the holdings data of index funds that track the performance of those indexes as a first approximation. Specifically, for each index, we select one index fund or ETF that has the lowest tracking error over the sample period. We use holdings information reported by that fund to approximate the actual index weights. If, in a particular quarter, the index fund has missing holdings information, we use the holdings data reported by the fund with the second lowest tracking error, and so on.

In Table C1, we present information about the benchmark indexes. The third column of Table C1 shows the source of holdings data we used in our sample, and the fourth and fifth columns show the start and end dates for the holding information.

After we obtain the information on benchmark weights, we select, for each mutual fund in each quarter, one benchmark index that minimizes the distance in portfolio weights between the fund and the index. Our measure of the distance between mutual funds and their benchmarks is the measure of Active Share as proposed by Cremers and Petajisto (2009):

$$ActivewShare = \frac{1}{2}\sum_{i=1}^{N}|w_{fund,i} - w_{index,i}|,$$

where $w_{fund,i}$ and $w_{index,i}$ are the portfolio weights of asset i in the fund and in the index, respectively. For each fund in each quarter, we select the index that generates the lowest Active Share for the fund. The advantage of this dynamic selection of performance benchmarks lies in its flexibility in allowing for drifts in a fund's style over time.

We also calculate the number of active funds that benchmark against each of the indexes and the total assets under their management. Columns 6 and 7 report these numbers for September 2008. Columns 8 and 9 further show the market share for each of the indexes.

Table C1: Summary Statistics for Benchmark Holdings

	Index Name	Index Inception Year	Source of Holdings Data	Holdings Data Starting Date	Holdings Data Ending Date	Cross-Section of 9/30/2008 No. of Funds	Total Fund Assets (Millions)	Proportion (No. of Funds)	Proportion (Total Fund Assets)
1	S&P500	3/1957	Vanguard Index 500 Fund	9/30/1980	9/30/1994				
			S&P	12/31/1994	9/30/2008	222	534576.86	15.38%	25.34%
2	S&P500 Value	5/1992	iShares S&P 500 Value Index	12/31/2000	9/30/2008	119	214327.40	8.25%	10.16%
3	S&P500 Growth	5/1992	iShares S&P 500 Growth Index	12/31/2000	9/30/2008	205	429213.14	14.21%	20.35%
4	S&P400	7/1991	S&P	12/31/1994	9/30/2008	111	81681.70	7.69%	3.87%
5	S&P600	1/1994	S&P	12/31/1994	9/30/2008	121	80384.98	8.39%	3.81%
6	Russell1000	1/1984	Russell Investments	3/31/1984	9/30/2008	3	1898.60	0.21%	0.09%
7	Russell1000 Value	6/1993	Russell Investments	6/30/1993	9/30/2008	94	81942.30	6.51%	3.88%
8	Russell1000 Growth	6/1993	Russell Investments	6/30/1993	9/30/2008	164	266439.87	11.37%	12.63%
9	Russell2000	1/1984	Russell Investments	3/31/1984	9/30/2008	12	27159.60	0.83%	1.29%
10	Russell2000 Value	6/1993	Russell Investments	6/30/1993	9/30/2008	43	24351.40	2.98%	1.15%
11	Russell2000 Growth	6/1993	Russell Investments	6/30/1993	9/30/2008	133	49738.20	9.22%	2.36%
12	Russell3000	1/1984	Russell Investments	3/31/1984	9/30/2008	5	103312.60	0.35%	4.90%
13	Russell3000 Value	7/1995	Russell Investments	9/30/1995	9/30/2008	0	0.00	0.00%	0.00%
14	Russell3000 Growth	7/1995	Russell Investments	9/30/1995	9/30/2008	0	0.00	0.00%	0.00%
15	Russell MidCap	11/1991	Russell Investments	12/31/1991	9/30/2008	7	26263.50	0.49%	1.24%
16	Russell MidCap Value	2/1995	Russell Investments	3/31/1995	9/30/2008	55	49118.60	3.81%	2.33%
17	Russell MidCap Growth	2/1995	Russell Investments	3/31/1995	9/30/2008	136	120957.60	9.42%	5.73%
18	Wilshire 4500	1/1983	Vanguard Extended Market Index Fund	12/31/1987	9/30/2008	8	12477.50	0.55%	0.59%
19	Wilshire 5000	1/1975	Wilshire 5000 Index Portfolio Fund	6/30/1999	9/30/2008	5	5716.00	0.35%	0.27%

3.D Comparison with Chen, Jegadeesh, and Wermers (2000)

Chen, Jegadeesh, and Wermers (CJW, 2000) assess the value of active portfolio management by examining the association between mutual fund trades and future stock returns. They provide compelling evidence that active funds add value through their trading activities. Following Grinblatt and Titman (1993), we may view fund holdings in the prior period as an implicit benchmark to evaluate fund performance. In other words, the CJW trade-based measure may be viewed as another way of measuring deviations from benchmarks. We argue that our measure of active funds' deviations from benchmarks is superior in aggregating fund managers' private information, because the trading decisions of mutual funds could reflect not only informational motives but also other motivations such as flow-driven liquidity needs (e.g., Alexander, Cici, and Gibson, 2007). Our measure of deviations from benchmarks is less subject to the influence of fund flows, because fund managers can simply scale up or down fund assets in response to flows, without having to substantially alter the composition of their active portfolios.

In Table D1, we provide more evidence that supports our claim. Specifically, at the end of each quarter from 1980Q3 to 2008Q3, we perform two-way independent sorts. Along one dimension, we sorts stocks into quintiles based on the magnitude of their deviations from benchmarks, and along the other dimension, we sort stocks into quintiles based on their quarterly trades measured as the change in the fraction of shares held by mutual fund in our sample. Twenty five portfolios thus form from these double sorts, with portfolio (1,1) containing stocks with the lowest value of the sorting variables and vice versa. We calculate the monthly equal-weight and value-weight returns on each of 25 portfolios for the subsequent quarter, and report their Carhart 4-factor alpha. The results in Table D1 show that stocks heavily overweighted by active funds significantly outperform those they choose to underweight, while controlling for their stock trades. In contrast, the trade-based measure has no return forecasting power once we control for funds' deviations from benchmarks.

Table D1: Deviation from Benchmarks and Chen, Jegadeesh, and Wermers (CJW) Trade Measure

This table compares the return forecasting power of mutual funds' deviations from benchmarks, DFB, and the measure of their trades based on Chen, Jegadeesh, and Wermers (CJW 2000). Specifically, at the end of each quarter from 1980Q3 to 2008Q3, we perform two-way independent sorts. Along one dimension, we sorts stocks into quintiles based on the magnitude of their deviations from benchmarks, and along the other dimension, we sort stocks into quintiles based on their quarterly trades measured as the change in the fraction of shares held by mutual fund in our sample. Twenty five portfolios thus form from these double sorts, with portfolio (1,1) containing stocks with the lowest value of the sorting variables and vice versa. We calculate the monthly equal-weight and value-weight returns on each of 25 portfolios for the subsequent quarter, and report their Carhart 4-factor alpha. Stocks with prices lower than 5 dollars at the quarter end are excluded. *** represents statistical significance at the 1% level, ** represents statistical significance at the 5% level, and * represents statistical significance at the 10% level.

	Equal-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)						Value-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)					
	Deviation from Benchmarks (DFB)						Deviation from Benchmarks (DFB)					
CJW Trade	1	2	3	4	5	Q5-Q1	1	2	3	4	5	Q5-Q1
1	-0.23	-0.11	-0.07	0.09	0.12	0.36***	-0.07	0.08	-0.06	0.07	-0.07	0.00
	(-2.64)	(-1.02)	(-0.73)	(0.93)	(1.20)	(2.64)	(-0.65)	(0.91)	(-0.54)	(0.66)	(-0.45)	(-0.02)
2	-0.21	-0.05	0.05	0.07	0.16	0.38***	0.03	-0.01	-0.03	0.00	0.12	0.09
	(-2.96)	(-0.5)	(0.51)	(0.72)	(1.46)	(3.23)	(0.38)	(-0.12)	(-0.21)	(0.03)	(0.61)	(0.45)
3	-0.24	-0.16	0.07	0.03	0.25	0.48***	0.16	0.16	-0.01	-0.11	0.25	0.09
	(-3.01)	(-1.56)	(0.66)	(0.31)	(2.48)	(3.90)	(1.24)	(1.00)	(-0.07)	(-0.83)	(1.41)	(0.38)
4	-0.33	-0.08	-0.16	0.04	0.24	0.57***	-0.17	0.02	-0.11	0.02	0.49	0.66***
	(-4.32)	(-0.97)	(-1.68)	(0.45)	(2.59)	(4.81)	(-1.71)	(0.18)	(-0.87)	(0.22)	(2.77)	(2.82)
5	-0.32	-0.28	-0.03	-0.09	0.31	0.63***	-0.31	-0.34	0.02	-0.09	0.19	0.50**
	(-2.58)	(-2.65)	(-0.33)	(-1.01)	(3.00)	(5.08)	(-1.84)	(-2.53)	(0.16)	(-0.81)	(1.12)	(2.36)
Q5-Q1	-0.09	-0.17	0.04	-0.19*	0.18		-0.24	-0.42***	0.08	-0.16	0.27	
	(-0.57)	(-1.41)	(0.32)	(-1.79)	(1.62)		(-1.21)	(-2.82)	(0.57)	(-1.17)	(1.39)	

Chapter 4

Do Mutual Fund Managers Trade on Stock Intrinsic Values?*

4.1 Introduction

When information and trading costs are not trivial in reality, stock prices may diverge from their intrinsic values.[1] Mutual funds, being good candidates for informed investors given their expertise in fundamental analysis, are supposed to make advantageous valuation-based portfolio bets and thus facilitate the convergence of price to value.[2] However, their informational role in determining stock prices remains inadequately addressed in the extant literature. Shleifer and Vishny (1997) suggest that delegated portfolio managers can become most constrained when they bet against the most mispriced securities. According to their performance-based arbitrage model, fund managers' fear of temporary money outflows may significantly limit their trading effectiveness in achieving price efficiency. This study attempts to shed light on the informational advantages of actively managed mutual funds in discovering mispricing and their role in bringing prices to fundamental values.

We use a residual income model operationalized by Frankel and Lee (1998) and Lee, Myers,

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[1]See Shiller (1984), Summers (1986), DeBondt and Thayler (1987), Lakonishok, Shleifer, and Vishny (1994), and Shleifer and Vishny (1997) for detailed discussion of inequality of price and value. Closed-end fund literature provides more direct evidence of price-value divergence (e.g. Lee, Shleifer, and Thaler (1991) and Swaminathan (1996)).

[2]Kosowski, Timmermann, Wermers, White (2006) and Fama and French (2010) use bootstrap tests for fund performance persistence and find supporting evidence of the presence of subgroups of skilled fund managers. For other recent supportive evidence of fund skills based on fund holdings data, see Avramov and Wermers (2006) and Wermers, Yao, and Zhao (2007).

and Swaminathan (1999) to obtain an empirical estimate of a stock's intrinsic value (V). We empirically examine whether active fund managers trade on the mispricing indicated by a value-to-price ratio (V/P).[3] By examining the quarterly holdings of 2,537 distinct U.S. active mutual funds over the 1981 to 2008 period, we find that mutual funds in aggregate tend to trade in the direction of V/P, and more intensively from six months before all necessary financial information for estimating the intrinsic value is publicly released. We attribute the mutual funds' exploitation of a stock's intrinsic value to their superior expertise in forecasting and processing fundamental information (Cheng, Liu and Qian, 2006). Our findings are not subsumed by controlling for various common stock return predictors in Fama-Macbeth regressions.

To characterize the portfolio choices of mutual funds based on V/P and assess how successfully they exploit such information, we construct a fund-level V/P-timing measure, VPT, in the spirit of Grinblatt, Titman, and Wermers (1995) and similar to the accruals investing measure created by Ali, Chen, Yao, and Yu (2008). VPT is the value-weighted average V/P decile rank of all stocks held by a mutual fund. A high value of VPT indicates that the fund manager actively trades on fundamentals and tilts her portfolio toward underpriced stocks (with high V/P). We sort all active mutual funds into ten decile portfolios in ascending order (1-10) on the basis of VPT. Examining the fund characteristics across the VPT deciles, we find that small and high-turnover funds tend to trade more on V/P mispricing. Further, we show that funds with high past one year performance and low return gap (the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings) tend to significantly exploit the V/P effect.

We use fund returns before fees, net of the realized transactions costs, to evaluate the actual profitability of trading on stocks' intrinsic values. In univariate portfolio sorts, D10 funds with the highest VPT have an average return of 1.19% per month over a six-month horizon starting from portfolio formation and significantly outperform the lowest-VPT funds in D1 by 0.55% per month. We also examine how well D10 funds perform relative to D5 funds that are neutral to the V/P effect with a VPT of 5.5. The return spread of 0.26% per month between D10 and D5 is statistically significant. Both return spreads are robust to different factor risk adjustments. More interestingly, the superior performance of D10 funds does not simply reflect that these

[3]Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999) find that V/P ratio has reliable cross-sectional and time-series predictive power for U.S. stock returns. They also find that residual income model is a more robust and richer valuation model than simple heuristics such as B/P and D/P that have been examined extensively in the prior finance literatures. Ali, Hwang and Trombley (2003) further show that the V/P effect is mainly concentrated around earnings announcement, consistent with the mispricing explanation for its return predictive power. Jiang and Lee (2005) find that book values and earnings in the residual income model contain more useful information than the traditional dividend discount model (DDM) for stock valuation.

funds take on high risks. The risk-adjusted returns on the D10 funds are 0.35%, 0.36%, and 0.27% per month based on the Capital Asset Pricing Model (CAPM), the Fama and French 3-factor model, and a 4-factor model including momentum, respectively. Hence, mutual funds that actively exploit the fundamental mispricing are able to benefit from such information and generate both statistically and economically significant profits.

Finally, we examine the impact of fund trading on V/P effect and find more pronounced effect among stocks with less intense past mutual funds' exploitation. Mutual funds with superior private information about stock values mitigate the mispricing by trading in the direction of V/P. We find that high-V/P stocks with the lowest mutual funds' ownership in each June (the time of information release) continue to generate a significant 4-factor alpha of 0.42% per month in the subsequent one year. Furthermore, we also show that high-V/P stocks that have been heavily sold by mutual funds in the recent past can generate even higher future performance. This evidence is consistent with our expectation that the tendency of mutual funds to trade in the direction of V/P facilitates impounding fundamental information into the current stock prices and thus pushes prices back toward their intrinsic values.

Our paper joins a small but growing literature that connects mutual fund investing to asset prices. Coval and Moskowitz (2001) find that fund managers have better access to local information and that their investments facilitate the transfer of information into the prices of local stocks. Cohen, Frazzini, and Malloy (2008) provide empirical evidence that information transfers through the social networks between corporate managers and fund managers into stock prices. Unlike these two studies that assume a priori links between firms and funds, we examine how actively managed mutual funds react upon the mispricing revealed by their fundamental analyses. Boehmer and Kelly (2009) show that institutional trading improves the short-horizon informational efficiency of prices, measured as deviations from a random walk. Distinct from their study, this paper is interested in the role of active mutual funds as informed traders in pushing stock prices toward their intrinsic values over a relatively longer horizon.

To the best of our knowledge, this study is among the first to empirically test the trading behavior of delegated informed traders using a stock mispricing measure based on a comprehensive valuation model.[4] Our findings that mutual funds tend to exploit mispricing opportunities are consistent with the theoretical prediction of Grossman and Miller (1988), De Long, Shleifer, Summers, Waldman (1990) and Campbell and Kyle (1993). We show that mutual funds that tilt their portfolios most aggressively toward underpriced stocks can profit from fundamental

[4] Dechow, Hutton, Meulbroek, and Sloan (2001) see short-sellers as informed investors and find that short-sellers use information in the fundamentals to market values ratios to take positions in stocks with lower expected future returns.

analysis, which confirms the findings of mutual funds benefiting from fundamental-relevant information in Campbell, Ramadorai, and Schwartz (2009), Baker, Litov, Wachter, and Wurgler (2010) and Jiang, Verbeek, and Wang (2011). In spite of this, our findings do not exclude the possible existence of limits of arbitrage (Shleifer and Vishny, 1997).

Our study is also related to a recent line of research in the accounting literature that attempts to address the issue of implementing the residual income model to measure intrinsic values. The valuation equation we use in this paper follows Frankel and Lee (1997, 1998), Penman and Sougiannis (1998), Dechow, Hutton, and Sloan (1999), Abarbanell and Bernard (2000), Gode and Mohanram (2003), Ali, Hwang, and Trombley (2003), Baginski and Wahlen (2003) and Jiang and Lee (2005). While these accounting studies examine the model prediction of both time-series and cross-section of stock returns, our investigation focuses on whether active fund managers exploit the fundamental information revealed by such a model. Closely related to ours is Ali, Chen, Yao, and Yu (2008), who document that on average mutual funds do not trade on the accruals anomaly. Compared with their study, our primary interest in this paper is in whether active funds benefit from more complete and comprehensive fundamental analyses and their role in impounding such fundamental information into stock prices. Moreover, we do find that mutual funds in aggregate trade on mispricing as indicated by the V/P ratio.

The remainder of the chapter proceeds as follows. Section 4.2 introduces the residual income model. Section 4.3 describes data, sample selection and summary statistics. Section 4.4 and 4.5 explore whether mutual funds trade on and profit from V/P effect. Section 4.6 investigates the relation between mutual fund trading and V/P effect. Section 4.7 concludes our paper.

4.2 The Residual Income Valuation Model

To determine the extent of mispricing, it is paramount to measure the stock intrinsic value (V) with a comprehensive valuation model.[5] In this study we use a discounted residual income approach.[6] This section presents the basic residual income equation and discuss the specifics of the model implementation procedure. A stock's fundamental value is generally defined as the present value of its expected future dividends conditional on all currently available information.

[5]Despite of the consensus that a stock's intrinsic value is the present value of the expected future cash flows, few academic studies have sufficiently addressed the problem of measuring it. Exceptions include a stream of studies in the accounting literature (e.g. Frankel and Lee (1997, 1998), Penman and Sougiannis (1998), Dechow, Hutton, and Sloan (1999), Abarbanell and Bernard (2000), Gode and Mohanram (2003), Ali, Hwang, and Trombley (2003), Baginski and Wahlen (2003), and Jiang and Lee (2005)).

[6]The residual income model is also referred to as the Edwards-Bell-Ohlson (EBO) valuation technique. Theoretical development of the model can be found in Ohlson (1990, 1995) and Feltham and Ohlson (1995).

Specifically,

$$V_t^* = \sum_{i=1}^{\infty} \frac{E_t[D_{t+i}]}{(1+r_e)^i}, \tag{4.1}$$

where V_t^* is the stock's fundamental value at time t, $E_t[D_{t+i}]$ is the expected future dividends for period $t+i$ based on information available at time t, and r_e is the cost of equity.

Under the clean surplus accounting assumption, the change in a firm's book value is equal to earnings minus net dividends. Following Frankel and Lee (1998), Equation (4.1) can be rewritten as the reported book value, plus the sum of an infinite series of discounted residual income:

$$V_t^* = B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+i} - (r_e B_{t+i-1})]}{(1+r_e)^i} = B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_e)B_{t+i-1}]}{(1+r_e)^i}, \tag{4.2}$$

where B_t is the book value at time t, NI_{t+i} is the net income for period $t+i$, and ROE_{t+i} is the after tax return on book equity for period $t+i$. Equation (4.2) shows that the intrinsic value of a firm can be decomposed into an accounting measure of capital invested (B_t), and a measure of the present value of future cash flows not captured in the current book value. Firms whose expected ROEs are higher (lower) than their cost of equity (r_e) will have intrinsic values greater (smaller) than their current book values.

In practice the implementation of the model requires forecasted ROEs ($FROE$s), dividend payout rates (k), current book value (B_t), cost of equity (r_e), and a terminal value, i.e. an estimate of the firm value based on the residual income earned after the explicit forecasting horizon. To calculate a stock's intrinsic value, we use a three-period expansion of the model which is the primary measure of firm value in Frankel and Lee (1998):

$$\widehat{V}_t^3 = B_t + \frac{(FROE_t - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2 r_e} B_{t+2}, \tag{4.3}$$

where

B_t: book value from the most recent financial statement.

B_{t+i}: forecasted book value for period $t+i$. $B_{t+i} = B_{t+i-1} + FY_{t+i} - FDIV_{t+i}$, where $FDIV_{t+i}$ is the forecasted dividends for year $t+i$, estimated using the dividend payout ratio k. Dividend payout ratio k is computed as the common stock dividends divided by net income before extraordinary items.[7] We assume that $FDIV_{t+i} = FY_{t+i} \times k$.

r_e: industry-specific cost of equity estimated from a three-factor risk model according to Fama and French (1997).[8]

[7] For firms with negative earnings, we divide dividends by 5% of total assets to derive an estimate of k. 5% is the average long run ROA in our sample period (see Table 4.1).

[8] Frankel and Lee (1998) and Abarbanell and Bernard (2000) find that the choice of r_e has little effect on the cross-sectional analyses.

$FROE_{t+i}$: forecasted ROE for period $t + i$. For the first two years, the variable is computed as $FY_{t+i}/[(B_{t+i-1} + B_{t+i-2})/2]$, where FY_{t+i} is the I/B/E/S consensus (mean) forecasted i-year-ahead earnings. For the third year, we use the five-year long term growth rate to compute a three-year-ahead earnings forecast: $FROE_{t+2} = FY_{t+2} * (1 + Ltg)$. When Ltg is missing in the I/B/E/S database, we use $FROE_{t+1}$ to proxy for $FROE_{t+2}$.

The model provides a framework for analyzing the relation between accounting numbers and firm value and features the importance of including forward-looking earnings information in the valuation. Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999) provide a detailed and comprehensive discussion of the insights of the model.

4.3 Sample Description and Summary Statistics

In this section, we describe our stock data set to analyze the V/P effect and the criteria of mutual fund sample selection, followed by the summary statistics for our sample.

4.3.1 Stock Data

The sample of stocks in this study includes all U.S. domestic non-financial companies traded on NYSE, AMEX, and NASDAQ in the Compustat/CRSP Merged database (hereafter, the CCM data) from 1981 to 2008. We require firms to have valid accounting data (for B_{t-1}, B_{t-2}, NI_{t-1}, and DIV_{t-1}) and CRSP stock prices and shares outstanding data for the fiscal-year-end $t - 1$ and the end of June in year t. We also require firms to have one-year-ahead and two-year-ahead earnings forecasts from I/B/E/S. We use I/B/E/S forecasts announced in May and constrain our sample to firms with fiscal-year-ends between June and December, inclusively. This constraint makes sure that the forecasted earnings correspond to the correct fiscal-year-end.

To ensure that accounting variables are known to the public before portfolio formation, we form and rebalance our stock portfolios at the end of June in year t using the V/P ratios computed based on the intrinsic value estimates and market equity values at the fiscal-year-end of calendar year $t - 1$. To be consistent with Fama and French (1992), we calculate the book-to-market ratio based on the book value of last fiscal-year-end and market equity in December of calendar year $t - 1$. In estimating Equation (4.3), we remove firms with negative book values and eliminate firms with absolute values of $FROE$s above 100% and with dividend payout ratios larger than 100%. To mitigate the concern that stock return tests might be influenced by return outliers, we eliminate stocks with prices below \$1.[9] Taken together, our filters eliminate 4,636 observations (approximately 9%), leaving a final sample of 50,246 firm-years.

[9] These firms have typically unstable B/M and V/P ratios and poor market liquidity.

4.3.2 Mutual Fund Sample Selection

We construct our mutual fund database by combining the Center for Research in Security Prices (CRSP) Survivor-Bias-Free US Mutual Fund Database (MFDB) and the CDA/Spectrum Mutual Fund Holdings Database from Thomson Financial.[10] As we wish to examine the informational advantages of mutual funds in stock markets, we only include, in our sample, active mutual funds that invest primarily in US common stocks. In particular, we eliminate balanced, bond, money market, international, index funds and sector funds, as well as funds not invested primarily in equity securities (see the Appendix A for details on how we select active U.S. domestic equity funds). Our final sample covers 2,537 distinct active equity funds over the period 1981 to 2008.

Data on monthly returns, prices, and market values of equity for common stocks traded on the NYSE, AMEX, and NASDAQ come from CRSP. Consistent with previous literature, we exclude closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, primes, and scores (we keep only shares with codes of 10 or 11).

4.3.3 Summary Statistics

Table 4.1 reports the summary statistics for our stock (Panel A) and mutual fund samples (Panel B). The average characteristics are calculated at the end of each June from 1981 to 2007. The average dividend payout ratio (k) for stocks in our stock sample decreases from 0.33 in 1981 to 0.11 in 2007. The average ROE and ROA also exhibit a decreasing pattern over time, though not strictly monotonically. The average ROE ranges from 0.04 to 0.16, while the average ROA stays between 0.01 and 0.07 over years. These results illustrate the stability of the key model inputs over time. Using the residual income model to estimate the intrinsic stock value, we observe that the average V/P ratio displays a general declining trend over our sample period, from 1.54 in 1981 to 0.65 in 2007. It appears that on average stocks have become more and more overvalued in recent years. Panel A of Table 4.1 also shows that in an average year mutual funds in aggregate hold 1,542 stocks out of 1,587 stocks that have valid data to compute V/P. Therefore, the mutual fund holdings data cover the majority of our stock sample. Furthermore, mutual funds increase their ownership in an average stock (defined as the fraction of the outstanding shares of a stock that is held by all mutual funds) almost monotonically from 2.77% in 1981 to 17.26% in 2007. The corresponding number of funds holding the stock also skyrockets from 8 to 70 over the sample period. These numbers illustrate that over the past decades mutual funds have become

[10] Our merging procedure uses the MFLINKS data set maintained by Russ Wermers and the Wharton Research Data Services (WRDS).

more important as shareholders of common equity.

Panel B of Table 4.1 presents the average mutual fund characteristics per year. We observe that the industry of active equity mutual funds has experienced a fast expansion: the number of actively managed equity funds in our sample increases from 179 in 1981 to 1,518 in 2007, with the average total assets under management growing from $million 195.51 to $million 1,743.51. On average, these funds invest 90% of their assets in common stocks, which suggests that our sample well represents the universe of U.S. active funds with an investment focus on domestic equity. Over our sample period, the expansion of mutual funds outpaced the growth of stock markets, which led them to become increasingly important shareholders of common equity. Finally, the 12b1 fees, expense ratio, and fund turnover ratio also display an increasing trend in general and a slight decrease after 2003.

4.4 Do Mutual Funds Trade on Intrinsic Value?

In this section, we explore whether intrinsic stock value reveal information concerning future stock returns over our sample period. More importantly, we investigate how mutual funds trade on the information content of the V/P effect and whether they can profit from discovering values.

4.4.1 Confirming the V/P Effect

Frankel and Lee (1998) examine an earlier stock sample from 1976 to 1993 and find that the V/P ratio is a good predictor for future cross-sectional stock returns. Specifically, they find a one-year return spread of 3.1% between the top and bottom V/P quintiles. The effect cannot be explained by a firm's market beta, size and book-to-market ratio. To confirm the V/P effect for stocks in our CCM stock universe covering the period 1981 to 2008, we employ a univariate portfolio approach and more comprehensive risk adjustment procedures.

At the end of June in year t, we compute V/P ratios for our sample of stocks using public financial information. Then we sort stocks into 5 quintile portfolios in ascending order based on their V/P ratios for the fiscal year that ends in calendar year $t-1$. To minimize the impact of any possible analyst forecast errors on more opaque/small firms, we compute the value-weighted portfolio returns over the following 12 months from July of year t to June of year $t+1$.[11] We also consider value-weighting to be a more conservative approach to discover superior trading strategies.[12] To compute portfolio returns, we use monthly stock returns from CRSP. In case of

[11]Gu and Wu (2003) show that analysts tend to issue more optimistic earnings forecasts for small firms.

[12]Fama and French (2008) point out that equal-weight portfolio return may be driven by tiny stocks that are

Table 4.1: **Summary Statistics: Stocks and Mutual Funds**

This table presents the summary statistics for our stock (Panel A) and mutual fund (Panel B) data (see Appendix A for details on sample selection). At the end of each June from 1981 to 2007, we compute the equal-weight average characteristics. In Panel A, V is the intrinsic value of a stock and estimated based on a residual income model operationalized by Frankel and Lee (1998). Value-to price ratio (V/P) is computed by dividing the analyst-based intrinsic value of a firm by its market capitalization at the fiscal-year-end in the last calendar year. k is the dividend payout ratio, computed as the common stock dividends divided by earnings to common shareholders. For firms with negative earnings, k is computed as common stock dividends divided by (total assets * 0.05). ROE is the return on equity for the last fiscal year computed as net income divided by the average book equity. ROA is the return on assets for the last fiscal year. We also compute the number of distinct stocks in the Compustat/CRSP Merged (CCM) database that have valid data to calculate V/P and the number of these stocks held by mutual funds. We also present the mutual fund ownership and the number of distinct mutual funds that hold a stock over years. Mutual fund ownership in a stock is the fraction of the stock's shares outstanding held by all mutual funds. The above calculations exclude stocks with prices lower than 1 dollar at the end of each June. In Panel B, we calculate the cross-sectional average of various fund characteristics over years, including the number of distinct mutual funds, total net assets, 12b1 fees, expense ratios, turnover ratios, and the percentage of fund common stock holdings. These fund characteristics are extracted from the CRSP fund summary database. 12b1 fees data in CRSP start from 1993 and fund turnover ratios are missing in CRSP in 1992. The last row of the table presents the time-series average of the annual cross-sectional means.

	Panel A: Stock Characteristics								Panel B: Mutual Fund Characteristics					
Year	V/P	k	ROE	ROA	No. of Stocks (V/P Universe)	No. of Stocks (V/P & Held by Funds)	Average Mutual Fund Ownership (%)	No. of Funds Holding the Stock	No. of Mutual Funds	TNA ($millions)	12b1 Fees (%)	Expense Ratio (%)	Turnover Ratio (%)	% of Common Stock Holdings
1981	1.54	0.33	0.16	0.07	938	836	2.77	8	179	195.51		0.95	73.81	88.57
1982	1.40	0.32	0.16	0.07	1043	934	2.68	7	176	187.35		0.90	71.09	83.58
1983	1.31	0.33	0.12	0.06	1070	979	3.35	7	203	209.39		1.00	79.56	86.31
1984	1.11	0.29	0.11	0.05	1276	1181	3.81	7	211	280.93		0.89	78.92	87.30
1985	1.17	0.26	0.13	0.06	1273	1200	4.21	8	242	264.57		0.95	74.83	85.38
1986	0.99	0.25	0.10	0.05	1305	1242	4.75	9	263	333.89		0.98	80.73	85.91
1987	0.95	0.24	0.09	0.04	1305	1231	4.77	10	299	366.27		0.98	80.65	85.63
1988	1.10	0.22	0.11	0.05	1298	1225	4.70	11	311	365.61		1.03	91.77	86.03
1989	1.07	0.21	0.14	0.06	1361	1307	4.71	13	344	371.25		1.21	78.93	85.13
1990	0.96	0.22	0.13	0.06	1371	1314	5.30	14	365	446.21		1.25	77.41	86.19
1991	1.12	0.24	0.12	0.05	1368	1298	5.67	16	389	395.01		1.27	82.54	85.09
1992	0.92	0.23	0.09	0.04	1411	1324	5.76	15	431	540.76		1.06		86.97
1993	0.87	0.21	0.10	0.04	1543	1448	6.99	21	566	552.25	0.18	1.22	68.69	86.29
1994	0.84	0.19	0.09	0.04	1768	1754	8.14	26	703	602.26	0.17	1.18	71.32	87.67
1995	0.98	0.17	0.11	0.05	1909	1894	9.04	29	813	588.74	0.17	1.20	77.75	90.97
1996	0.88	0.15	0.11	0.05	2075	2063	9.82	29	894	804.72	0.16	1.23	81.77	90.94
1997	0.85	0.14	0.10	0.04	2171	2143	10.42	31	1018	950.73	0.17	1.25	84.21	92.19
1998	0.81	0.12	0.09	0.04	2294	2276	11.62	32	1138	1165.31	0.19	1.24	86.27	93.40
1999	0.86	0.12	0.08	0.03	2175	2142	11.39	34	1180	1419.84	0.20	1.25	87.12	93.71
2000	0.89	0.12	0.10	0.04	1867	1846	12.06	47	1347	1646.00	0.31	1.27	91.40	92.91
2001	0.87	0.11	0.10	0.04	1638	1633	13.30	58	1417	1514.64	0.32	1.26	100.74	92.42
2002	0.69	0.11	0.04	0.01	1619	1613	15.47	65	1485	1279.09	0.33	1.30	105.25	93.56
2003	0.76	0.11	0.05	0.02	1653	1644	15.03	66	1512	967.75	0.32	1.34	105.34	94.08
2004	0.67	0.10	0.06	0.02	1778	1771	16.19	66	1542	1278.23	0.31	1.36	92.51	95.25
2005	0.66	0.11	0.11	0.05	1785	1782	16.50	70	1556	1466.28	0.29	1.30	83.94	94.19
2006	0.70	0.11	0.11	0.05	1782	1780	17.31	69	1556	1536.13	0.27	1.27	83.71	96.43
2007	0.65	0.11	0.10	0.04	1785	1778	17.26	70	1518	1743.51	0.24	1.24	83.52	96.80
Average	0.95	0.19	0.10	0.05	1587	1542	9.00	31.05	802.15	795.27	0.24	1.16	83.61	89.74

stock delisting, we use CRSP delisting returns when they are not missing; otherwise, we follow Shumway (1997) to replace missing delisting returns with -30% if the delisting is performance related (CRSP delisting codes 500 and 520-584).

Table 4.2: V/P **and Future Stock Returns: Quintile Portfolios**

This table presents the performance of the quintile portfolios formed on the basis of value-to-price ratios, V/P. V is an intrinsic value measure derived based on a residual income model using the current I/B/E/S consensus earnings forecast available prior to June 30 of each year. Specifically, at the end of each June from 1981 to 2007, we sort stocks into quintiles in ascending order based on V/P and compute the average monthly value-weight portfolio returns in the subsequent year. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with the Pastor and Stambaugh (2003) liquidity. Stocks with prices lower than 1 dollar at the time of portfolio formation are excluded. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Value-Weight Post-Ranking Portfolio Return (%/month)				
V/P Quintile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.74	-0.37	-0.36	-0.11	-0.09
	(2.47)	(-3.82)	(-3.73)	(-0.99)	(-0.82)
2	0.91	-0.09	-0.02	-0.02	0.00
	(3.68)	(-1.24)	(-0.35)	(-0.37)	(0.07)
3	1.06	0.12	0.10	0.05	0.09
	(4.83)	(1.61)	(1.52)	(0.78)	(1.27)
4	1.13	0.19	0.18	0.08	0.08
	(5.10)	(1.89)	(1.96)	(0.92)	(1.08)
5	1.46	0.44	0.46	0.33	0.32
	(6.31)	(2.73)	(3.33)	(2.69)	(2.52)
Q5-Q1	0.72***	0.80***	0.81***	0.44**	0.41**
	(3.29)	(3.65)	(4.24)	(2.39)	(2.22)

The results in Table 4.2 show that the V/P ratio strongly predicts future stock returns. A portfolio that buys stocks in Quintile 5 and sells stocks in Quintile 1 generates an average raw return of 0.72% per month on the value-weight basis. These excess returns are highly statistically significant, with a t-statistic of 3.29. To examine whether the high returns on heavily underpriced stocks (Q5) simply reflect the high systematic risks, we employ standard risk-adjustment models to examine the abnormal returns. The specific risk-adjustment models include the Capital Asset Pricing Model (CAPM), the Fama and French 3-factor model, a 4-factor model including momentum, and a 5-factor model further including the Pastor and Stambaugh (2003) liquidity factor.

Columns 2 to 5 of Table 4.2 show the results. The high returns on stocks heavily underpriced

numerous in number but small in economic significance. Furthermore, in a world with mispricing, value-weight approach tends to overweight overpriced stocks and underweight underpriced stocks. This makes profiting from mispricing more difficult.

in excess of the returns on their overpriced counterparts remain large and statistically significant after the above-mentioned risk adjustments. For example, the spread portfolio that buys stocks in Quintile 5 and shorts stocks in Quintile 1 earns abnormal returns of 0.80%, 0.81%, 0.44%, and 0.41% per month on an value-weighted basis after adjustments according to the CAPM, three-factor model, four-factor model, and five-factor model, respectively. All four versions of alphas are highly statistically significant with t-statistics ranging between 2.2 and 4.3. We note that the return-predictive power of V/P is independent of the book-to-market effect that is widely documented and applied in the prior literature. After adding the momentum factor in our risk adjustment model, the overpriced stocks in Quintile 1 do not generate significant negative abnormal return while the underpriced stocks in Quintile 5 continue to have superior and statistically significant performance. The finding suggests that overpriced stocks tend to have poor past performance. In contrast, the past good return records for underpriced stocks cannot explain all of their superior performance in the future. This is important for our subsequent analysis on mutual fund trading because mutual funds' informational advantage should be the most conspicuous among their long positions due to short-sale constraints.

Next, we examine the characteristics of stocks with low and high intrinsic values. We present univariate results based on quintile portfolios in Table 4.3. Specifically, using the same portfolio sorts we calculate the cross-sectional averages of stock characteristics, and then report their time-series means. The results show that the average V/P ratio increases from 0.40 in Quintile 1 to 1.77 in Quintile 5, whereas the corresponding B/M ratio displays much less dispersion across the V/P quintiles. Furthermore, we find that the most underpriced stocks in Quintile 5 tend to be small-caps with an average size quintile rank value of 2.17 based on NYSE market-cap breakpoints in ascending order; they also have a slight tendency to be growth stocks and winners in the past year. Stocks in the two extreme quintiles exhibit high return volatility and high turnover, especially for underpriced stocks with an average volatility of 13.80% per year and an annual turnover of 164.94%.

Due to the high volatility of both underpriced and overpriced stocks, their average mutual funds' ownership tends to be smaller than that of the rest of the stock universe. A typical stock in Quintile 5 with the highest V/P ratio has the average mutual funds' ownership of 8.60%, which is lower than the mutual funds' ownership of 9.22% for a typical stock in Quintile 3 with medium V/P ratio. The average number of mutual funds holding a stock shows a similar pattern. However, we observe an interesting pattern when looking at the change of mutual funds' ownership in a stock from June of year $t-1$ to June of year t. We observe that both the change in mutual funds' ownership and the change in number of funds holding a stock increase in V/P

Table 4.3: **Stock Characteristics across V/P Quintiles**

At the end of each June from 1981 to 2007, we compute for each stock a measure of mispricing, V/P, which is the value-to-price ratio based on a residual income model. We then sort stocks into quintiles in ascending order based on V/P and calculate the stock characteristics for each quintile portfolio. This table reports the time-series average the cross-sectional mean characteristics. Our set of characteristic variables includes the average value-to-price ratio V/P, the average book-to-market ratio, the average market cap, book-to-market, and past one year return (11-month cumulative return from the period $t-11$ to $t-1$) scores, the average total return volatility and stock turnover in the past year, and the levels and the changes of mutual fund ownership in a stock (or the number of funds holding s stock) in the past year and in the future one year. Market cap of a stock is computed by multiplying the stock price with the number of outstanding shares at each quarter end (in millions). V/P ratio is computed at the fiscal-year-end in the last calendar year. Book-to-market ratio is determined for each stock at the end of last calendar year using the book value of the stock at the end of last fiscal year and the market value of the stock at the end of last calendar year (see Fama and French (1992)). The stock volatility is the standard deviation of the monthly returns in the past year (we require that at least 6 monthly observations of stock return are available). Stock turnover is computed as the sum of stock volumes in the past year divided by the average stock price at the beginning and the end of the period. To facilitate comparison across deciles, we score for each year the size, book-to-market, and past returns from 1 to 5, with 5 representing the quintile with the largest market cap (based on NYSE break-points), highest book-to-market, and highest past one year return. Mutual fund ownership in a stock is the fraction of shares outstanding owned by all mutual funds. The changes in mutual fund ownership in a stock or the number of funds holding a stock is measured yearly at the end of June. Stocks with prices lower than 1 dollar at the end of each June are excluded.

V/P Quintile	V/P	B/M	ME Score (1∼5)	BM Score (1∼5)	Pr1Yr Score (1∼5)	Volatility (%)	Turnover (%)	MFO_t (%)	No. of Funds (NoF_t)	$\triangle MFO_t$ (%)	$\triangle NoF_t$	MFO_{t+1} (%)	$\triangle NoF_{t+1}$
1	0.40	0.62	2.40	2.70	2.44	13.30	155.29	8.57	26.56	0.08	-0.16	-0.24	0.29
2	0.67	0.58	2.80	2.59	2.86	10.78	124.98	9.40	35.46	0.26	1.03	-0.11	1.02
3	0.84	0.63	2.79	2.86	3.02	10.12	116.13	9.22	33.86	0.31	1.59	-0.14	1.10
4	1.05	0.66	2.66	2.92	3.14	10.75	126.70	9.22	33.04	0.43	2.14	-0.03	1.09
5	1.77	0.73	2.17	2.82	3.46	13.80	164.94	8.60	26.34	0.65	2.91	0.13	1.58
Q5-Q1	1.37	0.10	-0.23	0.12	1.02	0.50	9.65	0.03	-0.22	0.57	3.07	0.37	1.29

ratios. Mutual funds on average tend to buy (sell) underpriced (overpriced) stocks based on stock fundamental valuation and they start trading on such information during the one year prior to the release of public financial reports. The last two columns of Table 4.3 suggest that mutual funds continue to exploit stock intrinsic values after the financial information release at the end of each June. We will explore this issue in more detail in the next subsection.

4.4.2 Mutual Funds Trade on the V/P Effect

According to De Long, Shleifer, Summers, Waldman (1990) and Campbell and Kyle (1993), mutual funds can behave as informed traders, trading on the mispricing opportunities and bringing about market efficiency. However, Shleifer and Vishny (1997) argue that delegated portfolio managers may become capital constrained when they tilt their portfolios toward severely mispriced securities. Moreover, mispricing based on V/P is associated with high return volatility as shown Table 4.3. Hence, fund managers might have weak incentives to exploit stock intrinsic values. In this subsection, we examine the trading behavior of mutual funds in response to the information content of the V/P ratio in more detail.

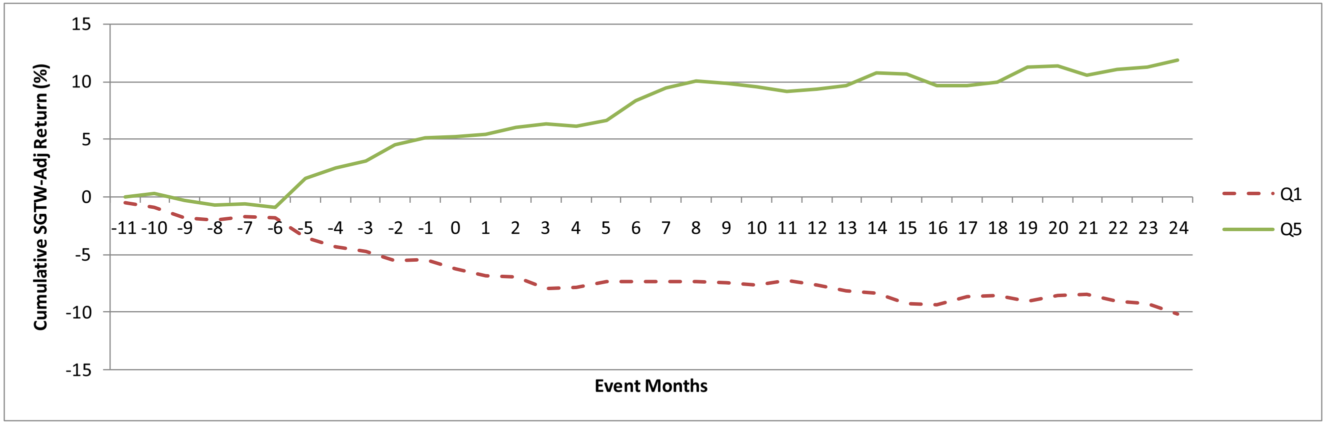
We first use an event study approach to illustrate how mutual funds trade on V/P information. At the end of each June between 1981 and 2006, we form 5 quintile portfolios of stocks based on their V/P ratios calculated using the value and price information at the fiscal-year-end of year $t-1$. Quintile 1 consists of the most overpriced stocks and vice versa. We then investigate the cumulative characteristic-adjusted portfolio performance of these portfolios during the one year prior to the portfolio formation and the subsequent two-year holding period (see Daniel, Grinblatt, Titman, Wermers, 1997; Cremers, Petajisto, Zitzewitz, 2008).[13] To further examine the trading activities of mutual funds, we calculate the time-series average mutual funds' ownership for the quintile portfolios over the same ranking and holding periods. To avoid the instability of aggregate mutual funds' ownership as documented by Gompers and Metrick (2001) and Jiang (2010), we cross-sectionally demean (market-adjusted) the firm-level ownership before computing the average portfolio-level mutual funds' ownership.

Figure 4.1 visualizes the results. Panel A plots the cumulative characteristic-adjusted monthly portfolio returns for the two extreme quintile portfolios from 12 months before to 24 months

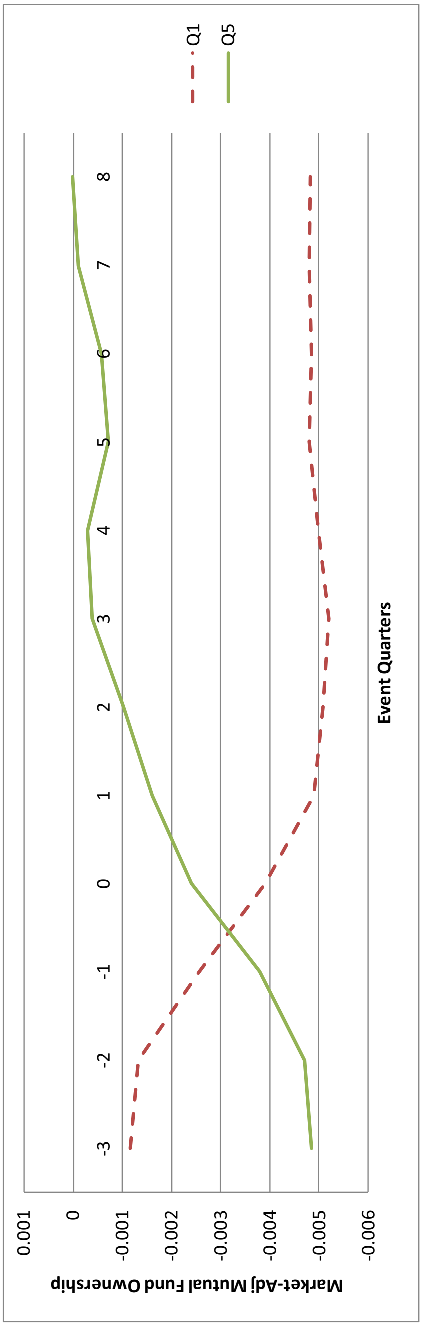
[13] Specifically, we assign a stock to one of the 125 characteristic-sorted portfolios at the time of portfolio formation and calculate the excess return of the stock relative to its benchmark portfolio. Then we use these excess returns to compute the equally weighted quintile portfolio returns. The DGTW benchmark portfolio returns are available at `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`. For a more detailed description of the concern, see Wermers (2006).

Figure 4.1: **DGTW-Adjusted Monthly Returns and Market-Adjusted Mutual Fund Ownership for Portfolios based on V/P, 1981-2006**
Panel A of this figure visualizes the cumulative performance of the quintile portfolios formed on the basis of value-to-price ratios, V/P. Specifically, at the end of each June from 1981 to 2007, we sort stocks into five quintile portfolios in ascending order based on V/P and compute the monthly value-weight average characteristic-adjusted returns for each portfolio from -12 months before portfolio formation to 24 months after portfolio formation. Month 0 is June of each year. Panel B corresponds to the end of each quarter. Quarter 0 is the second quarter of each calendar year. Using the same portfolio sorting procedure, we compute the equal-weight average of the cross-sectionally demeaned mutual fund ownership in stocks in each quintile portfolio from Quarter -4 to Quarter +8. Mutual fund ownership is defined as the fraction of shares held by all mutual funds. Both panels plot the time-series average returns and ownership numbers.

Panel A: Value-weight, DGTW -adjusted monthly returns



Panel B: Equal-weight, market-adjusted mutual fund ownership



after the portfolio formation. Month 0 is June of year t, and month -11 is July of year $t-1$. The results clearly show the strong return-predictive power of V/P ratio after the portfolio formation. The most underpriced stocks in Quintile 5 perform very well from then on till the nine months after the portfolio formation. After that, the cumulative abnormal returns start to flatten out till the end of June in year $t+2$. Similarly, the cumulative characteristic-adjusted return of the most overpriced stock in Quintile 1 start to decline after the portfolio formation and the pattern substantially weakens after one quarter. At the end of the holding period, the abnormal return differential between the two extreme quintile portfolios amounts to more than 20%, consistent with the findings of Frankel and Lee (1998). Furthermore, we do not observe a significant return reversal for stocks in both extreme quintiles, which indicates investors including mutual funds do not overreact on the information content of V/P.

Panel B of Figure 4.1 plots the equally weighted, market-adjusted mutual funds' ownership for these portfolios. Quarter 0 denotes the period of April to June in year t, and quarter -3 denotes July to September of year $t-1$. The results suggest that mutual funds in aggregate trade on the information contained in V/P ratios in a strong manner. Mutual funds start to increase their ownership in underpriced stocks from Quarter -1 and appear to stop trading on the same information after Quarter 3. On the other hand, mutual funds tend to decrease their ownership in overpriced stocks dramatically during a shorter period (from Quarter -1 to Quarter 1). Their trading horizons correspond to the profitability of the V/P effect as we see in Panel A. Combining the results in both panels, we see that mutual funds, as an investor group, trade on the mispricing opportunities based on intrinsic value estimation. More importantly, mutual funds appear to know such valuation information half a year before it is publicly released in June and they tend to trade on stock intrinsic values in the entire calendar year t. Given the ease to obtain book value of a firm and the superior earnings forecasts provided by mutual funds' in-house fundamental analysts, it should not be surprising to observe their exploitation on the V/P effect. The results suggest that mutual funds trade in the direction of V/P and are likely to facilitate impounding fundamental information into stock prices.

To provide a more comprehensive analysis of mutual fund trading behavior in response to V/P, we use multivariate cross-sectional regressions (Fama and MacBeth, 1973) relating the changes in mutual funds' ownership to V/P, while controlling for other stock characteristics. For each calendar quarter between 1981 and 2007, we estimate the change in aggregate mutual funds' ownership in a given stock. The quintile ranks of V/P, B/M and E/P, accruals, and earnings changes are determined at the end of each June and assigned to each calendar quarter in the same year. Accruals are constructed following Sloan (1996) and Ali, Chen, Yao, and Yu

Table 4.4: V/P **and Mutual Fund Trading: Fama and Macbeth (1973) Cross-Sectional Regressions**

This table presents the relation between stock value-to-price ratio, V/P, at the end of each June and mutual fund trading over the prior two quarters and the subsequent two quarters, controlling for other stock characteristics at the beginning of each quarter, following the Fama and MacBeth (1973) procedure. The dependent variable is the quarterly change of mutual fund ownership in a given stock. MFO is the fraction of shares held by mutual funds. We rank stocks at the end of June into five quintiles based on V/P and use the ranks 1-5 as the regression inputs from Model 1, 3, 5, and 7. Besides, we construct two dummy variables, Q1 (Q5) equals one when a stock in the Quintile 1 (5) and zero otherwise. We also construct quintile ranks for accruals, earnings surprises, B/M ratios, and E/P ratios at the end of last fiscal-year-end in a similar way to V/P. Analyst earnings forecast revisions are computed at the end of June as the difference in consensus forecast between June and last December. Market cap, the book-to-market ratio, past one year return, and stock turnover ratio are defined as previously. E/P ratio is calculated by dividing the earnings by the market cap at the last fiscal-year-end. Stock turnovers are now calculated on a quarterly basis. We also regress the daily stock returns against daily Fama French factors in a given quarter and use the standard deviation of the residuals as the residual volatility of the stock for that quarter (we require that at least 40 daily observations of stock returns are available). We also include the contemporaneous quarterly stock return to control for funds' return-chasing behavior. Stocks with prices lower than 1 dollar at the beginning of each quarter are excluded. The time-series average coefficients are reported in the table. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Dependent Variable: $\triangle MFO_t$ (%)							
	Quarter (-1)		Quarter (0)		Quarter (+1)		Quarter (+2)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
V/P Rank	0.0280**		0.0561***		0.0297**		-0.0047	
	(2.28)		(5.27)		(2.28)		(-0.36)	
Q1		-0.0759*		-0.1010***		-0.0594		0.0289
		(-1.92)		(-3.53)		(-1.46)		(0.63)
Q5		0.0227		0.1340***		0.0530*		0.0054
		(0.53)		(3.04)		(1.81)		(0.20)
B/M Rank	-0.0568***	-0.0551***	-0.0139	-0.0115	-0.0210	-0.0206	-0.0203	-0.0205
	(-3.58)	(-3.44)	(-1.21)	(-1.01)	(-1.65)	(-1.61)	(-1.53)	(-1.54)
E/P Rank	-0.0030	-0.0011	-0.0409***	-0.0376***	-0.0051	-0.0032	0.0058	0.0068
	(-0.18)	(-0.06)	(-3.15)	(-3.05)	(-0.44)	(-0.27)	(0.38)	(0.44)
Accruals Rank	-0.0184*	-0.0187*	-0.0141	-0.0143	-0.0170**	-0.0177**	0.0158	0.0155
	(-1.84)	(-1.87)	(-1.44)	(-1.47)	(-2.16)	(-2.23)	-1.54	-1.5
Earnings Changes Rank	0.0141	0.0161	-0.0196	-0.0197	-0.0249***	-0.0247***	-0.0136	-0.0144
	-1.2	-1.39	(-1.68)	(-1.67)	(-3.34)	(-3.31)	(-1.23)	(-1.29)
Analyst Rev	0.0194	0.0201	-0.0267	-0.0217	-0.0722	-0.0718	-0.0341	-0.0329
	-0.49	-0.51	(-0.80)	(-0.69)	(-1.21)	(-1.19)	(-1.52)	(-1.52)
$Log(ME)_{t-1}$	-0.0268**	-0.0273**	-0.0347**	-0.0359**	-0.0253	-0.0265*	-0.0386**	-0.0385**
	(-2.31)	(-2.31)	(-2.07)	(-2.18)	(-1.69)	(-1.83)	(-2.69)	(-2.70)
$Pr1Yr_{t-1}$	0.0322	0.0325	0.4196***	0.4200***	0.2772***	0.2816***	0.3792***	0.3795***
	-1.18	-1.21	-6.58	-6.63	-4.94	-4.97	-5.32	-5.39
$IdioVol_{t-1}$	-7.5841***	-7.2726***	-14.203***	-14.247***	-9.5613***	-9.4989***	-12.118***	-12.245***
	(-3.85)	(-3.69)	(-4.21)	(-4.24)	(-4.60)	(-4.51)	(-6.67)	(-6.61)
$Turnover_{t-1}$	0.2212**	0.2235**	0.1693	0.1657	0.0296	0.03	-0.0242	-0.0215
	-2.09	-2.09	-1.66	-1.61	-0.32	-0.32	(-0.25)	(-0.22)
$MFO_{t-1}(\%)$	-6.4185***	-6.4344***	-6.0269***	-6.0229***	-6.0739***	-6.0841***	-6.5123***	-6.5113***
	(-9.85)	(-9.89)	(-11.74)	(-11.72)	(-12.38)	(-12.42)	(-9.13)	(-9.10)
R_t	0.8707***	0.8779***	0.8056***	0.8042***	0.8386***	0.8409***	0.5202***	0.5239***
	-7.29	-7.4	-4.69	-4.64	-7	-7.05	-3.89	-3.93
Intercept	0.9982***	1.0731***	1.2248***	1.3771***	1.0094***	1.1007***	1.0758***	1.0576***
	-6.73	-7.24	-5.88	-6.62	-5.57	-6.2	-7.91	-7.73
Adj-R^2	6.25%	6.29%	5.73%	5.74%	5.47%	5.44%	5.81%	5.80%

(2008). Earnings changes are computed as the change in actual earnings for the last fiscal year scaled by price at the last fiscal year end (Bernard and Thomas, 1990). Analyst forecast revisions are calculated at the end of each June as the difference in consensus analyst earnings forecasts between June and last December scaled by the stock price at the end of last fiscal year. These revisions correpond to the fund trading for each quarter in the same calendar year. All other control variables are at the beginning of the quarter. We run quarterly cross-sectionally regressions and then report the time-series average coefficients in Table 4.4 for each calendar quarter (Quarter -1 to Quarter +2 with Quarter 0 denoting the period of April to June). Consistent with the pattern established in the event study, mutual funds' trades are positively and significantly associated with V/P ranks in the first three calendar quarters of a year even after we control for funds' return chasing behavior by including the contemporaneous quarterly stock returns in our quarterly regressions. The quintile ranks of other fundamental-to-price ratios such as B/M and E/P are either negatively or insignificantly associated with aggregate mutual fund trading. Mutual fund managers do not trade in the direction of these simple financial ratios and rather exploit mispricing as revealed by more comprehensive valuation models. Controlling for accruals anomaly, earnings changes, and analyst forecast revisions also does not subsume our findings. When we replace the V/P ranks with dummy variables indicating quintile memberships, the results show that mutual funds mainly trade on intrinsic value in the first two calendar quarters. Funds tend to sell overpriced stocks and buy underpriced stocks in Quarter 0. This positive association is robust to the inclusion of other return predictors such as firm size, the book-to-market ratio, past one-year returns, idiosyncratic volatilities, and turnover ratios. Therefore, mutual funds tend to trade more intensively in the direction of V/P during the first half of each calendar year before all necessary financial information for estimating stock values is releasesd publicly.

4.5 Do Mutual Funds Profit from Discovering Intrinsic Value?

In section 4, we have shown that mutual funds tend to trade on the information content of the V/P ratio, especially in the six months prior to the release of financial information to public. To ascertain that mutual fund managers have informational advantages in successfully exploiting the intrinsic value (rather than chasing the V/P effect passively) and that they are able to beat transactions costs, this section examines the profitability of mutual funds trading on V/P ratios. The stock holdings data have allowed us to test whether mutual funds actively trade on the V/P effect. Now we use fund net returns data to assess their actual profitability from implementing such fundamental-based investments

4.5.1 Mutual Fund V/P Timing Measure

To measure the cross-sectional dispersion in how actively mutual funds follow a V/P trading strategy, we construct a V/P timing measure in spirit of the momentum investing measure of Grinblatt, Titman, and Wermers (1995) and similar to the accruals investing measure of Ali, Chen, Yao, and Yu (2008). At the end of each June, we rank all stocks in our CCM universe into decile portfolios based on V/P and assign the ranks of 1 to 10 to each stock, with score 1 representing the 10% of the most overpriced stock and score 10 for the 10% of the most underpriced stocks.[14] The V/P timing measure for fund i at time t, $VPT_{i,t}$, is defined as the weighted average V/P rank of all stocks held by the fund:

$$VPT_{i,t} = \sum_{j=1}^{N_{i,t}} w_{i,j,t} * (V/PRank)_{j,t}, \tag{4.4}$$

where $(V/PRank)_{j,t}$ is the decile rank of stock j in ascending order based on V/P ratios. $N_{i,t}$ is the number of CCM stocks that are held by mutual fund i at time t, and $w_{i,j,t}$ is the stock j's weight in the fund i's portfolio at time t. A high VPT indicates that the fund tilts its portfolio toward underpriced or high-V/P stocks.

4.5.2 Characteristics of Funds with Extreme VPT

This subsection examines the characteristics of mutual funds across VPT decile portfolios. We also analyze the possible determinants of VPT using Fama-Macbeth regressions.

At the end of each June, we calculate VPT and sort mutual funds into deciles based on their VPT scores in ascending order. Then we compute the cross-sectional averages of fund characteristics and report their time-series means. Table 4.5 reports the results based on the univariate sorts. D5 funds with an average VPT of 5.5 appear to be neutral to V/P ratios. In contrast, the average VPT of D1 funds is 4.13 while the average VPT for D10 funds is 7.16, which suggests that D10 funds trade on V/P effect, whereas D1 funds trade against it. The results also show that funds in the two extreme VPT deciles tend to be younger funds with higher expense ratios. Besides, high-VPT funds in Decile 10 have smaller size and higher turnover ratios. A typical fund in Decile 10 with the highest VPT has an average TNA of $million 515, which is substantially lower than the average TNA in any other decile portfolio. These high-VPT funds also have the highest average turnover ratio of 102.01% among all deciles. Finally, there exists no apparent relation between VPT and the 12b1 fees.

[14] We use decile ranks to increase the variation of VPT. In unreported results, we replace the decile ranks with quintile ranks and find that the mainly results of our analysis are not affected at all.

Table 4.5: **Fund Characteristics across VPT - Sorted Decile Portfolios**
At the end of each June from 1981 to 2007, we compute for each fund a measure of V/P timing, VPT, which is defined as the weighted average of V/P decile ranks of individual stocks held by the mutual fund. We then sort mutual funds into deciles in ascending order based on VPT and calculate the equal-weight average fund characteristics for each decile portfolio. The D1 decile has funds with the lowest VPTs and D10 decile has funds with the highest VPTs. This table reports the time-series average the cross-sectional mean fund characteristics. Our set of characteristic variables includes the average V/P timing measure VPT, the average fund age (in years), the average fund size, 12b1 fees expense ratios, and fund turnover ratios. All fund characteristics are extracted from CRSP MFDB fund summary database. Stocks with prices lower than 1 dollar at the end of each June are excluded.

Decile	VPT	Age (years)	TNA ($Millions)	12b1 Fees (%)	Expense Ratio (%)	Turnover Ratio (%)
1	4.13	13.96	852	0.25	1.20	75.10
2	4.76	16.04	907	0.25	1.18	74.37
3	5.05	16.76	879	0.24	1.14	75.04
4	5.29	17.11	871	0.24	1.13	77.52
5	5.49	17.64	912	0.23	1.12	79.05
6	5.69	17.53	721	0.25	1.13	86.07
7	5.91	17.43	808	0.25	1.14	82.35
8	6.16	17.97	840	0.24	1.13	88.45
9	6.49	15.62	649	0.23	1.19	97.02
10	7.16	13.36	515	0.22	1.27	102.01
D10 - D1	3.03	-0.61	-337	-0.03	0.07	26.91

We next run Fama-Macbeth regressions to better understand the determinants of the use of V/P strategy by mutual funds. We regress VPT on various fund characteristics and fund performance predictors at the end of each June and report the time-series average coefficients in Table 4.6. The results of Model 1 confirm our findings using the univariate portfolio approach. VPT is positively associated with fund turnover and negatively related to fund size. In Model 2 and 3, we include past fund performance and some other fund portfolio characteristics that have been shown in prior studies to have predictive power for future fund performance. Past fund performance is measured by the cumulative fund return in the past 12 months. Active share measures the extent of fund portfolio deviation from its benchmark (Cremers and Petajisto, 2009). Following Baks, Busse, and Green (2007), we use the normalized Herfindahl index to measure the fund managers' willingness to take big bets on a relatively small number of stocks. Return gap is the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. It captures the unobserved fund intra-quarter trading activities (Kacperczyk, Sialm, and Zheng, 2008). We use the average monthly return difference over the past one year in our regressions. We find that past fund performance is positively and significantly associated with VPT. Replacing past fund performance with two dummy variables (P1 and P10) for the two extreme deciles of funds based on past performance, we find that mainly the past winning funds are inclined to exploit fundamentals. Among the three fund skills predictors, only return gap is significantly and negatively associated with VPT. Intuitively, this suggests that mutual funds that rely on frequent interim/short-term trades do not exploit investment opportunities of long-run price-value convergence. To summarize, mutual funds that engage in stock valuation and trade on such information tend to be small, active, and transparent past winners.

4.5.3 Do High-VPT Funds Profit from V/P Effect?

We have shown a wide cross-sectional dispersion in mutual funds' tendency to implement a V/P strategy. To better understand the informational role mutual funds play in financial markets, we next examine the actual fund performance taking into account the actual transactions costs that might be incurred in their V/P based trades. Since highly underpriced stocks are generally small stocks with high return volatility, mutual funds buying such stocks may face large trading friction and transactions costs. Therefore, it is of significant importance to evaluate the profitability of fund trading on V/P in reality.

We first compute the VPT scores in June of year t and then sort all active mutual funds into decile portfolios based on VPT. Since mutual fund manager may have private information about fundamentals from their in-house analysts at the beginning of the year, the June VPT best captures how actively managed mutual funds have traded on the fundamental mispricing in the first half of year t. Then we track the mutual fund performance in the subsequent one year (till June in year $t + 1$) and compute monthly TNA-weighted fund portfolio performance. For the performance evaluation, we use mutual fund performance before fees (by adding back expense ratios/12 to the net fund returns reported by CRSP) as a measure of the investment profitability because it is after the actual transactions costs and is not influenced by other fund expenses.

Table 4.7 reports the results on fund performance. Given our finding that active funds tend to trade on V/P most intensively during the first half of each calendar year, we split the evaluation period into two half-years to better understand the fund net performance and the possible price impact of fund trading. Panel A of Table 4.7 displays the performance results for the first six months after the portfolio formation in June. Over the six-month horizon (July-December in year t), D10 funds generate a significant return of 1.19% per month and significantly outperform their D1 counterparts by 0.55% per month. We also examine how well D10 funds perform relative to D5 funds (with a VPT score of 5.5) that are supposed to be neutral to the V/P effect. The return spread between D10 and D5 is 0.26% per month and is statistically significant. The significant return spreads are robust to various forms of risk adjustment. More importantly, the average return for D10 funds with the highest VPT is significantly positive. In terms of 4-factor alpha, D10 funds earn 0.27% per month with a t-statistic of 2.70. On the contrary, we observe

Table 4.6: **Determinants of VPT: Cross-Sectional Regressions**

This table presents the relation between fund V/P timing measure, VPT, at the end of each June and mutual fund characteristics, controlling for other stock characteristics at the end of June from 1981 to 2007, following the Fama and MacBeth (1973) procedure. The dependent variable is the VPT, which is defined as the weighted average of V/P decile ranks of individual stocks held by the mutual fund. Fund age, fund size (TNA), fund expense ratios and fund turnover ratios are included in Model 1 as control variables. In Model 2, we fruther add as control variables past fund performance measured as the cumulative fund return in the past 12 months, the average Active Share in the past one year, the portfolio concentration, and average return gap in the past one year. Active Share is a measure of the extent of fund portfolio deviation from their benchmarks developed by Cremers and Petajisto (2009). We follow Baks, Busse, and Green (2007) to measure portfolio concentration using a normalized Herfindahl inex. Return gap is the difference between the return on a hypothetical holdings-based portfolio and the realized fund return (see Kacperczyk, Sialm, and Zheng, 2008). For these regressions, we restrict our sample period to 1990-2006 since the Active Share data are available from 1990Q1 to 2006Q4 from the website of Antti Petajisto. In Model 3, we rank funds at the end of June into ten deciles based on their past one-year performance and construct two dummy variables, P1(P10) equals one when a fund in the Decile 1 (10) and zero otherwise. Stocks with prices lower than 1 dollar are excluded when calculating the I measures. The time-series average coefficients are reported in the table. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Dependent Var: VPT		
	Model 1	Model 2	Model 3
Log(1+Fund Age)	-0.0067	-0.0076	-0.0095
	(-0.54)	(-0.48)	(-0.65)
Log(TNA)	-0.0358**	-0.0178*	-0.0212**
	(-2.58)	(-2.04)	(-2.34)
Expense Ratio	0.0048	-0.0081	-0.0385
	(0.13)	(-0.24)	(-1.04)
Turnover Ratio	0.0011***	0.0013***	0.0011***
	(4.02)	(5.62)	(4.58)
Past Fund Performance		0.0146**	
		(2.31)	
P1			-0.1849
			(-1.35)
P10			0.2836**
			(2.22)
Active Share		0.2097	0.3439
		(0.72)	(1.17)
Portfolio Concentration		-0.0222	-0.0374
		(-0.96)	(-1.51)
Return Gap		-0.1915**	-0.1361**
		(-2.70)	(-2.30)
Intercept	5.5532***	5.2213***	5.2826***
	(46.49)	(21.83)	(17.95)
Adj-R^2	3.21%	17.86%	13.96%

Table 4.7: VPT and Fund Performance: Decile Portfolios

This table presents the performance of the decile portfolios formed on the basis of V/P timing measures, VPT, which is the weighted average of V/P decile ranks of individual stocks held by the mutual fund. The D1 decile contains funds with the lowest VPTs and D10 decile for funds with the highest VPTs. For each June from 1981 to 2007, we sort funds into deciles in ascending order based on VPT and compute the average monthly fund size-weight portfolio returns for the next 12 months (from June in year t to June in year $t+1$). Panel A and B present the results for the next two half-years, and Panels C shows the results for the next one year respectively. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Panel A: Size-Weight Fund Portfolio Returns July in Year t to December in Year t (%/month)				Panel B: Size-Weight Fund Portfolio Returns January in Year $t+1$ to June in Year $t+1$ (%/month)				Panel C: Size-Weight Fund Portfolio Returns July in Year t to June in Year $t+1$ (%/month)			
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha
1	0.64	-0.26	-0.07	-0.05	1.05	-0.17	0.02	0.07	0.85	-0.22	-0.08	-0.04
	(1.48)	(-2.28)	(-0.76)	(-0.57)	(3.10)	(-1.67)	(0.25)	(0.70)	(2.96)	(-2.52)	(-1.27)	(-0.55)
2	0.74	-0.14	-0.03	-0.03	1.06	-0.10	0.02	0.05	0.90	-0.12	-0.06	-0.02
	(1.83)	(-1.82)	(-0.43)	(-0.38)	(3.43)	(-1.27)	(0.21)	(0.63)	(3.41)	(-2.15)	(-1.08)	(-0.44)
3	0.84	-0.02	0.06	0.07	1.02	-0.12	-0.04	-0.05	0.93	-0.07	-0.01	-0.01
	(2.22)	(-0.28)	(1.06)	(1.12)	(3.45)	(-1.89)	(-0.59)	(-0.71)	(3.81)	(-1.48)	(-0.26)	(-0.26)
4	0.82	-0.04	-0.02	-0.05	1.09	-0.04	0.00	-0.01	0.95	-0.04	-0.03	-0.05
	(2.14)	(-0.77)	(-0.35)	(-0.85)	(3.76)	(-0.71)	(-0.01)	(-0.12)	(3.87)	(-1.11)	(-0.8)	(-1.07)
5	0.93	0.08	0.12	0.05	1.15	0.04	0.06	0.02	1.04	0.05	0.08	0.02
	(2.46)	(1.38)	(2.34)	(0.90)	(4.06)	(0.68)	(0.92)	(0.36)	(4.33)	(1.27)	(1.93)	(0.62)
6	0.93	0.08	0.09	0.03	1.20	0.10	0.07	0.06	1.06	0.09	0.07	0.04
	(2.53)	(1.56)	(1.73)	(0.65)	(4.32)	(1.90)	(1.30)	(1.11)	(4.64)	(2.04)	(1.90)	(1.03)
7	0.89	0.04	0.02	-0.03	1.19	0.10	0.01	-0.01	1.04	0.07	0.00	-0.04
	(2.40)	(0.66)	(0.37)	(-0.49)	(4.32)	(1.48)	(0.08)	(-0.18)	(4.42)	(0.99)	(0.02)	(-0.68)
8	0.93	0.10	0.05	0.06	1.23	0.15	0.01	-0.02	1.08	0.12	0.03	0.01
	(2.57)	(1.19)	(0.63)	(0.74)	(4.47)	(2.06)	(0.17)	(-0.24)	(4.69)	(1.55)	(0.51)	(0.17)
9	0.99	0.15	0.16	0.12	1.30	0.20	0.01	-0.03	1.15	0.17	0.10	0.05
	(2.65)	(1.60)	(1.77)	(1.27)	(4.52)	(2.11)	(0.18)	(-0.31)	(4.80)	(1.97)	(1.54)	(0.72)
10	1.19	0.35	0.36	0.27	1.34	0.26	-0.01	-0.04	1.26	0.29	0.19	0.13
	(3.15)	(3.15)	(3.66)	(2.70)	(4.61)	(2.11)	(-0.05)	(-0.39)	(5.21)	(2.80)	(2.39)	(1.53)
D10-D1	0.55***	0.61***	0.43***	0.33**	0.28	0.43**	-0.03	-0.11	0.42***	0.51***	0.28**	0.16
	(3.04)	(3.52)	(2.76)	(2.03)	(1.56)	(2.44)	(-0.18)	(-0.67)	(2.68)	(3.15)	(2.24)	(1.31)
D10-D5	0.26**	0.27**	0.24**	0.23**	0.18*	0.21*	-0.06	-0.06	0.22**	0.24**	0.11	0.10
	(2.30)	(2.42)	(2.29)	(2.08)	(1.69)	(1.93)	(-0.61)	(-0.6)	(2.19)	(2.26)	(1.25)	(1.16)

negative risk-adjusted returns for D1 funds although not significantly different from zero. Panel B presents the results for the second half-year after the portfolio formation (January-June in year $t+1$). The alpha generating abilities of the high-VPT funds seem to disappear after the first post-ranking half-year. Over this more intensive trading period (the first half of each calendar year), D10 fund managers fail to generate enough profits to offset the transactions costs associated with exploiting V/P. Besides, the stocks held by D10 funds are very likely to have been exploited the most over the ranking year. The resulting rapid convergence between price and value for these stocks over the ranking year renders their V/P anomaly much weaker during the second half-year after the portfolio formation.

Panel C of Table 4.7 presents the performance results over the entire future one year. D10 funds with the highest VPT have an average return of 1.26% per month and outperform the lowest-VPT funds in D1 by 0.42% per month. The return spread is highly statistically significant with a t-statistic of 2.68. However, the results are not robust to controlling for momentum. In untabulated results based on the post-1999 data, we further find that over the one-year horizon D10 funds can generate a significant 4-factor alpha of 0.18% per month. Moreover, the 4-factor alpha of the return spread is 0.31% per month and statistically significant over this subperiod. This finding suggests that the funds that trade most actively on fundamentals may have benefited from the operationalization of the residual income model by Frankel and Lee since 1998.

As shown in Table 4.3, stocks with extreme V/P ratios have small market capitalization and high idiosyncratic volatility, which makes them unattractive to mutual funds. To gain more insights on the source of profitability of high-VPT funds, we examine how funds exploit fundamental mispricing across V/P deciles. At the end of each June, we calculate for each VPT decile the aggregate portfolio weight of each V/P stock decile. Specifically, for D10 funds, the aggregate portfolio weight of a V/P decile is computed as the total value of the stocks in the V/P decile held by D1 funds divided by the total value of their equity holdings. We report the time-series averages of the portfolio weights for D1, D5, and D10 funds in Table 4.8. Consistent with our expectation, D5 funds that are neutral to V/P strategy invest almost equally in all ten V/P deciles. Relative to the neutral funds, D10 funds tend to overweight stocks in the highest V/P decile (16.99%) and underweight stocks in the lowest V/P decile (3.40%). The reverse pattern can be observed for D1 funds, which overweight low-V/P stocks and underweight high-V/P stocks. The portfolio weight differences between D10 and D1 and between D10 and D5 funds in the two extreme V/P deciles are statistically significant. We shall note that D10 funds are generally small funds (with an average TNA of $million 515, see Table 4.5). Although these high-VPT funds place large bets on underpriced stocks, their total investments in these stocks cannot be substantially large. This explains to some extent why the convergence of price and fundamental value is not immediate.

Table 4.8: **Portfolio Weights of D1, D5, and D10 Mutual Funds across V/P Stock Deciles**
At the end of each June from 1981 to 2007, we compute for each fund a measure of V/P timing, VPT, which is defined as the weighted average of V/P decile ranks of individual stocks held by the mutual fund. We then sort mutual funds into deciles in ascending order based on VPT and calculate the equal-weight average fund characteristics for each decile portfolio. The D1 decile has funds with the lowest VPTs and D10 decile has funds with the highest VPTs. This table reports the portfolio weights in each stock V/P decile for different groups of mutual funds, D1, D5 and D10 funds respectively. The portfolio weight of a stock V/P decile is the total value of the funds' equity holdings. We report the time-series means of the portfolio weights. The t-statistics in parentheses are computed using Newey-West standard errors.

V/P Decile	D1 Funds Portfolio Weights (%)	D5 Funds Portfolio Weights (%)	D10 Funds Portfolio Weights (%)	D10-D1	D10-D5
1	21.19	10.38	3.40	-17.79	-6.99
				(-11.26)	(-6.71)
2	16.70	10.37	2.93	-13.78	-7.44
				(-9.04)	(-6.91)
3	12.88	11.74	3.23	-9.65	-8.51
				(-7.12)	(-7.94)
4	9.78	11.93	4.87	-4.91	-7.06
				(-4.37)	(-5.94)
5	8.21	11.87	5.74	-2.46	-6.13
				(-2.13)	(-4.45)
6	6.34	11.56	7.43	1.09	-4.14
				(1.02)	(-2.90)
7	5.26	11.69	8.74	3.47	-2.96
				(2.86)	(-2.16)
8	4.51	10.78	10.04	5.52	-0.75
				(4.60)	(-0.51)
9	3.82	9.73	13.78	9.96	4.04
				(7.99)	(2.76)
10	3.97	9.67	16.99	13.01	7.32
				(7.93)	(3.86)

The above results suggest that mutual funds actively exploiting the fundamental mispricing are able to benefit from such information and generate both statistically and economically significant profits, net of actual transactions costs and before fund expenses, over a half-year horizon. Overall, our evidence confirms our expectation that mutual funds (at least a subgroup of funds), being good candidates for informed traders, can profit from their information-based trades.

4.6 Mutual Fund Trading and V/P Effect

Given the results that mutual funds tend to trade in the direction of V/P, their trading activities might mitigate mispricing by pushing stock prices back toward the fundamental values. In this section, we provide evidence consistent with this conjecture.

The idea is that the V/P effect is more pronounced among stocks with less mutual funds' exploitation. We use mutual funds' ownership in a stock as a proxy for investor sophistication for that stock. The more shares of a stock are owned by mutual funds, the more sophisticated investor base a stock should have. In particular, stocks with higher V/P ratios and lower mutual funds' ownership should have high future returns. Besides, change in mutual funds' ownership (or the change in the number of funds holding a stock) is a signed measure of the aggregate fund trading. We expect that less fund trading (in the direction of V/P) could result in stronger V/P effect in the future.

We use a two-way independent sorting procedure. Along one dimension, we first sort stocks into five quintiles on the basis of V/P at the end of each June. Then we sort them into three tertiles based on mutual funds' ownership in June or fund trading during the past 6 months respectively. Then we hold the 15 fractile portfolios for one year and value-weighted monthly portfolio returns are computed. The portfolios are rebalanced at the end of next June. We report the Carhart 4-factor alphas for these portfolios in Table 4.9. The results confirm our conjectures. Panel A shows that high-V/P stocks in Quintile 5 with less sophisticated investor base continue to generate superior performance in the subsequent one year. The Fractile portfolio (1,5) has a 4-factor alpha of 0.42% per month with a t-statistic of 2.04, which is higher than the average high-V/P stock performance of 0.33% per month reported in Table 4.2. A strategy that buys high-V/P and sells low-V/P stocks with the lowest mutual funds' ownership is able to earn a significant 4-factor alpha of 0.59% per month. When we measure fund trading using the change in the number of funds holding a stock in Panel B, we observe that stocks in Quintile 5 with the highest V/P ratios that have been sold by mutual funds in the past 6 months can generate a significant 4-factor alpha of 0.73% per month. Panel C presents similar results as in Panel B using the changes in mutual funds' ownership as a proxy for fund trading.

Therefore, we show that the trading activities of mutual funds help mitigate mispricing and bring stock prices back to fundamentals. Our results support the view that mutual fund trading tend to mitigate the mispricing as reflected in a V/P ratio. In unreported results, we postpone the portfolio formation of the V/P strategy by two months to take into account the reporting lag of fund holdings. We form portfolios at the end of August based on the V/P ratios known

Table 4.9: **Mutual Fund Trading and the Return-Predictive Power of V/P**

This table presents the performance of the quintile portfolios formed on the basis of value-to-price ratios, V/P conditional on mutual fund trading in the past 6 months. V/P, MFO, and number of funds holding a stock are defined as previously. We use independent two-way sorts. Specifically, at the end of each June from 1981 to 2007, we sort stocks into five quintile portfolios in ascending order based on V/P and independently sort these stocks again into three tertiles in ascending order based on mutual fund aggregate holding and trading information in the past 6 months (We use mutual fund ownership to measure fund holdings (Panel A) and use the changes of ownership or the changes of number of funds holding a stock to measure mutual fund trading (Panel B and C)). Then we compute the average monthly value-weight portfolio returns in the subsequent one year. This table presents the risk-adjusted performance of those portfolios based on the Carhart (1997) four-factor model. Stocks with prices lower than 1 dollar at the time of portfolio formation are excluded. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Value-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)					
Ranking Var	V/P					
Panel A: MFO	1	2	3	4	5	Q5-Q1
1	-0.17	0.03	0.11	0.28	0.42**	0.59**
	(-0.92)	(0.27)	(0.70)	(1.89)	(2.04)	(2.10)
2	-0.13	-0.02	0.05	0.16	0.37**	0.50**
	(-1.02)	(-0.3)	(0.55)	(1.29)	(2.11)	(2.26)
3	-0.07	-0.15	-0.03	-0.06	0.36	0.43
	(-0.47)	(-1.43)	(-0.24)	(-0.39)	(1.45)	(1.51)
T3-T1	0.09	-0.19	-0.14	-0.34	-0.06	
	(0.46)	(-1.16)	(-0.67)	(-1.56)	(-0.19)	
Panel B: $\triangle NoF$	1	2	3	4	5	Q5-Q1
1	0.00	-0.12	0.08	0.05	0.73***	0.73***
	(0.04)	(-0.96)	(0.61)	(0.35)	(3.38)	(3.02)
2	-0.12	-0.06	0.03	0.04	0.17	0.29
	(-0.84)	(-0.44)	(0.17)	(0.28)	(0.91)	(1.14)
3	-0.04	0.02	0.06	0.14	0.25	0.29
	(-0.27)	(0.24)	(0.80)	(1.31)	(1.60)	(1.25)
T3-T1	-0.04	0.14	-0.01	0.09	-0.48*	
	(-0.27)	(0.86)	(-0.08)	(0.56)	(-1.89)	
Panel C: $\triangle MFO$	1	2	3	4	5	Q5-Q1
1	-0.05	-0.02	0.01	0.04	0.52***	0.57**
	(-0.32)	(-0.15)	(0.05)	(0.29)	(3.17)	(2.30)
2	-0.01	-0.07	0.00	0.11	0.10	0.11
	(-0.04)	(-0.64)	(-0.01)	(0.82)	(0.57)	(0.40)
3	-0.17	-0.01	0.05	0.00	0.37	0.54
	(-1.05)	(-0.11)	(0.42)	(0.03)	(1.42)	(1.57)
T3-T1	-0.12	0.01	0.04	-0.04	-0.15	
	(-0.53)	(0.06)	(0.28)	(-0.18)	(-0.5)	

in June and holding the portfolios from September to the next August. Imposing this additoinal implementation lag does not affect the above results. Hence, individual investors may use the mutual fund trading information to refine the V/P strategy by identifying underpriced stocks that have not been exploited heavily by mutual funds in the recent past.

4.7 Conclusion

This paper explores how effectively active mutual funds trade on and profit from fundamental analyses. Over the 1981 to 2008 sample period, we find that active funds tend to trade on the V/P anomaly as documented by Frankel and Lee (1998). The V/P ratio measures the extent of stock mispricing relative to its intrinsic value based on a comprehensive valuation model, namely, residual income model. We use the residual income model and analyst earnings forecast to measure a firm's intrinsic value and show that mutual funds start to exploit such mispricing opportunities far before the financial information becomes public. Using fund returns data before fees, we show that funds that have the highest weights on underpriced stocks are able to generate a significant 4-factor alpha of 0.27% per month over a six-month horizon. Therefore, trading on V/P effect can be profitable even after the actual transactions costs for a relatively short period. Finally, we find evidence consistent with our conjecture that the V/P effect is more significant among stocks with less mutual funds' exploitation.

Our study suggests that mutual funds in aggregate trade on fundamental value and a subgroup of funds can earn significant risk-adjusted returns from it. This leaves space for the limits-of-arbitrage explanation for why other funds do not exploit the intrinsic value information as aggressively as those profitable ones. Future research could focus on examining the determinants of fundamental analyses implementation in different mutual funds. Besides, other types of institutions, such as pension funds, banks, and insurance companies, have played an increasingly important role in security markets. Given the enormous amount of resources they spend in the security analysis, those types of institutions might also be important for the incorporation of fundamental information into stock prices.

4.A Sample Selection

We start with all U.S. equity mutual funds from the intersection between the CRSP mutual fund database and the CDA/Spectrum mutual fund holdings database. We use the MFLINKS data set available from the WRDS to link the two databases. As our benchmark holdings data start from September 1980, our final sample of stock holdings spans the period from September 1980 through September 2008.

Because we wish to capture active mutual funds that invest primarily in U.S. equities, we follow Pastor and Stambaugh (2002) and Kacperczyk, Sialm and Zheng (2008), by eliminating balanced, bond, money market, sector, and international funds as well as funds that do not primarily invest in U.S. common equity. In particular, we use the following steps in sample selection. We select funds with the following Lipper class codes, provided by the CRSP: EIEI, G, I, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If a fund does not have any of these Lipper class codes, we select funds with the following strategic Insight objectives: SCG, GRO, AGG, ING, GRI, or GMC. If both codes are missing for a fund, we pick funds with the following Wiesenberger objectives: SCG, AGG, G, G-S, S-G, GRO, LTG, I, I-S, IEQ, ING, GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI, or MCG. If none of the objective codes are available, we require that a fund have a CS policy code.

We eliminate funds with any of the following investment objectives as provided by CDA/ Spectrum: International, Municipal Bonds, Bond and Preferred, and Balanced. Furthermore, we use the portfolio composition data provided by CRSP to exclude funds that invest less than 80% or more than 105%, on average, in common equity. To address the incubation bias documented by Elton, Gruber and Blake (2001) and Evans (2010), we exclude observations prior to the reported fund inception date, those for which the names of the funds are missing in the CRSP database, and funds whose net assets fall below $5 million. To prevent outliers from driving our measure of mutual funds' deviations from benchmarks, we also require that a fund have at least 10 stock holdings to be eligible for consideration in our analysis.

To ensure that we capture active mutual funds, we eliminate index funds whose names contained the following keywords: INDEX, INDE, INDX, INX, IDX, DOW JONES, ISHARE, S&P, S &P, S& P, S & P, 500, WILSHIRE, RUSSELL, RUSS, or MSCI. To lessen errors due to abbreviation and misspelling, we manually inspected fund names and filtered out remaining international funds, sector funds, tax-managed funds, fixed-income funds, balanced funds, real estate funds and annuities.

Chapter 5

Summary and conclusions

Mutual funds have been among the largest investors in the U.S. economy and world financial markets for the past 20 years. Where does the enormous appeal of mutual funds among investors come from? Do actively managed portfolios add value? Academics have debated these issues for many years. The majority of the studies have reached a consensus that actively managed funds, on average, underperform their passive benchmarks after transactions costs and fund expenses. This thesis attempt to solve the performance puzzle by looking at the performance of stocks held by mutual funds. The quarterly mutual fund holdings data allow a more comprehensive look at the value of active asset management at the security level. With this database, we empirically examine the information content of mutual fund portfolio holdings.

Chapter 2 analyzes the simplest way in which disclosed holdings can be used by outside investors. Portfolio disclosure can be costly to actively managed mutual funds because it enables competitors to construct portfolios that mimic, with a lag, the primitive fund's holdings. This chapter shows that, on average, copycat funds can produce returns that are close to their target funds, taking into account transaction costs and expenses. After extensive discussion and deliberation, the SEC increased the mandatory reporting frequency of mutual fund holdings from semi-annually to quarterly in 2004. Our results show that this policy change leads to an increase in the return differential between copycat funds and their targets, and a strong reduction in the volatility of the return differentials. This implies that since 2004 it is easier for outside investors to free-ride on disclosed fund portfolio selection, which might contradict the Commission's original intention to protect fund shareholders' interests. At the same time, the policy change has increased the representativeness of the reported holdings, which could indicate that window dressing and other ways of camouflaging the true fund's holdings have reduced in the situation where all funds are mandated to quarterly disclose their holdings. In this chapter, we also characterize certain subgroups of mutual funds whose disclosed holdings are most valuable for potential free-riding investors. We show that past fund performance and the representativeness of reported holdings are important determinants of the relative success of copycat funds. It appears that the smartest copycat strategy would be to mimic the portfolios of funds that disclose representative holdings and exhibit good recent performance. The net performance of such a selective copycat strategy is in general significantly better than that of the vast majority of mutual funds. Finally, our findings provide some insights into the hidden cost of frequent portfolio disclosure for active funds. Policymakers will also have to consider the benefits of portfolio disclosure such as increased transparency to strike a balance for an optimal disclosure policy design.

Chapter 3 addresses the question whether actively managed mutual funds attain informational advantages in financial markets as an investor group. We find strong evidence that supports an informational role of actively managed mutual funds in determining security prices. As the performance of an active fund is typically evaluated against a performance benchmark, the manager often invests a substantial portion of fund assets in the benchmark. Hence, we compare a fund portfolio to its own benchmark index and only focus on the excess long or short fund positions assigned to a stock on top of the benchmark portfolio to more precisely capture the fund manager's active forward projection on the stock return. Using a comprehensive sample of U.S. equity mutual funds during the period from 1980 to 2008, we find that stocks heavily overweighted by active mutual funds relative to their benchmarks generate superior performance relative the market and strongly outperform their underweighted counterparts. The return premium on stocks heavily overweighted by mutual funds, relative to their underweighted counterparts, reaches more than 7% per year even after adjustments for their loadings on the market, size, value, momentum, and liquidity factors. A significant portion of this premium occurs around corporate earnings announcements. Finally, to reconcile our findings with the overall lackluster performance of mutual funds as identified in the prior literature, we evaluate the performance of different portions of an aggregate mutual fund portfolio. We find that active funds in aggregate invest less than 10% of their assets in alpha-generating stocks. On the other hand, although stocks that are heavily underweighted by active funds generate a four-factor alpha close to zero, they receive approximately 34% of total active fund assets. As a result, a large four-factor alpha of 6% per year on largely overweighted stocks translates into a small average mutual fund alpha of less than 1% per year before fees and expenses. The results are consistent with the prediction of rational fund behavior by Berk and Green (2004). These results point to an informational link between mutual fund investing and asset prices.

As an extension of Chapter 3, Chapter 4 examines the nature of the information possessed by mutual fund managers. In particular, we explore how effectively active mutual funds trade on and profit from fundamental analyses. We find that active funds tend to trade on the V/P anomaly as documented by Frankel and Lee (1998). The V/P ratio measures the extent of stock mispricing relative to its intrinsic value based on a comprehensive valuation model, namely, residual income model. We use the residual income model and analyst earnings forecast to measure a firm's intrinsic value and show that mutual funds start to exploit such mispricing opportunities far before the financial information becomes public. Using fund returns data before fees, we show that funds that have the highest weights on underpriced stocks are able to generate a significant 4-factor alpha of 0.27% per month over a six-month horizon. Therefore, trading on V/P effect can be profitable even after the actual transactions costs for a relatively short period. Finally, we find evidence consistent with our conjecture that the V/P effect is more significant among stocks with less mutual funds' exploitation. Our study suggests that mutual funds in aggregate trade on fundamental value and a subgroup of funds can earn significant risk-adjusted returns from it. This leaves space for the limits-of-arbitrage explanation for why other funds do not exploit the intrinsic value information as aggressively as those profitable ones.

Our research suggests interesting paths for future research. First, our results indicate that mutual funds acquire information that is not fully reflected in prices for those stocks about which they display the most conviction. But it is unclear which potential channels might enable them to gain this superior information. Recent studies by Coval and Moskowitz (2001) and Cohen, Frazzini, and Malloy (2008) make some initial progress by suggesting that geographic proximity and shared educational experiences between corporate and fund managers provide important channels for mutual fund managers to access private information. It should be promising to connect the findings in this thesis to these two informational channels and explore additional networks of information flow to gain a better understanding of how information finds its way into security prices.

Second, a fund manager's optimal decision is jointly determined by three factors: degree of risk aversion, expected returns of securities conditional on the manager's information set, and risks of securities. We lack accurate estimates of these three variables, so we cannot provide a definitive answer to the question why fund managers only focus on the stocks for which they have private information. Our results lead us to conjecture that aversion to taking large active risks could have an important role in shaping the activeness of fund managers' portfolios. One exciting path for future research is to properly measure these important determinants of fund portfolio decision and integrate them with our current research. This can also shed some light on why certain mutual funds do not rely on fundamental analysis to explore mispricing opportunities.

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Nederlandse samenvatting (Summary in Dutch)

Sinds het baanbrekende werk van Jensen (1968) hebben academici zich verdiept in de waarde van actief portefeuillebeheer en de toegevoegde waarde van actieve beleggingsfondsen en hedgefondsen. Gezien de grote hoeveelheid geld en tijd die hiermee gemoeid is, is het te verwachten dat beleggingsfondsen geloofwaardige kandidaten zijn om de rol van geïnformeerde belegger te vervullen, dat wil zeggen dat de informatie die door hen wordt vergaard mede hierdoor haar weg vindt naar, en verwerkt wordt in, de aandelenkoersen. Desalniettemin komt een groot deel van de recente literatuur tot de conclusie dat actieve beleggingsfondsen, gemiddeld genomen, slechtere prestaties laten zien dan passieve benchmarks, na aftrek van kosten. Dit proefschrift probeert de mogelijkheid dat actieve fondsmanagers informatievoordelen bezitten te verenigen met hun globaal gezien tegenvallende performance, gebruikmakend van openbare informatie uit de portefeuille samenstelling van de fondsen. Hierdoor is het mogelijk een beter beeld te krijgen van de toegevoegde waarde van beleggingsfondsen en de mate waarin beleggers hiervan kunnen profiteren. De drie empirische hoofdstukken in dit boek geven op verschillende manier inzicht in de informatieve waarde van de portefeuille-samenstelling van beleggingsfondsen. Hoofdstuk 2 bestudeert de waarde van deze portefeuille-samenstelling voor externe partijen en analyseert in hoeverre copy-cat strategieën winstgevend zijn. Hoofdstuk 3 en 4 relateren de fonds portefeuilles aan aandelenkoersen om te analyseren of en in hoeverre beleggingsfondsen een rol spelen bij het verwerken van fundamentele informatie in de prijzen op financiële markten.

Als eerste analyseren we een eenvoudige manier waarop beleggers gebruik kunnen maken van de portefeuille-samenstelling van actieve beleggingsfondsen, simpelweg door het kopiëren van de gepubliceerde portefeuilles. Op het moment van publicatie zijn deze portefeuilles maximaal twee maanden oud. Hoofdstuk 2 laat zien dat gemiddeld genomen een hypothetisch copy-cat fonds rendementen kan produceren die slechts weinig afwijken van het fonds dat wordt gevolgd, rekening houdend met transactiekosten en beheerskosten. Een interessant resultaat is dat het relatieve succes van copy-cat strategieën significant is toegenomen na 2004, toen de

Amerikaanse SEC (Securities and Exchange Commission) voor alle beleggingsfondsen de verplichting invoerde van kwartaalrapportages over de portefeuille-samenstelling (in plaats van halfjaarlijks). Tegelijkertijd is ook de "representativiteit" van deze informatie toegenomen, door een afname van "window dressing" en andere activiteiten die de investeringswaarde van de openbaarmaking reduceren. In dit hoofdstuk laten we verder zien dat de relatieve performance van copy-cat fondsen in belangrijke mate afhangt van de historische presentaties van het gevolgde fonds, en de representativiteit van de gepubliceerde portefeuilles.

Hoofdstuk 3 onderzoekt het actieve deel van de portefeuilles van beleggingsfondsen door het analyseren van de afwijkingen, op aandeelniveau, van een fonds van zijn benchmark. We gebruiken dit om voor elk aandeel een maatstaf te creëren die gebaseerd is op het aggregeren van informatie waarover individuele fondsen de beschikking hebben, en die tot uiting komt in de mate van over- of onderweging van een aandeel. Op basis van een uitgebreide steekproef van Amerikaanse beleggingsfondsen over de periode 1980-2008, blijkt dat de gemiddelde afwijking van de benchmark, in sterke mate toekomstige aandelenrendementen voorspelt. Aandelen die het meest worden overwogen laten positieve abnormale rendementen zien in de daaropvolgende maanden, en het omgekeerde geldt voor aandelen die het meest worden onderwogen. Een belangrijk deel van deze rendementen concentreert zich rond de dagen waarop nieuws over ondernemingswinsten wordt vrijgegeven. Deze resultaten wijzen erop dat beleggingsfondsen beschikken over superieure informatie die nog niet verwerkt is in de aandelenkoersen, en op basis waarvan abnormale rendementen te behalen zijn. Desondanks slagen beleggingsfondsen er gemiddeld genomen niet in dit voordeel tot uitdrukking tot laten komen in hun netto rendementen. Slechts een beperkt deel van het belegd vermogen wordt belegd in aandelen die abnormale rendementen vertonen, terwijl ca. een derde van het vermogen zich in benchmark-aandelen bevindt die worden onderwogen. Uiteindelijk leidt dit tot een gemiddelde bruto alpha van slechts 1% per jaar (voor aftrek van kosten).

Hoofdstuk 4 gaat verder door de rol die actieve beleggingsfondsen spelen bij het verwerken van informatie in aandelenkoersen nader te onderzoeken. In het bijzonder wordt onderzocht in hoeverre actieve fondsen kunnen profiteren van fundamentele analyse. We meten de mate waarin een aandeel verkeerd geprijsd is ten opzicht van zijn intrinsieke waarde op basis van een veel gebruikt residual income model. De resultaten laten zien dat het gemiddelde fonds handelt op basis van dergelijke prijsafwijkingen. Fondsen die "te goedkope" aandelen een groot gewicht in hun portefeuille geven zijn in staat over een horizon van zes maanden significante outperformance te laten zien. Dit toont aan dat de groep actieve fondsen die gebruikmaakt van het modelleren van de intrinsieke waarde van aandelen hiervan sterk profiteert. Blijkbaar zijn fondsmanagers in staat fundamentele informatie beter te begrijpen of te voorspellen, en daarmee beter te benutten, dan de markt.

Biography

Yu Wang (Tianjin, 1982) joined the *Department of Finance* at *Rotterdam School of Management* of *Erasmus University* and the *ERIM* PhD program in September 2008. Before that, he held a BSc degree in Finance and Economics (*Nanjing University*, 2004) and an MPhil degree in Finance from *Erasmus Research Institute of Management* of *Erasmus University*. In 2007, he did an investment banking summer internship with the Quantitative Analytics Department of ABN AMRO Global Markets. From June 2011, he works as a portfolio manager/researcher for an in-house hedge fund at IMC Asset Management in Amsterdam.

Yu's research interests include institutional investors, empirical asset pricing, investments, and behavioral finance. In particular, he is interested in understanding the information content of mutual fund portfolio disclosure and whether active mutual fund managers attain informational advantages in financial markets. His research works have been presented at several major finance conferences including *Utah Winter Finance Conference*, *Eastern Finance Association Conference*, *Midwest Finance Association Conference*, *European Financial Management Association Conference*, *Financial Management Conferences (International and European)*, and *Rotterdam Professional Asset Management Conference*. His paper "Better than the Original? The Relative Success of Copycat Funds" received the *Outstanding Paper in Investments* award at the *Eastern Finance Association Conference* (Miami, April 2010). In December 2010, his project "Information Content when Mutual Funds Deviate from Benchmarks" received the *INQUIRE Europe Research Grant* (Institute for Quantitative Investment Research).

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