INFORMATION TO USERS

This manuscript has been reproduced from the microfilm master. UMI films the text directly from the original or copy submitted. Thus, some thesis and dissertation copies are in typewriter face, while others may be from any type of computer printer.

The quality of this reproduction is dependent upon the quality of the copy submitted. Broken or indistinct print, colored or poor quality illustrations and photographs, print bleedthrough, substandard margins, and improper alignment can adversely affect reproduction.

In the unlikely event that the author did not send UMI a complete manuscript and there are missing pages, these will be noted. Also, if unauthorized copyright material had to be removed, a note will indicate the deletion.

Oversize materials (e.g., maps, drawings, charts) are reproduced by sectioning the original, beginning at the upper left-hand corner and continuing from left to right in equal sections with small overlaps.

Photographs included in the original manuscript have been reproduced xerographically in this copy. Higher quality 6" x 9" black and white photographic prints are available for any photographs or illustrations appearing in this copy for an additional charge. Contact UMI directly to order.

ProQuest Information and Learning
300 North Zeeb Road, Ann Arbor, MI 48106-1346 USA
800-521-0600

UMI
THE INVESTMENT PERFORMANCE AND TRADING BEHAVIOR OF INSTITUTIONAL INVESTORS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for

the Degree Doctor of Philosophy in the Graduate School of

The Ohio State University

By

Christo A. Pirinsky, M.S.

The Ohio State University

2001

Dissertation Committee:

Professor René M. Stulz, Adviser
Professor Jean Helwege
Professor Andrew Karolyi
Professor Ingrid Werner

Approved by

Adviser

Graduate Program in Business Administration
ABSTRACT

Increasing institutional equity ownership has been one of the major trends in the U.S. stock market over the last three decades. Such a process can have important implications for both investors' welfare and properties of security prices. This dissertation investigates the investment performance and trading behavior of a comprehensive group of financial institutions including banks, insurance companies, mutual funds, independent investment advisors, and corporate and state pension funds based on quarterly disclosures of their equity-portfolio holdings.

The first dissertation essay analyzes the investment performance of institutional investors. Existing research has predominantly focused on mutual funds although they still represent a relatively small proportion of the pool of institutional investors. This part of the dissertation furthers the existing research on mutual funds of Jensen (1968), Ferson and Schadt (1996), Gruber (1996), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997) among many others, and presents a comprehensive comparative performance analysis of institutional investors. The major finding is that on aggregate, financial
institutions exhibit significant abnormal performance before expenses are subtracted. This result is robust with respect to several conditional and unconditional performance measures based on factor- and characteristic-benchmarks. Institutional performance is further related to the size of the managed portfolio, its stock characteristics, and its flows.

Next, I find that performance varies across types of institutions—banks, independent investment advisors, and mutual funds significantly outperform insurance companies and state pension funds. This pattern is not caused by systematic mispricings by the applied asset pricing models. The variation of performance across the major institutional types is consistent with agency theory (see Starks (1987), Admati and Pfleiderer (1997), Stoughton (1993), Lakonshok, Shleifer, and Vishny (1992a)) and the “transparency” hypothesis of Ross (1989).

The second dissertation essay is presented in Chapter 3 and investigates the intertemporal trading patterns of US institutional investors. I demonstrate that institutions tend to increase (decrease) their holdings in a stock after periods of significant aggregate institutional net buys (sells). Portfolio managers are also more likely to open a position in a stock after periods of increased aggregate institutional buys. There is a substantial variation in the tendency of institutional investors to follow aggregate trades across stocks. Institutions pay more attention to their peers' trades in small volatile stocks.
and in stocks experiencing significant price decreases. Institutions with the highest tendency to follow aggregate institutional trades do not realize significant abnormal performance and they significantly underperform the group of contrarian institutions, betting against the trend in aggregate institutional trades.

Institutional types differ in their trading decisions – banks, insurance companies, and investment advisors are more likely to act in conformity with their peers, corporate and state pension funds are not significantly influenced by previous institutional trades, while mutual funds exhibit contrarian behavior. Institutional investors further exhibit the tendency to target market weights. The results relate to a series of theoretical findings about herding and strategic trading in capital markets.
Dedicated to my caring parents, and in memory of my grandfathers
ACKNOWLEDGMENTS

I would like to express my profound gratitude to my adviser, René Stulz, for the inspiration, guidance, and insightful feedback that made this dissertation possible. He has set forth high standards of academic excellence, dedication to the profession, and professional ethic for me to aspire to.

I am extremely grateful to the other members of my committee, Jean Helwege, Andrew Karolyi, and Ingrid Werner, for the innumerable ideas and suggestions to enhance this dissertation. I also extend my gratitude to my family for their love and support; to my friends, Krassimir Petrov and Plamen Stoyanov, for their everyday help; and to my colleagues Protiti Dastidar, Craig Doidge, Jim Hsieh, Laura Tuttle, and Qinghai Wang for their help while working on this dissertation.

I also wish to thank Jeff Coles, John Griffin, Ro Goutierrez, Spencer Martin, Deon Strickland, and seminar participants at Arizona State University, Fannie Mae, Georgetown University, Texas A&M University, and The Ohio State University.
VITA

December 11, 1969......................Born – Pavlikeni, Bulgaria

1993...........................................B.S. Mathematics, Sofia University, Bulgaria

1995...........................................M.S. Statistics, Sofia University, Bulgaria

PUBLICATIONS


FIELDS OF STUDY

Major Field: Business Administration
Concentration: Finance
<table>
<thead>
<tr>
<th>Chapters</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Introduction</td>
<td>1</td>
</tr>
<tr>
<td>2. Investment Performance of Institutional Investors</td>
<td>4</td>
</tr>
<tr>
<td>2.1. Introduction</td>
<td>4</td>
</tr>
<tr>
<td>2.2. Sample Description</td>
<td>11</td>
</tr>
<tr>
<td>2.3. Methodology</td>
<td>15</td>
</tr>
<tr>
<td>2.3.1. Unconditional Performance Evaluation</td>
<td>19</td>
</tr>
<tr>
<td>2.3.2. Conditional Performance Evaluation</td>
<td>20</td>
</tr>
<tr>
<td>2.3.3. Performance Evaluation Based on Portfolio Weights</td>
<td>22</td>
</tr>
<tr>
<td>2.3.4. Mispricing-adjusted Performance Evaluation</td>
<td>24</td>
</tr>
<tr>
<td>2.4. Aggregate Institutional Performance</td>
<td>25</td>
</tr>
<tr>
<td>2.5. Performance by Institutional Type</td>
<td>29</td>
</tr>
<tr>
<td>2.6. Characteristics of Institutional Portfolios</td>
<td>32</td>
</tr>
<tr>
<td>2.7. Mispricing-adjusted Performance Evaluation</td>
<td>37</td>
</tr>
<tr>
<td>2.8. Determinants of Investment Performance</td>
<td>39</td>
</tr>
<tr>
<td>2.8.1. Portfolio Size</td>
<td>41</td>
</tr>
<tr>
<td>2.8.2. Stock Characteristics</td>
<td>43</td>
</tr>
<tr>
<td>2.8.3. Turnover</td>
<td>44</td>
</tr>
<tr>
<td>2.8.2. Flows</td>
<td>45</td>
</tr>
<tr>
<td>2.9. Discussion</td>
<td>46</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Sample Characteristics</td>
<td>98</td>
</tr>
<tr>
<td>2. Performance of Aggregate Institutional Portfolios</td>
<td>99</td>
</tr>
<tr>
<td>3. Performance of Aggregate Institutional Portfolios</td>
<td></td>
</tr>
<tr>
<td>Based on Portfolio Weights</td>
<td>100</td>
</tr>
<tr>
<td>4. Performance Evaluation by Institutional Type</td>
<td>101</td>
</tr>
<tr>
<td>5. Performance Evaluation by Institutional Type</td>
<td>102</td>
</tr>
<tr>
<td>Based on Portfolio Weights</td>
<td></td>
</tr>
<tr>
<td>6. Characteristics of Institutional Portfolios</td>
<td>103</td>
</tr>
<tr>
<td>7. Performance of 25 SZ/BM Portfolios Based on The</td>
<td>104</td>
</tr>
<tr>
<td>Based on The Fama and French Three Factor Model</td>
<td></td>
</tr>
<tr>
<td>8. Mispricing-adjusted Performance Measures Based on The</td>
<td>105</td>
</tr>
<tr>
<td>Fama and French Three Factor Model</td>
<td></td>
</tr>
<tr>
<td>9. Mispricing-adjusted Performance Measures by Institutional Type</td>
<td>106</td>
</tr>
<tr>
<td>Based on The Fama and French Three Factor Model</td>
<td></td>
</tr>
<tr>
<td>10. Variation of Performance Across Institutional Types:</td>
<td>107</td>
</tr>
<tr>
<td>Pair-wise Comparison</td>
<td></td>
</tr>
<tr>
<td>11. Performance of Institutional Portfolios Stratified by Portfolio</td>
<td>108</td>
</tr>
<tr>
<td>Characteristics Based on The Adjusted Three Factor Model</td>
<td></td>
</tr>
<tr>
<td>12. Performance of Institutional Portfolios Stratified by Portfolio</td>
<td>109</td>
</tr>
<tr>
<td>Characteristics Based on The Characteristic Selectivity Measure</td>
<td></td>
</tr>
<tr>
<td>13. Summary Statistics of Institutional trades</td>
<td>110</td>
</tr>
<tr>
<td>14. Cross-autocorrelations of Institutional Trades</td>
<td>111</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>15. Cross-autocorrelations of Institutional Trades by Institutional Type</td>
<td>112</td>
</tr>
<tr>
<td>16. Intertemporal Patterns in Aggregate Institutional Investors' Trades</td>
<td>114</td>
</tr>
<tr>
<td>17. Intertemporal Patterns in Aggregate Institutional Investors' Trades: Multiperiod Analysis</td>
<td>115</td>
</tr>
<tr>
<td>18. Intertemporal Patterns in Aggregate Institutional Investors' Trades: Buys vs. Sells</td>
<td>116</td>
</tr>
<tr>
<td>19. Intertemporal Patterns in Trades of Institutional Types Subsequent To Aggregate Institutional Trades</td>
<td>117</td>
</tr>
<tr>
<td>20. Intertemporal Patterns in Aggregate Institutional Investors' Following Trades of Institutional Types</td>
<td>118</td>
</tr>
<tr>
<td>21. Herding and Stock Characteristics</td>
<td>119</td>
</tr>
<tr>
<td>22. Intertemporal Patterns in Aggregate Institutional Investors' Trades in Stock Portfolios Stratified by Size</td>
<td>120</td>
</tr>
<tr>
<td>23. Intertemporal Patterns in Aggregate Institutional Investors' Trades in Stock Portfolios Stratified by Book-to-market Ratio</td>
<td>121</td>
</tr>
<tr>
<td>24. Intertemporal Patterns in Aggregate Institutional Investors' Trades in Stock Portfolios Stratified by Change in Stock Volatility</td>
<td>122</td>
</tr>
<tr>
<td>25. Performance of Financial Institutions Following Aggregate Institutional Trades</td>
<td>123</td>
</tr>
<tr>
<td>27. Past Performance of Financial Institutions Leading Aggregate Institutional Trades</td>
<td>125</td>
</tr>
<tr>
<td>28. Probabilities for Up- and Down-changes of Institutional Portfolio Weights</td>
<td>126</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Distribution of Institutional Ownership</td>
<td>128</td>
</tr>
</tbody>
</table>
CHAPTER 1

INTRODUCTION

The segment of institutional investors in U.S. capital markets has expanded in both scale and scope over the last three decades and currently constitutes a heterogeneous group of market participants with different organizational structures, objectives, investor base, and agency relations. Existing research has focused predominantly on mutual funds and little is known about the investment activity across other major types of financial institutions. This dissertation investigates the investment performance and trading behavior of U.S. institutional investors based on quarterly disclosures of their equity portfolio holdings. It furthers the research about mutual funds to a comprehensive study of U.S. institutional investors and extends some of the existing methodologies.

The first dissertation essay is presented in Chapter 2 and studies the investment performance of a comprehensive group of financial institutions including banks, insurance companies, mutual funds, independent investment advisors, and corporate and state pension funds based on quarterly disclosures of their equity-portfolio holdings. The analysis has implications for investors' welfare and moral hazard issues in portfolio management addressed by Starks (1987), Admati and Pfleiderer (1997), and Stoughton (1993), among others.

The major finding is that financial institutions exhibit significant abnormal performance before expenses are subtracted. Performance differs across types of institutions – banks, in-
dependent investment advisors, and mutual funds significantly outperform insurance companies and state pension funds while the performance of corporate pension funds is not significantly different from the performance all remaining institutions. I analyze the performance results in view of agency theory and demonstrate that the variation in institutional performance is consistent with institutional managers' compensation structure, investor base, and regulations.

The essay further investigates the portfolio characteristics and stock preferences of the major institutional types. Institutional investors are characterized in terms of their portfolio size, beta, portfolio allocation across industries, turnover, capital flow, and portfolio stock characteristics. I demonstrate that, institutional performance is related to the size of the managed portfolio, its stock characteristics, and its flows.

The second dissertation essay, presented in Chapter 3, studies the intertemporal trading patterns of US institutional investors. It analyzes institutional trades on both stock and institutional levels and studies the relation between institutional trading behavior and individual stock characteristics such as return volatility, past returns, market capitalization, etc. The analysis sheds additional light on a series of theoretical findings about herding and strategic trading in capital markets (De Long, Shleifer, Summers, and Waldman (1990), Scharfstein and Stein (1990), Banerjee (1992), Bikhandani, Hirshleifer, and Welch (1992), and Zwiebel (1995), among others).

I find that, institutions tend to increase (decrease) their holdings in a stock after periods of substantial aggregate institutional net buys (sells). They are also more likely to open
a position in a stock after periods of increased aggregate institutional buys. There is substantial variation in the tendency of institutional investors to follow aggregate trades across stocks. Institutions pay more attention to their peers' trades in small, volatile stocks and in stocks experiencing significant price decreases. Institutions with the highest tendency to follow aggregate institutional trades do not realize significant abnormal performance and they significantly underperform the group of contrarian institutions, betting against the trend in aggregate institutional trades. Institutional types differ in their trading decisions – banks, insurance companies, and investment advisors are more likely to act in conformity with their peers, corporate and state pension funds are not significantly influenced by previous institutional trades, while mutual funds exhibit contrarian behavior.

The tendency of institutional investors to follow their peers' trades in small volatile stocks suggests that institutional imitative behavior is largely driven by a search of investment information, which is more scarce for those securities. However, the fact that all herding institutions underperform their peers questions the rationality of this type of behavior. Compensation structures could also affect institutional trading decisions. I further demonstrate that institutions exhibit a strong tendency to target market weights, and this is probably related to the fact that portfolio managers are frequently evaluated relative to market indices.
CHAPTER 2

INVESTMENT PERFORMANCE OF INSTITUTIONAL INVESTORS

2.1 Introduction

Increasing institutional ownership has been one of the major trends in the U.S. stock market over the last three decades – the percentage of domestic equities held by institutions rose from 16% in 1965 to 59% in 1998. The segment of institutional investors has expanded in both scale and scope and currently constitutes a heterogeneous group of market participants with different organizational structures, objectives, investor base, and agency relations. With the increasing amount of funds delegated by individuals to professional money managers, the question about institutional investment performance could have important implications for investors' welfare. Existing research has, however, predominantly analyzed mutual funds although they still represent a relatively small proportion of the pool of institutional investors.¹ There have been a small number of studies about pension funds and little is known about the investment performance and trading activity across other major types of financial institutions.

This dissertation essay performs a comprehensive comparative analysis of the investment performance of several major classes of institutional investors. It analyzes the aggregate

¹Mutual funds held 16.2% of the equity market in 1998. All statistics are from the Securities Industry Factbook, 1999.
performance of "large" financial institutions based on the quarterly disclosures of their equity portfolio holdings (13F filings) to the Securities and Exchange Commission.\textsuperscript{2} Detailed information about portfolio holdings allows me to explore the link between institutional investment performance and portfolio characteristics. I further investigate and compare the performance of six major institutional types – trust departments of banks, insurance companies, mutual funds, independent investment advisors, and corporate and state pension funds, and analyze the variation in institutional performance.

I find that financial institutions exhibit significant abnormal performance before expenses are subtracted. This result is robust with respect to several conditional and unconditional performance measures based on factor- and characteristic-benchmarks. In a recent work, Nofsinger and Sias (1999) investigate the herding and feedback trading by institutional investors on NYSE traded stocks. They show that the stocks purchased by institutional investors subsequently outperform the stocks they sell over the next year, and the effect cannot be explained by simple momentum strategies. This suggests that institutional investors exhibit good stock-selection ability. The performance results corroborate this conjecture through a series of risk-adjusted performance tests.

Performance differs across types of institutions. I present evidence that banks, independent investment advisors, and mutual funds significantly outperform insurance companies and state pension funds while corporate pension funds do not perform significantly different.

\textsuperscript{2}13F filings cover all institutional investors with more than $100 million in securities under discretionary management. I discuss the sample in more details in Section 2.2.
from all remaining institutions. I would like to emphasize that the fact that some institutions exhibit better stock-selection ability than others does not imply that these institutions consistently deliver higher net returns to investors. This analysis does not include expenses which could be critical in the comparison of performance across institutional types from investors' point of view.

Why might investment performance vary across different types of institutions? One explanation could be found in agency theory. The classical principal-agent conflict in a portfolio management context has been analyzed in a series of studies,\(^3\) which show that the magnitude of these agency problems can be an important determinant of performance. The institutional types in this study differ substantially in their managers' compensation structure, their investor base, and institutional regulations. All these factors could naturally affect investment performance by creating varying incentives for managers to devote time and effort. My results support this argument — for example, for better performing mutual funds and investment advisors incentive-based compensation constitutes more than 50 percent of total managerial compensation while for the worse performing pension funds the proportion is less than 20 percent.\(^4\) The agency conflicts between managers and investors could also be related to the level of institutional transparency. Ross (1989) classifies financial

\(^3\)Starks (1987), Admati and Pfleiderer (1997), and Stoughton (1993), among others, analyze moral hazard issues in portfolio management. Lakonishok, Shleifer, and Vishny (1992a) discuss in detail the agency problems of the money management industry and particularly of pension funds.\(^4\)The information on managerial compensation is obtained from AIMR and Russell Reynolds Associates' Compensation Survey of Investment Management professionals (1999)).
institutions into transparent, translucent, and opaque depending on the level of observability of managers by outside investors. More transparent institutions could exhibit better performance because they are subject to stronger external monitoring by their investors. This process is facilitated by independent information providers, such as Morningstar in the case of mutual funds. As a result, investors in transparent institutions tend to be better informed and to condition their investment decisions on institutional performance. In addition, for most transparent institutions relative performance measures, such as ranking within their respective peer groups, are relevant. These additional performance dimensions make it easier to design performance-sensitive managerial contracts. As a matter of fact, at transparent institutions incentive-based compensation constitutes a substantially higher proportion of total managerial compensation.

The variation in institutional performance can also stem from the presumption that managers differ in their experience, background, and willingness to dedicate effort and personal time to their jobs. For example, Chevalier and Ellison (1999) show that mutual fund performance can be explained in part by characteristics of fund managers related to ability, knowledge, or effort. In a market of institutions with different transparency and populated with heterogeneous managers a separation equilibrium could emerge. In this equilibrium more skilled and hard-working managers will tend to work for more transparent institutions where managers' expertise and effort are better revealed and utilized than in less transparent institutions. Holmström (1979) demonstrates that additional information allows a more accurate judgment of the agent's performance and the design of better incentive contracts.
ent institutions. Over time, the more experienced and less effort-averse managers would have incentives to move to more observable positions. As a consequence, more transparent institutions will tend to perform better, demand more, and reward higher.

Since investment behavior closely relates to investment performance, I investigate the portfolio characteristics and trading behavior of the major institutional types. I characterize financial institutions in terms of their portfolio size, beta, portfolio allocation across industries, turnover, capital flow, and portfolio stock characteristics. Gompers and Metrick (1998) and Cohen (1999) document consistent differences in the security preferences and asset allocation decisions of individual investors and institutions. I take a closer look at the group of institutional investors and demonstrate a strong heterogeneity among financial institutions – their investment behavior varies substantially across institutional types.

I find that institutional performance is related to the size of the underlying portfolio - small-size portfolios tend to outperform large-size portfolios. This relationship is stronger for banks and pension funds. Next, I establish that small-cap, growth portfolios exhibit better overall performance. Moreover, for most institutions this performance is not significantly related to the turnover rate of the portfolio. The relation between performance and asset turnover is controversial. While Chen, Jegadeesh, and Wermers (1999) establish that high-turnover funds perform better before expenses, Carhart (1997) finds that after expenses fund performance is negatively related to asset turnover. Odean (1999) demonstrates that individual investors do not improve their performance by active trading either. I find that high turnover does not imply better performance for a comprehensive group of
financial institutions and provide various explanations. Better performing portfolios further exhibit higher levels of subsequent capital flows and the effect is the strongest for mutual funds and independent investment advisors. Gruber (1996) and Zheng (1999) document the same relation between performance and subsequent flows for mutual funds. I do not find strong evidence that high levels of capital inflow to the portfolio imply better subsequent performance.

Further, I analyze the intra-group variation of performance for each institutional type with respect to a certain portfolio characteristic. This allows me to address the question whether financial institutions recognize their relative advantage and accordingly bias their portfolios toward performance-maximizing characteristics. I present evidence that financial institutions adopt an investment style that improves their performance. However, they do not always specialize in stocks they evaluate best, presumably because of liquidity considerations or institutional regulations. Despite the above constraints, financial institutions realize significant abnormal performance.

It is difficult to distinguish between investment performance and benchmark inefficiency. Traditionally, the performance evaluation literature sets the null hypothesis for alphas to be equal to zero. This is correct only if the applied asset pricing model prices all individual stocks correctly. As discussed by Fama and French (1993) and Mitchell and Stafford (1999), the widely applied Fama and French three-factor model is unable to completely describe the returns of portfolios based on the size and book-to-market characteristics. Since most actively managed portfolios allocate disproportionately along these characteristics, a portfo-
folio's alpha could be significantly affected by these model mispricings. In order to correct for this effect, along with the traditional performance measures I develop mispricing-adjusted performance measures adjusting for the characteristics of the stocks in the evaluated portfolio. I demonstrate that the abnormal performance of financial institutions is not caused by systematic mispricings by the applied asset pricing models.

Pástor and Stambaugh (2000) develop a framework for evaluation of mutual fund performance distinguishing between pricing-model inaccuracy and managerial skill. They introduce non-benchmark passive assets for a more precise estimation of fund's alpha. Although their theory leads to estimates that vary less across alternative benchmark specifications, it does not provide insights for the specification of the non-benchmark assets. Additional data on portfolio disclosure allows me to disentangle directly the part of estimated alphas reflecting asset pricing model mispricings.

Studies since the 1960's find that mutual funds do not systematically outperform benchmark portfolios (see the classic papers by Jensen (1968), Grinblatt and Titman (1989), Connor and Korajczyk (1991), and Gruber (1996) among others). Carhart (1997) finds that more active trading is associated with even lower benchmark-adjusted net returns to investors. Using a different approach, some recent studies look at the performance of the stocks held by mutual funds (Daniel, Grinblatt, Titman, and Wermers (1997; DGTW), Grinblatt, Titman and Wermers (1995), Chen, Jegadeesh, and Wermers (1999), and Wermers
These papers conclude that mutual fund managers possess significant stock-picking ability and the evidence is especially strong among growth-oriented funds. My mutual fund-results are particularly consistent with the results from the above studies.

This chapter proceeds as follows. Section 2.2 describes the sample. Section 2.3 discusses the methodology. Sections 2.4 and 2.5 present the results from the aggregate institutional performance evaluation and the performance evaluation by institutional type. Section 2.6 describes the characteristics of institutional portfolios. Section 2.7 applies mispricing-adjusted performance measures and compares performance across institutional types. Section 2.8 studies the determinants of institutional performance, and Section 2.9 discusses the performance results. Section 2.10 concludes the essay.

2.2 Sample Description

My data sources are the Spectrum Database, the CRSP monthly tapes, and the COMPUSTAT annual files. The Spectrum Database provides information about the quarterly holdings of financial institutions with more than $100 million in securities under discretionary management over the time period 1982–1996. All common stock positions of these institutions greater than $200,000 or 10,000 shares must be reported quarterly on SEC's form 13F. Institutions are further classified into the following five groups: banks (Bnk), insurance companies (Ins), investment companies (Mut), independent investment advisors (Iadv), and other institutions (Othr.). I discuss the basic institutional types below.

*A 1978 amendment to the Securities and Exchange Act of 1934 requires all institutions with more than $100 million under discretionary management to report their portfolio holdings to the SEC on form 13F.
The group of banks refers to the trust departments of major bank holding companies. By law, banks' investments in equities are severely limited. However, their trust departments invest heavily in the equity market on behalf of their clients, who are usually wealthy individuals and pension plans. Bank clients invest substantial amount of their wealth with the trust and are strongly protected by prudent-man regulation laws (see Del Guercio (1996)). As a consequence, trust departments are held accountable which provides strong incentives for their portfolio managers. An additional incentive for good performance is created by the fact that banks are eager to develop long-term relationships with their major clients. Bank portfolio managers exhibit medium total compensation and medium incentive-based compensation (31 percent by the end of 1998). In the early 90's banks constituted one of the largest institutional groups (after private pension plans) and currently they hold approximately 4% of the equity market. Examples of institutions classified as banks in the sample are Bank of Boston Co., Bank of New York, and Washington Trust Bank.

The group of insurance companies covers the largest life- and property-casualty insurers in the country. Although they invest heavily in the bond market, equity is a substantial investment for all companies in the sample. Insurance companies invest mainly premiums prior to paying claims and the level of outside control on their investment decisions is extremely low. This classifies insurance companies as opaque institutions, according to Ross (1989), with severe agency problems between managers and investors. Consistent with

Financial institutions are required to report only long-positions in equities, convertible bonds, and equity options. The Spectrum database covers only equity holdings. It is also possible for an institution to be reclassified over time if its main business has changed.
this observation, they exhibit one of the lowest incentive-based compensation among all institutions (median of 26 percent by the end of 1998). As of 1998, insurance companies held 6% of the stock market.

The group of investment companies covers most mutual funds. Mutual funds are characterized by high level of transparency because at any moment of time the participants in the fund can be well informed about the assets of the fund. Incentive compensation is most significant at mutual fund firms accounting for roughly half of the median total compensation at these organizations. Mutual fund managers also earn the highest total compensation among all institutions (median of $200,000 by the end of 1998). 13F filings provide aggregate data on investment companies. For example, the fund-family Fidelity is represented by one data point although most funds in the family are managed differently. However, this is not very restrictive since the objective of the paper is not to analyze in detail the performance of mutual funds but to address the question of investment performance of financial institutions in aggregate and by type.

The group of independent investment advisors covers most large brokerage firms and investment banks. Some of the institutions in this group are complex and operate in multiple lines of business. Independent investment advisors invest on behalf of individual and corporate clients and exhibit very high performance-sensitive compensation structures (median of 50 percent). It is also common that investment advisors have a mutual fund

---

7This group includes also reportings of hedge funds managing more than 100 million in equities. Spectrum database does not cover hedge funds as a separate type but they represent relatively small fraction of the group.
as a subsidiary. In all these cases, the institution is classified by Spectrum officials as a mutual fund if the mutual fund manages more than 50% of institutional assets, and as an investment advisor otherwise. Among the companies in this group are Merrill Lynch & Co., Pacific Advisors, and Westridge Capital Management.

The group of other institutions covers the largest pension funds, foundations and university endowments. Since the group of other institutions is heterogeneous, I identify the subgroups of corporate and state pension funds and include them in the analysis. I classify all funds associated with a particular corporation, for example GE Pension Tr., as corporate pension funds and all funds associated with a particular state, for example Texas Teacher Retirement Sys., as state pension funds. Investments in pension funds are guided by corporate treasurers acting for the corporation that provides benefits for its employees. Lakonishok, Shleifer, and Vishny (1992a) perform a detailed analysis of the extra layers of agency problems in the pension fund industry. The pension fund industry is associated with relatively low total compensation and fraction of incentive-based compensation (median of 15 percent).

The CRSP tapes and the COMPUSTAT files provide monthly stock returns and annual accounting information, respectively. I restrict the sample to common stocks listed on the CRSP monthly tapes excluding ADRs. Whenever I need book value of equity, I further restrict the sample to firms from the COMPUSTAT annual tapes. Basic summary statistics of the sample are presented in Table 1, Panels A and B. Panel A presents the number of institutions, the number of stocks, and the average number of stocks per institutional
portfolio for selected years. All three characteristics are increasing over the sample period. At the beginning of the period, the average number of stocks is 3,186; at the end it is 7,518. Similarly, the total number of institutions increases from 621 to 1437 and the average number of stocks in a portfolio increases from 142 to 250. This suggests that institutions increase their level of diversification over time.

Panel B presents the total number of institutions in each group for selected years. The total number of banks reporting share holdings is decreasing over time. The number of insurance companies does not change significantly over time. The largest growth was realized by the groups of mutual funds and investment advisors. Especially pronounced is the change for the investment advisor sector with 182 institutions at the beginning of the period and 978 institutions at the end. Corporate and State pension funds represent the smallest groups in the sample.

2.3 Methodology

Here, I discuss issues on the data and on the performance evaluation methodologies applied in this article: unconditional performance evaluation (2.3.1), conditional performance evaluation (2.3.2), performance evaluation with characteristic-based benchmarks (2.3.3), and mispricing-adjusted performance evaluation (2.3.4).

The data provides quarterly snapshots of the portfolio holdings of "large" financial institutions. Portfolio holdings are reported as of the last date of the quarter. I construct all portfolio returns based on past portfolio weights and future individual stock returns.
This portfolio is a proxy of the true institutional portfolio and it would match the institutional investment strategy perfectly if institutions rebalanced their portfolios only at the end of quarter. I constructed alternative portfolio proxies utilizing information about future portfolio weights. The major results in this paper do not change significantly under the alternative portfolio specifications. These issues are discussed in more detail in Section 2.7.

One limitation of the data is that it provides information only about equity holdings. Since institutional investors usually hold cash and government bonds, my analysis does not provide a complete picture of the performance of financial institutions but mostly of their stock-picking ability. Another limitation is that institutions are not required to report stockholdings below the threshold levels of $200,000 or 10,000 shares. Although institutions are not required to report these positions, on average they disclose holdings in approximately 20 stocks below the reporting barrier each quarter. Since I construct the portfolio returns based on current holdings and future individual stock returns, I exclude from the analysis all positions reported at the end but not at the beginning of each quarter, as a result of threshold up-crossing due to stock price appreciation. This could introduce a downward bias in all performance measures. It is also possible that there are additional biases associated with reportings below the threshold level. In order to control for these effects I performed a

Institutions are also not required to disclose their short-positions on form 13F. Due to institutional regulations and higher transaction costs the short positions represent a small percentage of institutional holdings and are short-lived. I believe that their inclusion would not change significantly the performance results.

I am thankful to John Griffin for discussion on these issues.
series of robustness checks. First, I excluded from the sample all stock positions of less than $200,000 and 10,000 shares. Next, I shifted the barrier up proportionally by 50, 100, 150, and 200 percent. My analysis shows that less than 3.5% of the portfolio value is allocated in positions below $400,000 and 20,000 shares and less than 6% of the portfolio value is allocated in positions below $600,000 and 30,000 shares. Replication of all tests only with stock holdings above these barriers does not alter the main results of the article.

A potential bias in all studies using portfolio disclosure data arises from the fact that the process of disclosure could create an incentive for portfolio managers to change the composition of their portfolios (this practice is sometimes referred to as *window dressing*). Musto (1999) presents evidence of risk-shifting by money market funds toward safer portfolios by the end of the year. Although the "window dressing"-conjecture is difficult to test directly, it is very unlikely that its presence will introduce a systematic upward bias in any risk-adjusted performance measure. In addition, the magnitude of the effect could be small since transaction costs would make large deviations of disclosed portfolios from undisclosed portfolios particularly expensive. Lakonishok, Shleifer, Thaler, and Vishny (1991) detect very little window-dressing for a sample of equity pension fund managers. I address this problem in more detail in Section 2.7.

One advantage of concentrating on actual portfolio holdings instead on net returns is that it allows me to extend the analysis for institutions other than investment companies. An additional advantage is that information about portfolio weights allows me to apply various alternative performance measures and to adjust traditional performance measures, such
as Jensen's alpha, for systematic model mispricing. Finally, working with gross portfolio returns, instead of net returns, provides undistorted estimation of managerial performance: if portfolio managers have superior investment talent, they may be able to capture the rents from their superior performance in the form of higher fees or perquisites. This issue has been addressed by Grinblatt and Titman (1989).

In this paper, I apply various performance and timing measures to equally- and value-weighted portfolios of financial institutions. Working with portfolios instead of individual institutions reduces the noise in the estimates and mitigates the bias toward better performing institutions. For example, out of 590 institutions at the beginning of the period, only 231 were present in the whole period (all 60 quarters). Very likely, most of the remaining 359 institutions were excluded from the database because their portfolio capitalization fell below the threshold level of $100 million. Thus, the portfolio approach allows me to include all institutions in the analysis without introducing survivorship bias or additional noise in the estimates due to short estimation windows. The equally-weighted institutional portfolio provides inference about the performance of the average institution from the group, while the value-weighted portfolio presents direct evidence about the performance of the group. At the same time, I would like to emphasize that value-weighting could introduce a bias if performance is systematically related to portfolio size.
2.3.1 Unconditional Performance Evaluation

A classical approach to measuring performance is to regress the excess return of a portfolio on the excess return of the market factor. Assuming that the market beta is constant, the slope coefficient is an unbiased estimate of beta, while the intercept, $\alpha$, is the performance measure proposed by Jensen (1968). I apply estimates of Jensen's alpha based on the market model, the Fama and French three-factor model, and the Carhart four-factor model:

$$R_{p,t} - R_{f,t} = \alpha + b_p (R_{m,t} - R_{f,t}) + \epsilon_{p,t},$$  \hspace{1cm} (1)

$$R_{p,t} - R_{f,t} = \alpha + b_p \text{rmf}_{t} + s_p \text{smb}_{t} + h_p \text{hml}_{t} + \epsilon_{p,t},$$  \hspace{1cm} (2)

$$R_{p,t} - R_{f,t} = \alpha + b_p \text{rmf}_{t} + s_p \text{smb}_{t} + h_p \text{hml}_{t} + m_p \text{pryr}_{t} + \epsilon_{p,t},$$  \hspace{1cm} (3)

where $[R_{p,t} - R_{f,t}]$ is the excess return of the portfolio, $\text{rmf}_{t} = R_{m,t} - R_{f,t}$ is the excess return of the market, $\text{smb}_{t}$ is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, $\text{hml}_{t}$ is the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks, and $\text{pryr}$ is the difference between the return on a portfolio of stocks with the highest realized returns over the previous one year and the return on a portfolio of stocks with the lowest realized returns over the previous year.\(^\text{10}\) Fama and French (1996) demonstrate that\(^\text{10}\) $\text{rmf}_{t}$, $\text{smb}_{t}$, and $\text{hml}_{t}$ are the factors introduced by Fama and French (1993). $\text{pryr}$ is constructed similarly to Carhart (1997). Each month all stocks listed in CRSP tapes are sorted according to their realized one-year return lagged one month. Then all stocks are assigned to one of ten portfolios according to their past return rank and $\text{pryr}$ is defined as the difference of the equally weighted returns of the top 3 and
model (2) explains most of the return anomalies documented in previous studies except for the persistence of short-term returns. Carhart (1997) extends the model to (3) in order to control additionally for stock momentum.

I use Jensen's alpha to evaluate portfolio performance, which is defined as the estimated intercept term $\hat{\alpha}_p$ of the above regressions. One common criticism of the Jensen measure is that it can assign negative performance to a successful market timer. Jagannathan and Korajczyk (1986) and Glosten and Jagannathan (1994) further warn that the presence of derivatives and dynamic trading strategies could lead to spurious conclusions about timing and selectivity. Grinblatt and Titman (1989) argue that in most cases the magnitude of these effects is small.

### 2.3.2 Conditional Performance Evaluation

If expected returns and risks vary over time, an unconditional asset-pricing model would confuse risk premiums with average performance. Recent studies have documented that the returns and risks of stocks and bonds are predictable over time using dividend yields, interest rates, and other information variables and that conditional versions of asset pricing models explain better the cross-section of expected returns (e.g. Cochrane (1992), Jagannathan and Wang (1996)). Ferson and Schadt (1996) introduce conditional performance evaluation based on conditional asset pricing models. Eckbo and Smith (1998) extend some

---

11 For a detailed discussion see Jensen (1972), Admati and Ross (1985), and Dybvig and Ross (1985).
of these results in a performance analysis of insider trades. In order to control for common variation caused by public information, I apply the following conditional version of the models from (1), (2), and (3), respectively.

\[ R_{p,t} - R_{f,t} = a_p + b_p [z_t (R_{m,t} - R_{f,t})] + \epsilon_{p,t}, \quad (4) \]

\[ R_{p,t} - R_{f,t} = a_p + b_p (z_t R_{mf,t}) + s_p (z_t S_{mb,t}) + h_p (z_t H_{ml,t}) + \epsilon_{p,t}, \quad (5) \]

\[ R_{p,t} - R_{f,t} = a_p + b_p (z_t R_{mf,t}) + s_p (z_t S_{mb,t}) + h_p (z_t H_{ml,t}) + m_p (z_t P_{yr,t}) + \epsilon_{p,t}, \quad (6) \]

In the above regressions, \( z_t \) is a vector of information variables which includes a dummy variable for the month of January and the lagged values of the dividend yield of the CRSP value-weighted index, the three-month T-bill rate, the slope of the yield curve, and the quality spread in the corporate bond market. The dividend yield is the difference between the monthly returns of the CRSP equally-weighted index with and without dividends; the slope of the yield curve is the difference between the 10-year Treasury bond yield and 3-month T-bill yield; and the corporate bond yield spread is the difference between Moody’s BAA-rated corporate bond yield less the AAA-rated corporate bond yield. The above information variables are similar to those applied by Ferson and Schadt (1996) and Eckbo and Smith (1998); they represent available public information over the sample period and were promoted as predictors of security returns in a series of academic studies since the late 70’s.
2.3.3 Performance Evaluation Based on Portfolio Weights

Here I outline three additional performance measures utilizing information about institutional portfolio holdings. The first measure, $GT$, was proposed by Grinblatt and Titman (1993). It represents the difference between the actual return of the portfolio and the return that the portfolio manager would have earned if he did not rebalance his portfolio over the past 4 quarters. The measure demonstrates the gross benefits (gains) of trading and it is formally represented as follows:

$$GT_t = \sum_{j=1}^{N} (\tilde{\omega}_{j,t-1} - \tilde{\omega}_{j,t-4}) \tilde{R}_{j,t}, \quad (7)$$

where $\tilde{\omega}_{j,t-1}$ is the portfolio weight of stock $j$ in the portfolio at time $t - 1$, $\tilde{\omega}_{j,t-4}$ is the portfolio weight of stock $j$ in the portfolio at time $t - 4$, and $\tilde{R}_{j,t}$ is the return realized by security $j$. The performance measure, $GT$ is defined as the time-series average of $GT_t$.

Since the $GT$ measure reflects both actual changes in the portfolio composition and passive changes in portfolio weights due to changes in stock prices, it will be tilted toward past winners. As a result, it will reward funds implementing momentum strategies.

Following Daniel, Grinblatt, Titman, and Wermers (1997) I construct additional measures of portfolio performance that use benchmarks based on the stock characteristics of the evaluated portfolio. At the end of each quarter, I place all stocks in my sample into 125 portfolios. The composition of each portfolio is based on a triple-sort on each firm's market value of equity (size), book-to-market ratio, and momentum (past 12 month return lagged one month). The book value of equity is as of the end of the firm's fiscal year and the market value of equity is as of December prior to the formation date. The sorting procedure
is completed at the end of June of each year in the following way: first, I sort all firms into size quintiles, then I sort all firms within each size quintile into quintiles based on their book-to-market ratios, and finally, I sort all stocks within each of the resulting 25 groups into quintiles based on their momentum. The returns of each of the resulting $5 \times 5 \times 5$ portfolios are calculated by value-weighting the stocks in the portfolio.

The second measure is CS (Characteristic Selectivity) and is designed to assess the ability of the portfolio manager to select stocks with the corresponding characteristics. Each quarter, each stock is assigned to a passive portfolio according to its size, book-to-market, and momentum rank. The excess return of each stock is then calculated by subtracting the passive portfolio's return from the stock's realized return. The value-weighted excess return is the quarter $t$ component of the performance measure and is defined as follows:

$$CS_t = \frac{1}{N} \sum_{j=1}^{N} \omega_{j,t-1} \left( \bar{R}_{j,t} - \bar{R}_{i,t}^{b,j,t-1} \right),$$

where $\omega_{j,t-1}$ is the weight of stock $j$ in the portfolio at time $t - 1$, $\bar{R}_{j,t}$ is the return realized by security $j$, and $\bar{R}_{i,t}^{b,j,t-1}$ is the return realized by the corresponding benchmark portfolio.

The performance measure $CS$ is defined as the time-series average of $CS_t$.

The third performance measure is CT (Characteristic Timing) and is designed to assess the ability of the portfolio manager to time stocks with the corresponding characteristics. It is defined as follows:

$$CT_t = \frac{1}{N} \sum_{j=1}^{N} \left( \omega_{j,t-1} \bar{R}_{i,t}^{b,j,t-1} - \omega_{j,t-4} \bar{R}_{i,t}^{b,j,t-4} \right).$$

Here, the portfolio weight of stock $j$ at quarter $t - 4$ is multiplied by $\bar{R}_{i,t}^{b,j,t-4}$, the quarter
return of the characteristic-based benchmark portfolio that is matched to stock \( j \) during quarter \( t - 4 \). Again, the performance measure \( CT \) is defined as the time-series average of \( CT_i \).

2.3.4 Mispricing-adjusted Performance Evaluation

If an asset pricing model systematically misprices some groups of stocks, the alpha of a portfolio that allocates more in those stocks will significantly reflect both the model’s alpha and managerial performance. Recent studies of Brav and Gompers (1997) and Mitchell and Stafford (1999) argue that a series of “anomalies”, such as the underperformance of IPO’s, are significantly related to model misspecification. Here, I propose a methodology for adjusting portfolio alphas based on the widely applied Fama and French three-factor model for potential model mispricings.

In order to correct for these model mispricings, I construct for each evaluated portfolio a benchmark portfolio that has similar characteristics to the original portfolio and represents a static investment strategy. Afterwards I estimate the evaluated portfolio’s alpha net of the benchmark portfolio’s alpha. More precisely: First, I construct the 25 size/BM portfolios based on two independent sorts with NYSE quintile breakpoints. Second, I match each stock in the institutional portfolio with its corresponding size/BM portfolio on a monthly basis and calculate the 25 weights of the portfolio allocation in the 25 characteristic portfolios. Third, I find the time-series average of the above weights. As a result, I obtain 25 weights which capture the average size/BM allocation of the portfolio over the period. Fourth, with
the above 25 weights and the monthly returns of the 25 size/BM portfolios, I construct the returns of a benchmark portfolio \( R_{p,t}^{\text{bench}} \). It represents a static investment strategy in the 25 characteristic portfolios and as a result, it is free of any performance. In addition, this benchmark portfolio has similar characteristics to the original portfolio and therefore its alpha incorporates the model mispricing over the period. Fifth, I estimate the models:

\[
R_{p,t}^{\text{bench}} = \alpha_p^{\text{bench}} + b_p \cdot Rmrf_t + s_p \cdot Smb_t + h_p \cdot Hml_t + \epsilon_{p,t} \tag{10}
\]

\[
R_{p,t} = \alpha_p + b_p \cdot Rmrf_t + s_p \cdot Smb_t + h_p \cdot Hml_t + \epsilon_{p,t}, \tag{11}
\]

where \( R_{p,t}^{\text{bench}} \) is the return of the benchmark portfolio and \( R_{p,t} \) is the return of the evaluated portfolio. Finally, I evaluate performance with the adjusted intercept, \( \alpha_p^{\text{adj}} \) and its t-statistic \( t_p^{\text{adj}} \):

\[
\alpha_p^{\text{adj}} = \hat{\alpha}_p - \hat{\alpha}_p^{\text{bench}}, \quad t_p^{\text{adj}} = \frac{\hat{\alpha}_p - \hat{\alpha}_p^{\text{bench}}}{\hat{s}(\hat{\alpha}_p)}, \tag{12}
\]

where \( \hat{s}(\alpha_p) \) is the estimated standard deviation of the estimate \( \hat{\alpha}_p \) from Eq. (11). The t-statistic, \( t_p^{\text{adj}} \), results from the test of the Null-hypothesis \( H_0: \alpha_p = \hat{\alpha}_p^{\text{bench}} \) in the estimation of (11).

### 2.4 Aggregate Institutional Performance

Now, I apply all performance and timing measures introduced in the previous section to equally- and value-weighted portfolios of financial institutions (Tables 2 and 3).

Table 2 (Panels A, B, and G) presents the unconditional alphas and factor loadings from models (1), (2), and (3). All performance measures are positive, and the three- and four-factor model alphas are significantly different from zero. For example, an equally-weighted
Institutional portfolio achieves an annualized abnormal return of 1.02% (t-statistic of 3.23) with respect to the three-factor model. With respect to the same model, a value-weighted portfolio earns an abnormal return of 0.79% (t-statistic of 2.39). In all cases, the sensitivity of the institutional portfolios to the market factor is highly significant. This is not surprising since I evaluate large portfolios accounting for nearly half of the equity market.

Table 2 (Panels D, E, and F) presents the results from the conditional performance evaluation. It exhibits the estimated intercepts and factor loadings from the models in (4), (5), and (6). The incorporation of lagged information variables (introduced in Section 3) is based on the view that a managed portfolio strategy that can be replicated using publicly available information should not be judged as having superior performance. The conditional alphas for equally- and value-weighted institutional portfolios with respect to the four-factor model are 1.22% (t-statistic of 3.32) and 1.09% (t-statistic of 2.83), respectively. The conditional alphas are higher in both magnitude and significance than the unconditional ones. A similar effect was detected by Ferson and Schadt (1996): they demonstrate for a sample of mutual funds that the introduction of conditional models shifts the distribution of the estimated alphas to the left, indicating better overall performance.

Table 3 presents the GT (Grinblatt and Titman), CS (Characteristic Selectivity), and CT (Characteristic Timing) performance measures from (7), (24), and (9). It reports annual averages of the performance measures and averages for the whole sample period. As discussed in Section 3, GT assesses the benefits of portfolio rebalancing; CS - the ability of the manager to select among stocks with similar characteristics; and CT - the ability of the
manager to time the corresponding characteristics. The GT and CS measures are positive in most years. The highest significance is achieved by the CS measure and documents a substantial ability of financial institutions in picking winning stocks. I do not present evidence that financial institutions time the size, book-to-market, and momentum characteristics (CT measure). These measures provide additional information about the source of the superior investment performance of financial institutions. The result that institutions derive their superior performance mostly from good selection of stocks is similar to this obtained for mutual funds by Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2000).

In all applied tests, equally-weighted portfolios realize better performance than the value-weighted portfolios. One explanation of the above effect is the presence of a “size-effect” in institutional performance: small portfolios tend to outperform large portfolios. Indeed, I present evidence that portfolio size is related to performance in Section 8. An additional explanation could be due to the fact that the market factor is represented by a value-weighted market index. In this case, the value-weighted institutional portfolio resembles more the market portfolio than the equally-weighted institutional portfolio. This is confirmed by the fact that for value-weighted portfolios the loadings on the market factor are slightly higher than for equally-weighted portfolios (Table 2, Panel A). Related to this is the observation that equally-weighted portfolios exhibit positive sensitivity to the size-factor, while value-weighted portfolios exhibit negative sensitivity. This suggests that small institutional portfolios invest proportionally more in small stocks than large institutional portfolios. Under this assumption, equally-weighted portfolios of institutions would place more weight on...
small portfolios, and hence on small stocks, than value-weighted institutional portfolios. As a result, whenever small stocks outperform large stocks both the equally-weighted portfolio and the size factor itself will realize a positive return. In fact, I showed that small-size portfolios invest significantly more in small-stocks than large-size portfolios.\footnote{I ranked all portfolios into quintiles according to their size. Afterwards, I demonstrated that the average market capitalization of the stocks in the small-size quintile is significantly smaller than this in the large-size quintile.}

All institutional portfolios exhibit a negative sensitivity to the book-to-market factor and a low positive sensitivity to the momentum factor (Table 2, Panels B and C). This suggests that on aggregate, financial institutions can not be classified as momentum traders. As a matter of fact, Gompers and Metric (1998) demonstrate that large financial institutions prefer stocks with lower realized returns over the previous year. I analyze the characteristics of institutional portfolios in Section 6.

The addition of the size, book-to-market, and momentum factors improves institutional performance. This result suggests that large financial institutions manage to achieve high compensation for the risks proxied by those factors. Since, the high abnormal returns (1.22\% with respect to the conditional four-factor model) cannot be compensated by the "classical" risk factors, I consider two possible explanations. One explanation could be model misspecification. It is possible that large institutions bear risks orthogonal to the market, size, book-to-market, and momentum factor-portfolios and the proposed models do not completely describe the trade-off between risk and expected return. Another explanation is that large institutions are better investors. Later, in this article I apply alternative
performance evaluation methodologies and present various stratifications of the pool of institutional investors. I present evidence (Section 7) that the performance results are not affected significantly by systematic model mispricings.

I would like to stress that my analyzes do not account for transaction costs and other expenses carried by institutional investors. Certainly, accounting for transaction costs will reduce all performance measures. At the same time, I would like to emphasize that every market participant is subject to those costs. In Section 6, I analyze the trading activity of institutional investors. A comparison of my results with those for individual investors (Barber and Odean (1999)), suggests that financial institutions bear substantially lower transaction costs than individual investors. Despite this, the fact that institutions achieve higher risk-adjusted gross returns and lower transaction costs than individual investors still does not imply that investors benefit from this superior performance. It is possible that fees and other expenses offset institutional abnormal returns.

2.5 Performance by Institutional Type

I established in Section 4 that financial institutions achieve significant abnormal performance with respect to the three- and four-factor asset pricing models. Further, I documented that they exhibit significant ability to select among stocks with similar characteristics (CS measure). Here, I would like to explore whether all types of financial institutions contribute proportionally to this superior performance. I apply the same performance measures by institutional type: banks, insurance companies, mutual funds, independent investment ad-
visors, and corporate and state pension funds. Tables 4 and 5 present the estimates of portfolio alphas and the characteristic-based performance measures, respectively. The exposition of the performance results is organized by institutional type in the order specified above.

Banks achieve the highest alphas based on all three asset pricing models. All alphas, conditional and unconditional, are significantly different from zero. Equally-weighted bank portfolios earn an annualized excess return of 1.35% with respect to the market model. The value-weighted portfolios achieve slightly lower performance measures, but all of them are significantly different from zero. For example, with respect to the conditional four-factor model banks earn an abnormal return of 1.37% with a t-statistic of 3.28. Their Characteristic Selectivity measure is significantly positive both for the equally- and value-weighted bank portfolios (Table 5). I do not find evidence that banks time either individual stocks or stock characteristics. Both the GT and CT performance measures are not significantly different from zero.

The performance measures of insurance companies are not significantly positive in all of the applied tests. Their value-weighted characteristic timing measure, CT (Table 5), is negative and marginally significant. This implies that insurance companies are more likely to lose money on all transactions switching between stock with different characteristics. Since insurance companies invest heavily in the bond markets, it is possible that they sacrifice some of the expected returns in the stock market, maximizing the performance of their overall portfolio. At the same time I would like to emphasize that all insurance companies disclosing
their stockholdings to SEC manage at least $100 mil. in stocks and have an average equity portfolio size of $1.714 billion (median of $0.44 billion). In addition, insurance companies exhibit relatively high turnover rates of 12.2% per quarter, as indicated in Table 6. The above facts suggest that stocks represent a major investment for these companies and they manage their equity portfolios actively beyond the single purpose of hedging their bond portfolios.

Mutual funds have significantly positive alphas with respect to the three- and four-factor conditional models, while their alphas from the unconditional models are not significantly different from zero. Mutual funds achieve a relatively high GT measure and a significantly positive CS measure. I note that the data is aggregated and does not distinguish between funds within the same family. Grinblatt and Titman (1989) demonstrate that small funds perform significantly better than large funds. Since the data puts proportionally more weight on large funds and excludes the smallest funds, this hurts the performance of the average mutual fund in my study as compared to this in the studies of Grinblatt and Titman (1989); Daniel, Grinblatt, Titman, and Wermers (1997); and Chen, Jegadeesh, and Wermers (1999).

Independent investment advisors realize significantly positive alphas with respect to the Fama and French conditional and unconditional three-factor models. Their conditional four-factor model alphas are significantly positive also. Independent investment advisors have the highest values of the GT performance measure, 0.85 with a t-statistic of 1.86, among all institutions and significantly positive CS measure. Corporate and state pension funds
do not exhibit superior investment performance with respect to all performance measures. The only exception is the equally-weighted unconditional four-factor alpha for state pension funds.

2.6 Characteristics of Institutional Portfolios

In order to understand the performance results better, I investigate the distinguishable characteristics of institutional portfolios across the following types of institutions: banks, insurance companies, investment companies, independent investment advisors, and public and private pension funds.

I define the following portfolio characteristics:

- $PSZ$ is the market capitalization of the portfolio.

- $Beta$ is the sensitivity of the excess return of the portfolio to the excess return of the market. It is estimated as the value-weighted average of individual stock betas based on the previous 5 years of data.

- $SZ$ is the average market capitalization of the stocks in the portfolio.

- $BM$ is the average book-to-market ratio of the stocks in the portfolio.

- $Mom$ is the average momentum (past 6 month returns lagged one month) of the stocks in the portfolio.

- $HISIC$ is the Herfindahl index of the portfolio allocation across two-digit industries (according to the standard industry classification).
• $TO$ is the quarterly portfolio turnover defined as follows:

$$TO_t = \sum_{j=1}^{J} \min(Buys_{j,t}, Sells_{j,t}) \over ASZ_{j,t},$$

where $Buys_{j,t}$ is the total value of stock $j$-purchases during the quarter $t$, while $Sells_{j,t}$ is the total value of stock $j$-sells during the same quarter. $ASZ_{j,t}$ is the average market capitalization of the portfolio over the same quarter. This definition of turnover follows the CRSP definition of mutual fund turnover and captures portfolio trading that is unrelated to investor inflows or redemptions.

• $FL$ is the quarterly net flow of funds into the portfolio and is defined as follows:

$$FL_t = \sum_{j=1}^{J} (num_{j,t} - num_{j,t-1}) P_{j,t},$$

where $num_{j,t-1}$ ($num_{j,t}$) is the number of shares of stock $j$ at the beginning (end) of quarter $t$ and $P_{j,t}$ is the market price of stock $j$ at the end of the quarter.

Averages and medians of the above characteristics for the whole sample and by institutional type are presented in Table 6. The average institutional portfolio has 194 stocks, a quarterly turnover of 14.5%, and a mean quarterly flow of funds of 53.4 millions. The positive portfolio capital flow points to the institutionalization of the capital markets. The annualized turnover of institutional investors is 58%. Interesting is the comparison between the trading behavior of institutional and individual investors (households). Barber and Odean (1999) demonstrate that the average household turns over more than 75% of its common stock portfolio each year. The turnover ratio of individual investors is even higher.
than the turnover ratio of most institutional types (the only exception are mutual funds). This observation suggests that when compared to individual investors, financial institutions bear substantially lower transaction costs.

The distribution of the above portfolio characteristics is highly skewed – their mean values deviate substantially from the sample medians. I further detect a significant variation in portfolio characteristics across institutional types – all F-statistics in column 8 reject the null hypothesis that the intergroup means are identical at any conventional level of significance.

The portfolios of the bank sector are characterized in Column 2. Banks manage the third-largest portfolios with average market capitalization of 1.734 billion dollars (median of 0.35 billion). They also maintain the second-largest number of stocks in their portfolios. As a result, banks achieve the lowest Beta among all financial institutions; on average, it is smaller than one (0.983). Banks exhibit strong preference toward large-cap, low-book-to-market, and low-momentum stocks. Their portfolios have one of the lowest turnover ratios, 8% per quarter, and relatively low rates of capital flow.

Column 3 characterizes the portfolios of insurance companies. Insurance companies manage medium-size portfolios in terms of both market capitalization and number of stocks. They exhibit moderate preferences for stock characteristics and medium turnover rates.

Properties of mutual fund portfolios are presented in Section 4. Mutual funds manage the second-largest portfolios with average market capitalization of 2.710 billion dollars (median of 0.50 billion) but maintain a relatively small number of stocks in their portfolios. This
could result from the fact that mutual funds maintain a large number of relatively small equity holdings (less than $200,000/10,000 shares), which are not required to be reported. The beta of mutual funds is the second largest: 1.125. Mutual funds hold the stocks with the smallest market capitalization in their portfolios and the stocks with the highest momentum. They have the highest turnover rate among all institutions (21.3%). The turnover estimate, 85.2% per year, is particularly close to the annual estimate of Carhart (1997)–77%. Mutual funds are associated with one of the highest levels of capital flow among all institutions.

Falkenstein (1996) shows that mutual funds, when compared to the rest of the market, prefer larger and more visible stocks. It is interesting that when compared to all other institutions, mutual funds demonstrate the strongest bias toward small-cap stocks. Their high turnover rates and strong momentum preferences could be induced by the close monitoring by the market and the frequent evaluation of the fund managers by investment information providers, such as Morningstar. I note that an analysis based on more disaggregated data on mutual fund holdings could provide additional insights about the trading behavior of this industry.

According to Column 5, independent investment advisors manage portfolios with a market capitalization below the average. Their portfolios have the smallest number of stocks and achieve the highest Beta (1.136). They exhibit strong preference for value, high-momentum stocks. Their portfolios have high turnover rates (16.8%) and the second-lowest level of capital flow (after corporate pension funds). One possible explanation of the high turnover rate is that independent investment advisors face smaller transaction costs due to the fact
they provide most brokerage services in the market. Another possible explanation could be that their special place in the market for collection and distribution of financial information could provide an additional incentive for frequent trading. Since this is the industry with the largest aggregate growth (Table 1), I conclude that the high entry level but not the individual firm growth account for the high growth of the industry.

Corporate pension funds, Column 6, manage the smallest-size portfolios with average market capitalization of 0.943 billion dollars and Beta of 1.087. Corporate pension funds hold large-cap, low-momentum stocks. Corporate pension funds have low turnover ratios, 10.7%, and the lowest levels of capital flow into their portfolios, 1.26 mil. Their portfolios exhibit the lowest level of diversification across industries. This is partially related to the fact that a quarter of the corporate pension funds invest disproportionately in their own stock—approximately 5% of their wealth.

Properties of state pension fund portfolios are presented in Column 7. State pension funds manage the largest portfolios among all institutions with average market capitalization of 6.343 billion dollars (median of 3.86 billion). Although they maintain the largest number of stocks in their portfolios (526), state pension funds do not achieve the lowest beta among all financial institutions. State pension funds prefer large-cap stocks and stocks with lower book-to-market ratios. They maintain the largest diversification across industries and the largest rate of capital flow into their portfolios.
2.7 Mispricing-adjusted Institutional Performance

I have established that the various institutional types achieve performance measures with different magnitude and significance. At the same time, institutions exhibit different preferences for stock characteristics. Since, it is possible that the performance results are significantly affected by systematic model mispricings, here I adjust for such mispricing the widely applied Fama and French three-factor model. In Table 7 I present the estimated alphas from a regression of 25 size/BM portfolio returns (based on independently constructed NYSE size and book-to-market quintiles) on the Fama and French three-factor model. As shown in the table, in 8 out of 25 cases the estimated alphas are significantly different from zero. Over the sample period, the model significantly overprices small and medium size low book-to-market stocks and significantly underprices small high book-to-market stocks. Here, I evaluate institutional performance (Tables 8 and 9) and compare the variation of performance across institutional types (Table 10) based on the corrected model.

As explained in Section 3, I evaluate performance with the adjusted alpha, $\alpha_p^{adj}$, and its t-statistic, $t_p^{adj}$:

$$
\hat{\alpha}_p^{adj} = \hat{\alpha}_p - \hat{\alpha}_p^{bench}, \quad t_p^{adj} = \frac{\hat{\alpha}_p - \hat{\alpha}_p^{bench}}{\hat{s}(\alpha_p)},
$$

where $\hat{\alpha}_p$ and $\hat{s}(\alpha_p)$ are the estimated intercept and its standard deviation from the regression of the evaluated portfolio returns on the Fama and French factors, (11), and $\hat{\alpha}_p^{bench}$ is the estimated intercept from the regression of the returns of a benchmark portfolio with similar size/BM characteristics on the same factors. The t-statistic, $t_p^{adj}$, results from the test of the Null-hypothesis $H_0 : \alpha_p = \hat{\alpha}_p^{bench}$ in the estimation of (11).
Table 8 presents mispricing-adjusted alphas from the FF three-factor model together with unadjusted alphas. I observe that the adjusted measures are slightly smaller in both magnitude and significance but they remain statistically different from zero. The decrease in the estimated performance measures could be due to the aggregate preference of financial institutions for high book-to-market stocks (as documented by Gompers and Metrick (1998)), which are systematically overpriced by the three-factor model (see Table 9). Table 9 presents the same performance measures for the various institutional types. Again, the adjusted measures are slightly smaller than the unadjusted measures but the results do not change qualitatively. My conclusion is that, although financial institutions are biased toward stocks with specific characteristics, their abnormal performance is not driven by mispricings of the applied asset pricing models.

In Table 10 I provide a pairwise comparison of the performance of the various institutional types. I compare the performance across institutional types for value-weighted portfolios of institutions based on the adjusted three-factor model. The above-diagonal elements of the table present the difference between the estimated alphas of the institutional types in the corresponding columns and rows. The below-diagonal elements present symmetrically their t-statistics. I establish that banks and independent investment advisors significantly outperform insurance companies and state pension funds. Mutual funds tend to outperform insurance companies and state pension funds as well but with a marginal significance. The performance of corporate pension funds is not significantly different from the performance of all other institutional types.
It is possible that the performance results are significantly affected by the fact that quarterly snapshots present a noisy proxy of institutional portfolio returns. Since institutions trade within the quarter, my analysis could underestimate performance and the institutions with the highest turnover, mutual funds and independent investment advisors, would be affected most strongly. As a robustness check, I constructed two additional sets of portfolio returns based on end-quarter weights, as well as on averages of beginning- and end-quarter-weights. All performance measures increase significantly and the largest change is for mutual funds and independent investment advisors. The increase of the performance measures is also strongly influenced by the fact that institutions apply positive feedback trading strategies. Buying past winners and selling past losers could be a result of momentum trading or "window dressing" practices. Independently of the return construction methods, insurance companies and pension funds perform significantly worse than all remaining institutions. I note that this does not imply that they deliver lower net returns to investors. My results do not include expenses which could be critical in the comparison of performance across institutional types from investors' point of view.

2.8 Determinants of Investment Performance

In an attempt to better understand the performance results in this paper, I analyze the relation between performance and various characteristics of the managed portfolio, such as portfolio size; average size, book-to-market ratio, and momentum of the stocks in the portfolio; turnover; and portfolio capital flow.
The variation in performance within the corresponding institutional types prompts me to address the question whether financial institutions adopt investment style from which they benefit the most. For example, if for banks large-cap portfolios significantly outperform small-cap portfolios, this suggests that banks have a relative advantage in evaluating large companies. Further, if banks bias their portfolios toward large-cap stocks compared to the rest of the market, this means that they recognize their relative advantage. I advocate the view that this could be an important component and determinant of performance.

In Subsections 2.8.1–2.8.4, I analyze the relation between performance and portfolio size, stock characteristics, turnover, and capital flow, respectively. In Table 11, Panel A, I sort all institutions within each institutional type into equally-weighted quintile portfolios according to their portfolio size. The sorting procedure is repeated every quarter. Afterwards, I compare the performance of the top-quintile portfolio (quintile 5) and the bottom quintile portfolio (quintile 1) by estimating the adjusted three-factor model:

\[ R_{p,t}^5 - R_{p,t}^1 = \alpha_p + b_p R_{mr} f_t + s_p Smb_t + h_p Hml_t + \epsilon_{p,t}, \]

where \( R_{p,t}^5 \) is the return on the top-quintile (highest) portfolio and \( R_{p,t}^1 \) is the return on the bottom-quintile (lowest) portfolio. T-statistics result from the test of the Null-hypothesis

\[ H_0 : \hat{\alpha}_p = \hat{\alpha}_p^{bch5} - \hat{\alpha}_p^{bch1}, \]

where the parameters \( \hat{\alpha}_p^{bch5} \) and \( \hat{\alpha}_p^{bch1} \) are the estimated intercepts on benchmark portfolios with similar size/BM composition to the original quintile-portfolios (see Section 7). In Panels B through G, I perform similar stratifications with respect to the average stock size, average
stock book-to-market ratio, average stock momentum, turnover, and prior and subsequent capital flow of the evaluated portfolios. Results for the group of all institutions are presented in the last column.

In Table 12, Panels A through G, I analyze the relation between performance and portfolio size, stock characteristics, turnover, and capital flow, respectively, based on the characteristic selectivity measure

\[ CS_t = \sum_{j=1}^{N} \omega_{j,t-1} \left( \bar{R}_{j,t} - \bar{R}_t^{b,j,t-1} \right) , \]

As in Table 11, I stratify all institutions within each institutional type into equally-weighted quintile portfolios according to each of the above characteristics. The table reports the differences between the CS performance measures in the fifth (highest) and the first (lowest) quintiles and their t-statistics.

2.8.1 Portfolio Size

The performance of financial institutions could be related to the size of the managed portfolio. On the one hand, institutions benefit from the larger size of their portfolios due to economies of scale. On the other hand, the large size of the institutional portfolio could negatively affect performance due to reduced coordination, inability to specialize, and stronger liquidity constraints. In addition, for large trades, it would be more difficult to remain anonymous, which puts the institution at an informational disadvantage. Walter (1999) advocates the view that such diseconomies of scale contributed to the catastrophic performance of Fidelity Magellan Fund in 1995 after a “stellar” long-term performance.
Grinblatt and Titman (1989) present empirical evidence for a sample of mutual funds that portfolios with the smallest net asset value realize the highest abnormal performance.

Portfolio size could be positively related to the probability of survival. In a recent study, Malkiel (1995) presents evidence about the significant magnitude of the survivorship bias in mutual fund performance evaluation. In this case I would expect large portfolios to perform better. However, the overall performance results suggest the opposite: small equity portfolios tend to outperform large portfolios. As indicated in Panels A of Tables 11 and 12, a large portfolio is a strong deterrent for banks and state pension funds. For example, the difference between the CS measures of small- and large-size bank portfolios is 78 basis points. For state pension funds, small portfolios perform significantly better than large portfolios. It is possible, that the inferior investment performance of state pension funds is largely driven by the fact that they manage the largest equity portfolios among all institutions.

Mutual funds' and independent investment advisors' portfolios are not sensitive to the size factor. I note that the mutual fund data is aggregated and it does not distinguish between various funds within the same fund-family. A more disaggregated analysis of the impact of portfolio size on mutual fund performance is presented in Grinblatt and Titman (1989).
2.8.2 Stock Characteristics

Here I investigate the relation between performance and the average size, book-to-market-ratio, and momentum of the stocks in the portfolio. Recall that the Characteristic Selectivity performance measure is adjusted for all three of the above characteristics, while the mispricing-adjusted alpha is adjusted for the size and book-to-market characteristics.

Panels B of Tables 11 and 12 analyze the relation between performance and the average market capitalization (size) of the stocks in the portfolio. I present evidence that financial institutions investing in small stocks tend to perform better. Gompers and Metcalf (1998) demonstrate that institutional investors exhibit consistent preference for large-cap stocks. This preference is probably related to the higher liquidity costs associated with institutional investments in small companies. Very likely, liquidity is a serious constraint in the portfolio allocation decision of financial institutions. This could limit their investment in this segment of the market even if they know it especially well. I would like to emphasize that despite those liquidity constraints, financial institutions manage to achieve substantial abnormal returns.

and DGTW show that portfolios of growth funds earn significantly positive risk-adjusted returns; here I similarly conclude that portfolios with growth characteristics outperform portfolios with value characteristics.

The superior performance of growth portfolios is strongly pronounced for insurance companies, mutual funds, and independent investment advisors. At the same time, according to Table 6, the various institutional types do not exhibit distinctive preferences for the book-to-market characteristic. This "misallocation" along the value-growth line probably hurts the performance of insurance companies, mutual funds, and independent investment advisors.

Panels D of Tables 11 and 12 analyze the relation between performance and average momentum of the stocks in the portfolio. I establish that high-momentum portfolios outperform low momentum portfolios. The effect is largely driven by independent investment advisors and mutual funds which hold the highest-momentum stocks in their portfolios. Gompers and Metrick (1998) show that large financial institutions prefer stocks with lower realized returns over the previous year. This suggests that momentum is a factor for the superior investment performance of financial institutions but it is not the only one.

2.8.3 Turnover

Here, I analyze the relation between investment performance and portfolio turnover (Panels E). I show that, in aggregate, high-turnover institutional portfolios do not outperform significantly low-turnover portfolios. Carhart (1997) presents similar evidence for a
sample of mutual funds. Odean (1999) indicates that trading activity does not improve the performance of individual investors. I further document that this applies for a comprehensive group of financial institutions. I would like to remind that all of the performance measures are based on gross portfolio returns and they do not account for transaction costs. The inclusion of transaction costs in the analysis would definitely lower the returns of high-turnover portfolios relative to low-turnover portfolios.

The result that more frequent trading does not imply better performance could be justified by investor irrationality. This is the approach advocated by Gervais and Odean (1999). They develop a model, in which investors become overconfident because they take too much credit for their successful trades and as a result trade excessively. I note that this behavioral explanation is more likely to hold for individual investors than for financial institutions. An alternative explanation of the above results could be found in agency theory. If managers’ compensation is not directly tied to the performance of their portfolio, it is more likely for them to trade excessively. Lakonishok, Shleifer, and Vishny (1992) advocate the view that managers of corporate pension plans might have the incentive to trade actively in order to simulate business and hard work.

2.8.4 Flows

Here I address the relation between investment performance and portfolio capital flow. In Panels F (Tables 11 and 12) I stratify all portfolios with respect to their flows over the previous quarter, while in Panels G I stratify all portfolios with respect to the subsequent
flows over the next quarter. Note that I do not provide an estimate of the flow of funds to the portfolio but only to the equity part of the portfolio. Part of this flow could be due to the fact that the institution reduces its cashholdings, closes some of its positions in the bond market, or increases its leverage.

I do not find that performance is positively associated with the level of capital flow into the portfolio preceding the formation dates (Panels F). Institutional performance is further positively associated with the capital flow into the portfolio subsequent to the formation dates (Panels G). The effect is well pronounced among mutual funds and independent investment advisors. Related to these results are the results for mutual funds by Gruber (1996) and Zheng (1999) who find that mutual funds that receive more money perform subsequently better than funds that lose money. Del Guercio and Tkac (2000) analyze the determinants of the flows of mutual fund and pension fund managers. They demonstrate that for both manager types flows are significantly positively related to Jensen's alpha and other quantitatively sophisticated performance measures such as tracking error and outperformance of a market benchmark.

2.9 Discussion

I have established that financial institutions realize significant abnormal performance. In order to investigate its determinants, I analyzed separately all institution types. I found that the superior investment performance of financial institutions is largely driven by banks, independent investment advisors, and mutual funds. I did not find that insurance companies
and corporate and state pension funds achieve significant abnormal performance. Further, I studied the relation between performance and properties of the managed portfolio. In this section, I provide more detailed analysis of the results and propose various alternative explanations.

The stratification with respect to various portfolio characteristics explains the sources of institutional abnormal returns. In particular, the superior performance of independent investment advisors could be attributed to their investments in small growth high-momentum stocks. Consistent with this result, Table 6 indicated that independent investment advisors bias their portfolios toward small high-momentum stocks. It seems that they allocate disproportionately in high-book-to-market stocks, while at the same time significantly underperform in those stocks. This misallocation along the value-growth characteristic definitely hurts their performance. Next, I present a weak evidence that banks investing in small stocks perform better, and bank performance is not sensitive to the book-to-market characteristic. Further, growth momentum oriented mutual funds perform significantly better. Similar effects were documented by Grinblatt and Titman (1989) and Grinblatt, Titman, and Wermers (1995). My results demonstrate that those effects are robust and preserve on aggregate fund-family level. Finally, part of the inferior equity investment performance of insurance companies and state pension funds could be attributed to those companies investing in value stocks.

One explanation of the variation in performance could be found in agency theory. Financial institutions are subject to agency problems since portfolio managers might not always
act in the best interest of outside investors. Since the magnitude of these problems varies across institutional types, the variation in performance could be attributed to different exposures to these agency conflicts. According to Ross (1989), financial institutions could be classified as transparent, translucent, and opaque depending on the level of their connection with retail investors. He further argues that the magnitude of these agency costs is inversely related to the level of transparency, and it is the strongest for opaque institutions. According to Ross, most mutual funds are transparent institutions, most pension funds are translucent institutions, while insurance companies and savings and loan organizations are opaque. Banks and independent investment advisors typically invest on behalf of individual and corporate clients. Since their clients invest substantial wealth with the institution, they hold the institution accountable. As a result, banks and independent investment advisors could be classified as transparent institutions. The performance results in the article are highly consistent with this agency-theoretical explanation: transparent institutions significantly outperform translucent and opaque institutions.

The abnormal performance of some financial institutions could be further explained by better flow of information. For example, banks through their credit departments and other businesses have a direct access to inside information, detailed financials, projects, and future prospects and profitability of businesses. They acquire information about firms' growth opportunities well before this information appears in accounting reports. This could
allow banks to make better informed investment decisions. This is reflected in their trading behavior – banks do not time individual securities and their superior performance is entirely driven by good selection of stocks.

Another explanation of the distinctive investment style of banks could be found in prudent-man laws\textsuperscript{13}. Bank managers are more sensitive to prudent-man regulations since they invest on behalf of private trust and pension plan clients and as a result are more likely to face legal actions. Del Guercio (1996) demonstrates that prudent man laws significantly influence banks' investment choices: bank managers protect themselves by tilting considerably the composition of their portfolios toward prudent stocks (stocks ranked A+ by Standard and Poor's). However, the resulting bias towards safer assets can not explain the abnormal returns of the banking sector since all applied performance measures are adjusted for risk.

Better information could also explain the good investment performance of independent investment advisors. They dominate the market for collection, processing, and distribution of financial information. For example, most security analysts are associated with those institutions. The nature of this superior information, however is different from the information of banks. It is more short-lived and it includes earnings forecasts, buy- and sell-recommendations, etc. In addition, the information flow to independent investor advisors is particularly frequent. The high turnover rate of their portfolios, 64% per year, could

\textsuperscript{13}The Model Prudent-Man Investment Act was developed by the Trust Division of the American Banker Association in the early 40's. Prudent-man laws are designed to protect beneficiaries by allowing them to seek damages from a fiduciary who fails to invest in their best interest.
be a response to this frequent information flow; in fact, the turnover of investment advisor portfolios is twice as high as the turnover of bank portfolios. I note that independent investment advisors demonstrate the strongest ability to time individual stocks: their GT measure (Table 7) is the most significant among all institutions.

Relative to banks and independent investment advisors, all remaining financial institutions are at an informational disadvantage since they are not involved in any special relationships with businesses. It is possible that this hurts their performance. One exception are corporate pension funds which know particularly well their own company. Although one fourth of corporate pension funds invest on average 5% of their wealth in their own stock, they do not achieve significant abnormal performance.

Institutional performance could be also related to several exogenous factors such as regulations and economies of scale. Regulations, in a fully rational economy, hurt institutional performance because they impose additional restrictions on institutional portfolio choice. For example, institutions that are restricted from selling short might be at a disadvantage in down-markets. In a not fully rational economy, though, such regulations could affect positively performance because they would prevent the institution from excessive trading and risk-bearing. However, in my study most institutional types are subject to similar regulations. Similarly, portfolio size could be negatively related to performance due to diseconomies of scale. I presented statistical evidence for such diseconomies in Section 9.
2.10 Conclusions

In this dissertation essay, I evaluate the investment performance of a comprehensive group of financial institutions including banks, insurance companies, mutual funds, independent investment advisors, and corporate and state pension funds. Based on quarterly portfolio disclosure data, I establish that financial institutions demonstrate considerable ability to manage portfolios of stocks. This result is robust with respect to several conditional and unconditional performance measures based on factor- and characteristic-benchmarks.

Most actively managed portfolios allocate disproportionately along various stock characteristics. As a result, a performance measure based on these characteristics needs to be corrected for potential model mispricings. Along with the traditional performance measures I develop mispricing-adjusted performance measure adjusting for the characteristics of the stocks in the evaluated portfolio. I demonstrate that the abnormal performance of financial institutions is robust with respect to the above mispricing-adjusted measures.

I further demonstrate that the various institutional types do not contribute equally to this superior performance: banks, independent investment advisors, and mutual funds outperform significantly insurance companies and state pension funds while corporate pension funds do not perform significantly different from all remaining institutions. In order to shed more light on the performance results, I investigate the relation between investment performance and characteristics of the evaluated portfolios. I establish that institutional performance is related to the size of the managed portfolio, its various stock characteristics, and capital flow.
Good investment performance is determined by both better information and better managerial incentives. I presume that the top-performers in the study exhibit both characteristics, while the bottom performers exhibit none. On the one hand, the results are consistent with the predictions of agency theory and support the “transparency” hypothesis of Ross. Banks, investment advisors, and mutual funds are more transparent than insurance companies and pension funds. In addition, banks and independent investment advisors, due to their concentrated investor base and prudential regulations, provide stronger incentives for managers to perform better. On the other hand, the results could be partially explained by different investment information. Through their credit departments and analyst meetings, banks and independent investment advisors have a direct access to inside information and future prospects and profitability of businesses. As a result, they are in a position to make better informed investment decisions. Most of the above conjectures are testable and a further research in this direction would be worthwhile.
CHAPTER 3

HERDING AND CONTRARIAN BEHAVIOR OF INSTITUTIONAL INVESTORS

3.1 Introduction

Institutional investors are sophisticated and increasingly influential players in financial markets. Their complex investment decisions, though largely based on firm-specific and market-wide information, also involve agency considerations, emotions, and mistakes. Institutional investors are often depicted as ruthless speculators moving in herds and are frequently blamed for increased stock market volatility and contagious transmission of shocks across markets. The research on herding and strategic trading in capital markets offers a considerable amount of theoretical hypotheses but relatively little empirical evidence.

This dissertation essay investigates the intertemporal trading patterns of US institutional investors distinguishing among the institutional types of banks, insurance companies, mutual funds, investment advisors, and corporate and state pension funds, based on quarterly disclosures of their equity portfolio holdings. It analyzes the cross-autocorrelations in institutional trades by both type of institution and type of security. In particular, it studies the relationship between institutional trading behavior and individual stock characteristics such as return volatility, past returns, market capitalization, etc. The essay further
investigates the relationship between institutional trading behavior and overall investment performance. The analysis sheds additional light on a series of theoretical findings about herding and strategic trading in capital markets.

Why follow the herd? There are a variety of reasons for institutional investors to imitate one another's trading decisions. For one, they may believe that some institutions have better investment information (see Banerjee (1992), Bikhandani, Hirshleifer, and Welch (1992), Avery and Zemsky (1998)). Another reason is reputation – when managers are uncertain about how others assess their ability they might have a tendency to conform their decisions with their peers (the idea stems from Keynes (1936) and was formalized by Scharfstein and Stein (1990)). Relative compensation structures could also induce herding behavior according to Maug and Naik (1996). In their framework, deviations from the benchmark could be very costly and as a result, managers could ignore their own superior information and “go with the flow”.

Why oppose the herd? Institutions could be contrarian because they believe that some groups of investors are consistently wrong and doing the opposite would be a profitable strategy. An additional reason could be strategic trading against positive-feedback traders (see De Long, Shleifer, Summers, and Waldman (1990)). Contrarian behavior also emerges in all cases of stock market manipulation by “large” traders (Jarrow (1992)).

The intertemporal analysis of institutional investors' trades reveals that institutions are more likely to increase (decrease) their holdings in a stock after periods of significant institutional net buys (sells). During quarters of “intense” institutional buys (sells), institutions
with constant (non-zero) positions in a stock are further more likely to join the herd and buy (sell) the stock over the subsequent quarter. Institutions are also more likely to open a position in a stock after periods of increased institutional buys. They tend to herd on both the buy- and the sell-side and the effect is more pronounced for institutional buys. Institutional types differ in their tendency to imitate – banks, insurance companies, and investment advisors are more likely to act in conformity with their peers, corporate and state pension funds are not significantly influenced by previous institutional trades, while mutual funds exhibit contrarian behavior.

I detect substantial variation in the tendency of institutional investors to herd across different classes of stocks. Institutions pay more attention to their peers' trades in stocks experiencing significant price decreases. Stocks with more intense institutional herding are also associated with substantially higher volatility. I do not find evidence, though, that institutional herding behavior increases stock volatility. Further, institutions are more likely to herd in small, value stocks.

The analysis on institutional level reveals that individual institutions with the highest tendency to follow aggregate institutional trades significantly underperform all remaining institutions and particularly the group of contrarian institutions, who trade against the trend in aggregate institutional trades. Further, individual institutions leading aggregate institutional trades realize significant abnormal performance. Surprisingly, all institutions trading in an opposite direction to future aggregate institutional trades perform equally
well. One possible explanation is that these managers possess better long-lived investment information and they gradually reverse their position as their information is being revealed to all other institutions.

These results allow me to look into the motives underlying institutional trading decisions. The tendency of institutional investors to follow their peers' trades in small, volatile stocks suggests that institutional imitative behavior is largely driven by a search of investment information, which is more scarce for those securities. However, the fact that all herding institutions underperform their peers questions the rationality of this type of behavior. It also suggests that the explanation of institutional imitative behavior lies beyond the reputation-based herding theories. For example, compensation structures could significantly affect institutional trading decisions. I demonstrate that each quarter, institutions exhibit a strong tendency to converge toward market weights. This "benchmarking effect" is probably related to the fact that portfolio managers' performance is frequently evaluated relative to market indices.

I further find that institutional trades are not sensitive to return momentum. It seems that institutions consider momentum only in the case of new buys. This result is consistent with a recent finding by Badrinath and Wahal (1998). Related to this research are also the papers by Nofsinger and Sias (1999) and Cai, Kaul, and Zheng (2000) who study the relation between institutional trading and stock returns. These studies find that institutional trades are strongly associated with past, contemporaneous, and future stock returns. Consistent
with these results, I also find that institutional demands are positively related to past stock returns – positive-feedback trading. However, this paper presents evidence that prices are not the only channel for communication of information between investors.

There are several possible channels through which information could circulate among institutional investors. One such channel is disclosure — investors disclose their holdings on a quarterly basis and corporations also disclose information about their largest shareholders. Another possible channel is information leakage during the order execution process. An additional information source could be informal communications between managers. For example, Coval and Moskowitz (2001) argue that this might be the main factor explaining the fact that mutual funds generate higher returns in firms which are geographically close to the fund. Finally, the investment management industry is characterized with high levels

\[14\]

A quick search on the Internet generates plenty of announcements about portfolio holdings of major institutional investors. One example is: “According to the most recent Fidelity Fund Guide and the firm’s Web site, manager John Muresianu had eliminated Fidelity’s entire technology stake as of June 30, 2000.” — Christopher Traulsen, Morningstar.com, July 28, 2000. An additional example is: “Mutual funds manager Janus Capital is poised to dump 15 million shares of health data exchange site WebMD that are worth about $191 million. In a filing with the SEC, WebMD disclosed that Janus has decided to sell all of the stock it purchased early this year.” — Dick Kelsey, BizReport.com, October 6, 2000. An example for institutional buy-transactions is: “On the eve of its own IPO, Goldman Sachs, the venerable New York-based investment bank, has made an unusual investment. It bought a 22 percent stake in Wit Capital Group, an online broker and investment bank.” — Stephanie Gates, RedHerring.com, March 31, 1999. Not surprisingly, most of the information is from the end of the quarter and the usual reporting lag is 5-6 weeks.
of migration of managers, analysts, and research staff among various institutions which could naturally communicate information about institutional portfolio compositions, stock preferences, and investment styles.

Lakonishok, Shleifer, and Vishny (1992b) (LSV) define and measure herding as the average tendency of a group of managers to trade a stock in the same direction at the same time. The analysis of herding and contrarian behavior of a group of investors substantially depends on how fast information flows among investors. Part of the investment information could be transmitted immediately through brokers and exchanges and in all these cases the LSV approach would be suitable in separating spurious from non-spurious herding. Another part of the information could be diffused with a delay of weeks and even months. In addition, because of liquidity considerations institutions might have the incentive to spread their large trades over extended time periods. Bikhandani and Sharma (2000) argue that it is very unlikely that investors observe each other's stock holdings immediately and for an investor to imitate or oppose the behavior of others, he must be aware of their actions. In all these cases, this study offers a more suitable alternative approach to the topic, analyzing sequential instead of contemporaneous institutional trades.

The chapter proceeds as follows. Section 3.2 reviews the theoretical and empirical literature. Section 3.3 discusses the data. Sections 3.4 analyzes institutional trades on stock level. Section 3.5 investigates the relation between institutional trading behavior and investment performance. Section 3.6 discusses the relation between institutional trades and the market portfolio. Section 3.7 concludes.
3.2 Literature Review

Here I discuss in brief the theoretical and empirical work on investors’ herding and trading behavior. Bikhandani and Sharma (2000) provide an excellent up-to-date review of the literature on herding in financial markets.

3.2.1 Theoretical Issues

The finance literature has distinguished between three major types of herding behavior. The first type, information-based herding, was introduced by Banerjee (1992), Bikhandani, Hirshleifer, and Welch (1992), and Welch (1992). It is based on the idea that individuals' actions reveal information about their private information and as a result, later decision-makers could rationally ignore their own signals and follow the actions of earlier decision-makers. Because these theories are built on strong assumptions they can not be applied directly to the stock market where the investment decisions of early individuals are incorporated in prices. Avery and Zemsky (AZ) (1998) extend the behavioral results on information-based herding to a model of the stock market. They establish, in a setting with competitive market-makers, that when there is uncertainty only about the value of the underlying security, the stock-market prices are informationally efficient and herd behavior will not occur. However, when there is uncertainty about shocks in the asset value (event uncertainty) and additional uncertainty about the proportion of informed and uninformed investors in the market, herd behavior may arise and trigger significant mispricings of the security.
The second type of herding behavior, reputation-based herding, was introduced by Scharfstein and Stein (1990). They follow John Maynard Keynes (1936, pp.158) who argues that professional managers concerned about how others will assess their ability would tend to follow the decisions of their peers, or in Keynes' words, "Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally". According to Scharfstein and Stein, when both investment managers and investors are uncertain about managers' stock-picking ability, the managers who move first follow their own signals; the managers who move subsequently, ignore their own information and imitate the actions of the first managers. However, in their model security prices are held constant throughout the game and in a more realistic model with dynamic prices, the herding effect could be substantially mitigated.

Compensation-based herding is a third type of imitative behavior. Maug and Naik (1996), consider a risk-averse portfolio manager whose compensation increases with her/his own performance and decreases with the performance of another investor (the benchmark). They show that this compensation structure provides an additional reason to imitate the benchmark. Zwiebel (1995) shows that when the market has limited information about managerial ability and infers managerial ability based on relative performance, managers who undertake the industry standards are consequently evaluated with a more accurate benchmark than those innovating. In this economy the very high- and very low-ability managers are more likely to undertake innovative investments than those of average ability.
Many trading decisions are based on the idea of contrary opinion. For example, a popular “odd-lots trading strategy” assumes that small investors are always wrong because they react emotionally to the market and are usually guilty of bad timing. In a rising market, an increased odd lot buying is considered an indication of a technical weakness in the market and a signal to sell. Conversely, in a declining market, a lot of odd lot selling is seen as an indication of technical strength and a signal to buy. Two recent studies by Odean (1999) and Barber and Odean (2000) demonstrate that individual investors indeed tend to close their “winning” positions too soon and to keep their “losing” positions open for too long. Contrarian investment decisions could also be a result of strategic trading. De Long, Shleifer, Summers, and Waldman (1990) demonstrate that rational speculators could trade against irrational positive feedback traders, profit from it, and destabilize security prices. Jarrow (1992) further investigates market manipulation trading strategies (these are strategies which affect security prices and generate positive real wealth with no risk) by large traders in security markets and demonstrates the existence of such strategies under reasonable assumptions.

It is difficult to distinguish among the predictions of the above trading theories\(^\text{15}\) because the data usually does not reveal information about the motives underlying institutional

\(^{15}\)The chances of testing the compensation-based herding hypothesis might be higher since information about the compensation structure of portfolio managers could be obtained (see Bikhandani and Sharma (2000)).
trades. In addition, cross-autocorrelated trading patterns of institutional investors could emerge because some managers consistently receive information before others (Hirshleifer, Subrahmanyam, and Titman (1994)) which is difficult to measure.

3.2.2 Empirical Findings

The major contribution in the measurement of herding is by LSV. They define and measure herding as the average tendency of a group of managers to trade a stock in the same direction at the same time. More precisely, their measure for herding in stock \( i \) over quarter \( t \) is defined as follows:

\[
H(i, t) = \left| p(i, t) - p(t) \right| - E[\left| p(i, t) - p(t) \right|]
\]

where \( p(i, t) = \frac{B(i, t)}{B(i, t) + S(i, t)} \) is the ratio of the number of investors who buy the stock over quarter \( t \) and the number of investors who trade in the stock over the same quarter. \( p(t) \) is the average of \( p(i, t) \) across all stocks \( i \) that were traded by at least one of the fund managers in the group. The second term is an adjustment factor and the expectation is calculated under the null hypothesis that \( B(i, t) \) follows a binomial distribution with parameter \( p(t) \).

In this contemporaneous approach, the overall evidence on herding is mixed. LSV (1992b) use data of a sample of U.S. tax-exempt equity pension plans fund and conclude that money managers in their sample do not exhibit significant herding. Herding seems to be more pronounced among small stocks. They explain it with less public information about small public companies. Grinblatt, Titman, and Wermers (GTW) (1995) use data on port-

62
folio weights of 274 mutual funds between 1974 and 1984 to examine herd behavior. Using the LSV measure they find very little evidence of herding among mutual fund managers. They further establish that herding is related to momentum trading and that funds exhibit greater tendency in buying past winners than in selling past losers. Surprisingly, when they disaggregate the data according to funds' investment objective, they find even weaker evidence of herding behavior. GTW also develop a measure of herding by individual fund in order to assess to what extent a particular fund has the tendency to invest in conformity with the group. They establish that herding funds perform better but the effect is mostly driven by their tendency to engage in momentum trading. Wermers (1999), using the LSV measure and data on quarterly equity holdings of all mutual funds between 1975 and 1994, finds some evidence of herding among mutual funds. He further finds that growth-oriented funds exhibit stronger tendency to herd than income-oriented funds. Herding is also stronger for small growth stocks. Further, herds form more often on the sell side than on the buy side, and herding does not appear to be related to individual funds' flows and redemptions.

How accurate is the LSV herding measure? As discussed by Bikhandani and Sharma (2000), this measure has a limited power in assessing herding behavior since correlated trading patterns do not always imply herding – it is possible that a group of investors make similar investment decisions because they share the same information sets. They further argue that since information about investors' holdings gets transmitted with considerable
lag, intentional herding can not arise over short periods because “what cannot be observed cannot be imitated”. Wylie (2000) discusses additional biases of this herding measure related to short-sale constrains and institutional clienteles.

Related to this research are also the studies about the trading behavior of individual investors by Odean (1998) and Barber and Odean (2000). The authors document the tendency of individual investors to hold losing investments too long and sell winning investments too soon, by analyzing trading records for 10,000 accounts at a large discount brokerage house. Further, the trading behavior of individual investors does not appear to be motivated by a desire to rebalance portfolios, or to avoid the higher trading costs of low price stocks. Nor is it justified by subsequent portfolio performance. This dissertation essay demonstrates that the trading patterns of institutional investors are substantially different than those of individual investors. In addition, it shows that institutional investors form a very heterogeneous group – institutional trading behavior varies significantly across institutional types.

3.3 Data

The data sources of this dissertation essay are also the Spectrum Database, the CRSP monthly tapes, and the COMPUSTAT annual files. As in the previous chapter, I utilize the classification of institutions by Spectrum officials into the following five groups: banks (Bnk), insurance companies (Ins), investment companies (Mut), independent investment advisors (Indv), and other institutions (Oth.). Unlike in the previous chapter, here I do not separate from the group of other institutions corporate and state pension funds, since this group
includes relatively small number of institutions, 95 by the end of the period. One advantage of the data for this type of analysis is that institutional trades over previous quarters are public information. More detailed description of the data is presented in Chapter 2.

Figure 1 further presents the average institutional ownership in a stock and the distribution of institutional ownership across banks, insurance companies, mutual funds, investment advisors, and corporate and state pension funds. By the beginning of the period, institutions in our sample held 38% and by the end of the period, they held 53% of the stock market. The largest institutional share by the beginning of the period was held by banks and investment advisors, while by the end of the period by investment advisors and mutual funds.

3.4 Analysis on Stock Level

This section analyzes the subsequent trades of institutional investors on the level of individual stocks. Let us consider a particular stock and a group of investors periodically disclosing information about their holdings in the stock. Denote with \( B_{i,t} \) the increase (buys) and with \( S_{i,t} \) the decrease (sells) of aggregate institutional ownership in stock \( i \) over period \( t \) as a percentage of the total number of shares outstanding. Looking one period backwards, I can decompose \( B_{i,t} \) into

\[
B_{i,t} = NB_{i,t} + CB_{i,t} + SB_{i,t} + BB_{i,t},
\]

where \( NB_{i,t} \) indicates “new buys” of institutions which did not hold the stock over the previous period \( t - 1 \); \( CB_{i,t} \) indicates the percent of “induced buys” of institutions which
had a position in the stock over period \( t - 1 \) but did not trade it; \( SB_{i,t} \) indicates the percent of "reversed buys" of institutions which were net sellers of the stock over the previous period; and \( BB_{i,t} \) indicates the percent of buys by institutions which were net buyers of the stock over the previous period. In a similar way, I decompose \( S_{i,t} \) into

\[
S_{i,t} = CS_{i,t} + SS_{i,t} + BS_{i,t},
\]

where \( CS_{i,t} \) indicates the percent of "induced sells" of institutions with constant holding of the stock over period \( t - 1 \); \( SS_{i,t} \) indicates the percent of sells of institutions which were also net sellers of the stock over the previous period; and \( BS_{i,t} \) indicates the percent of "reversed sells" of institutions which were net buyers of the stock over the previous period.

Note that the decomposition of sells has only three terms because the data does not cover short positions. This is not very restrictive since most of the institutions in the sample are not allowed to short-sell securities.

Throughout this section, I concentrate on the following variables:

- \( BMS_{i,t} = B_{i,t} - S_{i,t} \), aggregate net buys in stock \( i \) over period \( t \) as a percentage of the total number of shares outstanding.

- \( IBMS_{i,t} = CB_{i,t} - CS_{i,t} \), induced net buys in stock \( i \) over period \( t \), defined as the percentage of net buys over period \( t \) of all institutions with constant nonzero holdings in the stock over period \( t - 1 \).

- \( NB_{i,t} \), new buys of stock \( i \) over period \( t \).
Induced net buys account for the trades of all managers who were aware of the stock over the previous quarter but did not interpret their information as a buy or sell signal. The inclusion of this variable in the analysis could provide additional information about institutional tendencies to imitate their trades. All institutional holdings in a stock are further normalized with the total number of shares outstanding. I choose to work with percentage holdings instead of absolute holdings in order to control for stock splits and reverse splits, which would otherwise introduce additional noise in the results. Some previous studies concentrate on the number of managers trading a security ignoring the size of individual trades. Here, I account for the trade size because I believe that it contains more information about the confidence of portfolio managers in their private signals than the direction of the trade only.

Throughout this section, I investigate how each one of the three components of institutional trades, $BMS_{t,t}$, $IBMS_{t,t}$, and $NB_{t,t}$, correlates with aggregate institutional trades over previous periods. These variables represent a cross-sectional time-series panel and they could be analyzed in a variety of ways. The most important parameter in the analysis is the sensitivity of institutional subsequent trades to the explanatory variables. I believe that this sensitivity is firm-specific, and identifying the characteristics of the firms with more intense herding behavior is one of the major objectives in this study. Gompers and Metrick (2000) demonstrate that institutional investors are biased toward large, value, low-momentum stocks. As a result, if I restrict some parameters in the model to be the same
across firms, this would impose systematic biases in the estimation of the trade-sensitivity parameters. In order to prevent similar misspecifications I estimate all regressions by stock and analyze the cross-sectional distribution of the estimates.

Prices can communicate information to investors and changes in institutional portfolios could be related to past prices. In order to separate this effect in the analysis, I introduce two stock performance measures. The first one, $R_{i,t}$, is the cumulative return of stock $i$ over quarter $t$. The sensitivity of portfolio changes to past individual stock returns present evidence for the importance of positive- and negative-feedback trading in institutional decision-making. The second measure, $M_{i,t}$, is a relative performance measure for stock $i$ over quarter $t$. It is a qualitative variable taking value of 1 if the stock belongs to the top performing decile among all stocks over the quarter (winner), taking value of -1 if the stock belongs to the bottom performing decile (loser), and taking value of 0 otherwise. The sensitivity of institutional portfolio changes to this relative strength performance measure indicates to what extend the trades of the corresponding institutional groups in a particular stock are motivated by momentum strategies.

Changes of aggregate institutional ownership in a stock are also related to the total level of institutional ownership by the beginning of the period. On the one hand, if institutional ownership is close to 100%, it is more likely that we observe subsequent decreases in institutional ownership than subsequent increases. On the other hand, if there is no institutional ownership in the stock at beginning of the period, the expected changes in institutional ownership are always positive. In general, there exists a nonlinear relationship between cur-
rent level of institutional ownership in a stock and future institutional ownership changes: the probability for positive change in institutional ownership first increases with the current level of institutional ownership and then decreases - reaching zero in the case of 100% ownership. In order to account for this effect, I introduce the fraction of total institutional ownership at the beginning of quarter $t$, $TOTI_{t,t}$, and its squared term, $TOTI_{t,t}^2$, as control variables in all regression equations.

### 3.4.1 Summary Statistics

This subsection studies the distributional and dynamic properties of the components of institutional trades introduced in the previous section. Table 13 presents summary statistics of quarter-end total institutional ownership in a stock (TOT), quarterly changes of total institutional ownership in a stock - net buys (BMS), quarterly changes of the ownership of all institutions with constant holding in the stock over the previous quarter - induced net buys (IBMS), and the aggregate buys of all institutions which did not hold the stock before - new buys (NB). All institutional trades are normalized with the total number of shares outstanding. In addition to aggregate institutional trades, the table summarizes also the trades of the following institutional types: trust departments of banks, insurance companies, mutual funds, investment advisors, and all remaining institutions.

The average institutional ownership in a stock is 31.09%. The fact that institutions own approximately 38% of the stock market by the beginning of the period and 53% by the end of the period (Figure 1) suggests that institutional investors are significantly biased toward
large stocks. Institutions are net buyers in the average stock – the estimated quarterly change in institutional ownership in a stock is 0.076% and is significantly positive. Institutional net buys are positive across all five institutional types and they achieve the highest magnitude for mutual funds and investment advisors – the fastest growing segments in the market. Induced net buys carry a negative sign across all institutional types which indicates that institutions with constant holdings in a stock over a particular quarter are more likely to decrease their holdings in the stock over the next quarter. The average percentage of new buys is 0.194 and investment advisors account for 0.125% of aggregate new buys. This is closely related to the fact that investment advisors exhibit the highest turnover rate across all institutional types.

Table 14 presents correlations and cross-autocorrelations of quarterly stock returns (RET) and the following components of aggregate institutional trades: changes of total institutional ownership in a stock - net buys (BMS), quarterly changes of the ownership of all institutions with constant holding in the stock over the previous quarter - induced net buys (IBMS), and the aggregate buys of all institutions which did not hold the stock over the previous quarter - new buys (NB). Aggregate institutional net buys and new buys are highly correlated with contemporaneous stock returns (correlation coefficients of 0.15 and 0.16, respectively). All variables are significantly autocorrelated and the magnitude of their autocorrelations is decreasing with the number of lags. In addition, all components of institutional trades are positively correlated with past aggregate institutional trades.
Table 15 presents correlations and cross-autocorrelations of quarterly stock returns (RET), net buys (BMS), induced net buys (IBMS), and new buys (NB) for all five institutional types. The highest level of autocorrelation of aggregate institutional buys is achieved by the group of mutual funds. The highest level of correlation between current new buys and past aggregate net buys is for mutual funds and investment advisors. Mutual funds and investment advisors exhibit also the highest correlations of aggregate institutional trades and individual stock returns. This result is consistent with the recent paper by Cai, Kaul, and Zheng (2000) about institutional trading and stock returns.

3.4.2 Aggregate Institutional Analysis

First, I estimate for each stock \( i \) present for at least 24 quarters over the sample period the following model:

\[
BMS_{i,t+1} = a_i + h_i BMS_{i,t} + \delta_{i,1} TOTI_{i,t} + \delta_{i,2} TOTI^2_{i,t} + \gamma_{i,1} R_{i,t} + \gamma_{i,2} M_{i,t} + \epsilon_{i,t},
\]  

(19)

where \( TOTI_{i,t} \) is the percentage of institutional ownership in the stock at the end of period \( t \), \( TOTI^2_{i,t} \) is \( TOTI_{i,t} \) squared, \( R_{i,t} \) is the return of the stock over period \( t \), and \( M_{i,t} \) is a dummy variable equal to 1 if \( R_{i,t} \) is within the top decile across all stocks, -1 if \( R_{i,t} \) is within the bottom decile, and 0 otherwise.

Equation (19) measures the sensitivity of the buy-sell institutional imbalance to aggregate buy-sell imbalance over the previous period. If the corresponding group of investors has the tendency to follow aggregate institutional trades, the coefficient \( h_i \) in the above regression will be significantly positive; if the group of institutional investors has the tendency
to be contrarian, the coefficient $a_i$ will be on average negative. At this level of the analysis, I do not disaggregate the total level of institutional ownership. Since it is possible that some groups of institutions exhibit a stronger tendency to imitate or to influence the market, I present a more disaggregated analysis in the next subsection. The coefficient $a_i$ captures systematic differences of new buy- and sell-orders unrelated to herding and positive- (negative-) feedback trading. I expect for all securities with increasing institutional ownership, such as large value stocks, the coefficient $a_i$ to be positive. The coefficients $\delta_{i,1}$ and $\delta_{i,2}$ separate the impact of current levels of institutional ownership on future institutional ownership changes. As discussed in the previous section, I expect the sign of the coefficient $\delta_{i,2}$ to be negative indicating that the probability for positive change in institutional ownership first increases with the current level of institutional ownership and then decreases. Finally, the coefficients $\gamma_{i,1}$ and $\gamma_{i,2}$ assess to what extend the institutions engage in positive-feedback and momentum trading.

Panel A of Table 16 presents the distribution of the estimated coefficients from (19) and t-statistics of the estimated mean values. As expected, the intercept term is on average positive which indicates that, everything else held constant, institutions are net buyers in the average stock over the sample period. Also consistent with the predictions, the coefficient $\delta_{i,2}$ carries a negative sign. Institutional trades in the average stock are highly autocorrelated - both the mean and median $\tilde{h}_t$ are positive (t-statistic for the mean of 9.94). This indicates that large institutional trades in one direction are continued in the subsequent quarter. It is difficult to identify the mechanism transmitting information between institutional investors.
although part of the information in this process is communicated through stock prices – the coefficient $\gamma_{i,1}$ is significantly positive. On average, stock momentum is not a significant determinant of institutional trades, since $\gamma_{i,2}$ is not significantly different from zero.

Panel B of Table 16 presents the distribution of the estimated coefficients from

$$IBMS_{i,t+1} = a_i + h_i BMS_{i,t} + \delta_{i,1} TOTI_{i,t} + \delta_{i,2} TOTI^2_{i,t} + \gamma_{i,1} R_{i,t} + \gamma_{i,2} M_{i,t} + \epsilon_{i,t}, \quad (20)$$

where $IBMS_{i,t+1}$ (induced net buys) are defined as the percentage of net buys over period $t$ of all institutions with constant holdings in the stock over period $t - 1$. The sensitivity of induced net buys to aggregate net buys over the previous period is very high (t-statistic of 10.43) which presents stronger evidence for herding behavior of institutional investors. In other words, all institutions that were aware of the stock over period $t$ but did not interpret the information about the stock as a buy or sell signal, after observing the increased interest in the stock of all remaining institutions become more likely to act in conformity with the group. Induced net buys are also motivated by past stock price appreciation, positive feedback trading, ($\gamma_{i,1}$) and are not significantly affected by the relative performance of the stock, momentum trading, ($\gamma_{i,2}$).

Panel C of Table 16 estimates the following model

$$NB_{i,t+1} = a_i + h_i BMS_{i,t} + \delta_{i,1} TOTI_{i,t} + \delta_{i,2} TOTI^2_{i,t} + \gamma_{i,1} R_{i,t} + \gamma_{i,2} M_{i,t} + \epsilon_{i,t}, \quad (21)$$

where $NB_{i,t+1}$ (new buys) are the aggregate buys over period $t + 1$ of all institutions which did not hold the stock in their portfolios over period $t$. The sensitivity of new buys to aggregate net buys over the previous period is significantly positive (t-statistic of 5.78) which
presents evidence that institutional investors are more likely to open a new position in a stock after a significant increase in the total institutional ownership of the stock. Interestingly, new buys are the only institutional trades significantly affected by stock momentum - $\gamma_{1,2}$. This result is consistent with Badrinath and Wahal (1998) who establish that financial institutions are not momentum traders and they consider momentum only in the case of new buys.

In order to assess whether the herding effects discussed so far are long-lived, I run a multiperiod specification of the regressions from (19)

$$BMS_{i,t+1} = a_t + h_{i,1} BMS_{i,t} + h_{i,2} BMS_{i,t-1} + h_{i,3} BMS_{i,t-2} + \delta_{i,1} TOTI_{i,t} + \delta_{i,2} TOTI_{i,t}^2 + \gamma_{i,1} R_{i,t} + \gamma_{i,2} M_{i,t} + \epsilon_{i,t}.$$  

The equations from (20) – (21) are generalized in the same way. Table 17 presents averages of the estimated coefficients and their t-statistics. I observe that the one-lag patterns in institutional trades remain. Interestingly, institutions react as contrarians to institutional trades from two quarters back. Institutional trades beyond 6 months in the past contain no information about institutional trading decisions.

Next, I decompose institutional trades into aggregate buys and sells and estimate the model:

$$BMS_{i,t+1} = a_t + h_t BMS_{i,t} I_{\{BMS_{i,t}>0\}} + h_t BMS_{i,t} I_{\{BMS_{i,t}<0\}} + \delta_{i,1} TOTI_{i,t} + \delta_{i,2} TOTI_{i,t}^2 + \gamma_{i,1} R_{i,t} + \gamma_{i,2} M_{i,t} + \epsilon_{i,t},$$

where $I_{\{BMS_{i,t}>0\}}$ is an indicator variable equal to one whenever $BMS_{i,t} > 0$ and equal to
zero otherwise and \( I_{(BMS_{i,t} < 0)} \) is an indicator variable equal to one whenever \( BMS_{i,t} < 0 \) and equal to zero otherwise. All remaining variables are defined similarly to the variables in equation (19).

Panel A, of Table 18 presents averages of the estimated coefficients and their t-statistics and Panels B and C regress induced net buys (IBMS) and new buys (NB) on the same set of independent variables. Table 18 indicates that institutions as a group tend to herd on both the buy- and sell-side. Undecided institutional investors are more likely to join the herd after significant buys. Surprisingly, they are more likely to be contrarian after periods of significant sells.

3.4.3 Analysis by Institutional Type

It is possible that some institutions systematically lead and some institutions systematically follow the group. In order to investigate for such differences across institutional types, I disaggregate institutional trades into the types of banks (Bnk.), insurance companies (Ins.), mutual funds (Mut.), investment advisors (Iadv.), and other institutions (Othr.) described in Section 3. All these institutions differ in their organizational structure and they might exhibit different incentives to follow or oppose the trend in aggregate institutional trades. In order to assess this effect, I define the variables \( BMS^J, IBMS^J \), and \( NB^J \) based on the trades of all institutional investors of type \( J \), where \( J \) corresponds to each of the above institutional types. In addition, I also construct the variable \( BMS^{Tot/J} \) as the aggregate net buys of all institutions which are not of type \( J \).
Panel A of Table 19 presents averages of the estimated coefficients $h_t^J$ and $h_t^{TOL/J}$ from the following regression

$$BMS_{i,t+1}^J = a_t^J + h_t^J BMS_{i,t}^J + h_t^{TOL/J} BMS_{i,t}^{TOL/J}$$

$$+ \delta_{i,1}^J TOTI_{i,t}^J + \delta_{i,2}^J TOTI_{i,t}^{TOL} + \gamma_{i,1}^J R_{i,t} + \gamma_{i,2}^J M_{i,t} + \epsilon_{i,t},$$

where $J$ corresponds to each one of the basic institutional type. Banks and investment advisors exhibit the strongest tendency to follow the aggregate trend in the trades of their own type. The net buys of insurance companies are most strongly influenced by the previous trades of all other institutional types. Interestingly, mutual funds have the tendency to bet against the trend in the trades of all remaining institutions. This demonstrates that mutual funds are possibly more sophisticated investors.

In Panel B, the dependent variable is induced net buys, $IBMS^J$. Banks exhibit the strongest tendency to follow their own type. This is probably related to the strong tendency of banks to index their portfolios. In panel C, the dependent variable is new buys, $NB^J$. In the case of new buys, banks, insurance companies, and investment advisors are most strongly influenced by the trading decisions of all other institutional types. Again, mutual funds are contrarian and they are most likely to open new position in a stock after periods of substantial sells of all remaining institutions. In all cases, the trading decisions of corporate and state pension funds are not significantly influenced by past institutional trades.
Table 20 investigates to what extend the trades of the various institutional types influence the market. In Panel A, I estimate the following model

\[ BMS_{it,t+1} = a_t + h_t BMS_{it,t} + \delta_{i,1} TOT_{it,t} + \delta_{i,2} TOTI_{it,t}^2 + \gamma_{i,1} R_{it,t} + \gamma_{i,2} M_{it,t} + \epsilon_{it,t}, \]  

(22)

and present averages of the estimated coefficients \( h_t \) and their t-statistics. \( J \) corresponds to each one of the institutional types. In Panels B and C, the dependent variables are \( IBMS \) and \( NB \) respectively. Table 20 reveals that the only institutional type significantly influencing the market is the group of independent investment advisors.

3.4.4 Institutional Trading Behavior and Stock Characteristics

Institutional trading behavior varies across stocks. One factor affecting the tendency of institutional investors to herd could be the overall informational environment of the stock, its volatility, size, etc.. Researchers have also argued that the trading behavior of large investors could significantly affect the properties of security prices and particularly stock volatility.\(^{16}\) In this subsection, I analyze the relation between institutional trades and stock characteristics.

In order to assess the determinants of herding behavior, I propose the following Fama-MacBeth two-step procedure. First, I estimate the following regression

\[ BMS_{it,t+1} = a_t + h_t BMS_{it,t} + \delta_{i,1} TOT_{it,t} + \delta_{i,2} TOTI_{it,t}^2 + \gamma_{i,1} R_{it,t} + \gamma_{i,2} M_{it,t} + \epsilon_{it,t}, \]

\(^{16}\)Sias and Starks (1997) show that autocorrelations in individual stock returns are related to institutional trades.
for all stocks over the first five years of the sample period (1982-1986). Afterwards, I regress the estimated trade-sensitivity coefficients $\hat{h}_i$ (one for each stock) on stock characteristics:

$$\hat{h}_i = a + \beta_1 \hat{\sigma}_i + \beta_2 R E T_i + \beta_3 S Z_i + \beta_4 B M_i + \epsilon_i,$$

where $\hat{\sigma}_i$ is the estimated standard deviation of monthly stock returns over the period, $R E T_i$ is the average stock cumulative return, $S Z_i$ is the market capitalization of firm's equity (in billions) at the end of the period, and $B M_i$ is the book-to-market ratio of the stock at the end of the period. The same two-step procedure is estimated subsequently rolling forward the estimation window by a quarter. Time-series averages of the estimated coefficients and their $t$-statistics are presented in Panel A of Table 21. Panels B and C report similar estimates for the determinants of induced net buys and new buys.

I observe that stock-periods of more intense herding by institutional investors ($\hat{h}_i$) are associated with higher stock return volatility. One possible explanation is that, when investing in more volatile stocks institutions might have greater tendency to conform their investment decisions with those of their peers because of the higher uncertainty of their investment. This behavior is consistent with the predictions of information-based herding theories. Induced net buys and new buys are also more sensitive to previous trading decisions for stocks with higher volatility. Institutions are also more likely to follow the trend in aggregate trades in stocks which have experienced significant price decrease — it seems that herding is more pronounced in bad than in good times. Part of this effect could result from the fact that institutions do not interpret macro-economic information simultaneously and they increase and decrease their exposure to the market over extended time periods.
Another possible explanation could be that negative firm-specific information diffuses gradually across the investing public as a result of short-selling constraints (Hong and Stein (2000), Hong, Lim, and Stein (2000)).

The relations between herding and stock size, and herding and book-to-market ratios are not pronounced. Since both characteristics change substantially over time, it is possible that their average values are not very informative. In order to design a more powerful test of these effects, I construct dynamic portfolios on both characteristics. First, all stocks are sorted into five portfolios according to their market capitalization. Afterwards, for each portfolio the value-weighted change in the fraction of total institutional ownership over quarter $t$, $BMS_{i,t}$, is regressed on the change over the previous quarter.

$$BMS_{t+1} = a + h BMS_t + \delta_1 TOTI_t + \delta_2 TOTI_t^2 + \gamma_1 R_t + \gamma_2 M_t + \epsilon_{i,t},$$

where $TOTI_t$ is the value-weighted percentage of institutional ownership in the stocks at the end of period $t$, $TOTI_t^2$ is the average of $TOTI_t$ squared, $R_t$ is the value-weighted average of $R_{i,t}$ – the returns of the stocks in the portfolio over period $t$, and $M_t$ is the average of $M_{i,t}$ – a dummy variable equal to 1 if $R_{i,t}$ is within the top decile across all stocks, -1 if $R_{i,t}$ is within the bottom decile, and 0 otherwise. Estimates of the trade-sensitivity coefficients, $h$, are presented in Panel A of Table 22. Panels B and C, present the sensitivity of induced net buys and new buys. Table 23 presents similar estimates for portfolios stratified according to stock book-to-market ratios.

Table 22 reveals that institutions are more likely to follow aggregate institutional trades for small stocks and the effect is particularly strong in the case of new buys. LSV establish
for a sample of pension funds that the managers in their sample are more likely to trade in the same direction in small stocks and justify their finding with the fact that limited public information is available for such companies. The paper by Hong and Stein (2000) and Hong, Lim, and Stein (2000) is also related to this result. The authors argue that small stocks exhibit less public information (e.g., lower analyst coverage) and as a result for such stocks information is incorporated gradually into prices. Hong, Lim, and Stein show that momentum strategies work better among small stocks. My results suggest that these effects are strongly related to institutional trades.

Table 23 studies the relation between institutional trades and stock book-to-market ratios. It seems that institutions are more likely to influence their trades for stocks with medium book-to-market ratios (Panel A). Interestingly, in the case of new buys the relation between book-to-market ratios and herding is monotonically increasing but of marginal significance. This could result from the fact that value stocks are more popular among institutions investors (Gompers and Metrick (2001)).

In order to further explore the relation between institutional trades and stock volatility, I construct portfolios according to quarterly changes in their volatility. First, for each stock-quarter stock volatility is estimated based on the stock daily returns. Afterwards, all stocks are sorted into five portfolios according to the changes in their quarterly volatility. Then, for each portfolio, the value-weighted change in the fraction of total institutional ownership, induced buys, and new buys over the same quarter are regressed on the same set of dependent variables as in Tables 22 and 23 and the estimates are presented in Table
24. The data does not reveal any systematic relation between the auto-correlated trading patterns of institutional investors and shocks in stock volatility. It seems that although institutions are more likely to imitate their trades in more volatile stocks, this does not increase the variability of the stocks they trade in.

3.5 Analysis on Institutional Level

The objective of this section is to investigate the relationship between institutional trading behavior and investment performance. This analysis is interesting for a variety of reasons. For one, it could provide additional information about the motives underlying institutional tendencies to imitate other institutions' investment decisions. In particular, it could help distinguishing between reputation-based and non-reputation-based herding theories—if herding institutions significantly underperform their peers, very likely the explanation of their behavior lies beyond the reputation-based theories. Another motivation for this analysis is that it could provide additional information about the trading patterns of institutional investors.

In order to answer these questions, I estimate for each institution-quarter the sensitivity of its trades to aggregate institutional trades over the previous quarter. More precisely, for each institution \( j \), the change in the fraction of institutional ownership in a stock over quarter \( t + 1 \), \( \text{BMS}_{i,t+1} \), is regressed on the change of aggregate institutional ownership in the stock over the previous quarter, \( \text{BMS}_{i,t-1} \)

\[
\text{BMS}_{i,t} = \alpha^j + h^j \text{BMS}_{i,t-1} + m^j R_{i,t-1} + \epsilon_{i,t-1}, \tag{23}
\]
where \( R_{t,t-1} \) is the return of the stock over period \( t-1 \). Afterwards, all institutions are sorted into five quintile portfolios according to their estimated herding measure \( \tilde{h}^q \) over the previous quarter. Constructed are also five portfolios for banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (Iadv.), and all remaining institutions (Othr.).

The performance of each of the above quintile-portfolios is evaluated with the Characteristic Selectivity (CS) measure introduced by Daniel, Grinblatt, Titman, and Wermers (1997). At the end of each quarter, all stocks are placed into 125 portfolios. The composition of each portfolio is based on a triple-sort on each firm's market value of equity (size), book-to-market ratio, and momentum (past 12 month return lagged one month). The book value of equity is as of the end of the firm's fiscal year and the market value of equity is as of December prior to the formation date. The sorting procedure is completed at the end of June of each year in the following way: first, all firms are sorted into size quintiles, then all firms within each size quintile are sorted into quintiles based on their book-to-market ratios, and finally, all stocks within each of the resulting 25 groups are sorted into quintiles based on their momentum. The returns of each of the resulting 125 benchmark portfolios, \( \bar{R}_{t,t-1}^{Bt} \), are calculated by value-weighting the stocks in the portfolio. The excess return of each stock in the evaluated portfolio is then calculated by subtracting the passive portfolio's return from the stock's realized return. The value-weighted excess return is the quarter \( t \)
component of the performance measure:

\[ CS_t = \sum_{j=1}^{N} \omega_{j,t-1} \left( \tilde{R}_{j,t} - \tilde{R}_{t}^{b,j,t-1} \right), \] (24)

where \( \omega_{j,t-1} \) is the weight of stock \( j \) in the portfolio at time \( t - 1 \), \( \tilde{R}_{j,t} \) is the return realized by security \( j \), and \( \tilde{R}_{t}^{b,j,t-1} \) is the return realized by the corresponding benchmark portfolio.

The performance measure \( CS \) is defined as the time-series average of \( CS_t \).

Time-series averages of the measures for each quintile portfolio and their t-statistics are presented in Table 25. The last two rows present the difference between the performance measures in the fifth (highest) and the first (lowest) quintiles and their t-statistics. The table shows that institutions with the highest tendency to follow aggregate institutional trades do not realize significant abnormal performance. They significantly underperform the group of contrarian institutions, investing against the trend in aggregate institutional trades. The effect is particularly strong for mutual funds and independent investment advisors – the two most competitive sectors of the money management industry. I have also performed the analysis based on aggregate institutional trades of each institutional type and the results are qualitatively similar. This result implies that herding behavior among financial institutions is not consistent with the reputation-based theories. It is also unlikely that information-based herding behavior will lead to systematic underperformance of the herding institutions.

Next, I estimate for each institution-quarter the sensitivity of its trades to aggregate institutional trades over the following quarter. More precisely, for each institution \( j \), the change in the fraction of institutional ownership in a stock over quarter \( t \), \( BS_t^{j,i} \), is re-
gressed on the change of aggregate institutional ownership in the stock over the next quarter

\[ BMS_{i,t}^i = a^i + h^i BMS_{i,t+1} + \theta^i R_{i,t-1} + \epsilon_{i,t}. \]  

(25)

Afterwards, all institutions are sorted into five quintile portfolios according to their estimated leading measure \( h^i \). The performance of the quintile portfolios over the next quarter is estimated with the characteristic sensitivity measure, CS, and are presented in Table 26.

The leading institutions realize significant abnormal performance, probably because of short-lived informational advantage. Surprisingly, all institutions trading in opposite direction of future aggregate institutional trades perform equally well. One possible explanation of the result is that these institutions possess better long-lived investment information. They gradually increase (decrease) their positions as their information is being revealed to all other investors. The remaining institutions herd on the information over later periods and compete away their abnormal profits. If this hypothesis is correct, I would expect all institutions from the first quintile to realize superior investment performance over the previous quarter. Table 27 evaluates the performance of the same quintile portfolios prior to the formation quarter. I observe that the institutions within the first quintile realize significant abnormal performance in most cases.

3.6 Institutional Trades and The Market Portfolio

So far, I have analyzed the relation between current and past institutional trades but institutional imitative behavior could go beyond past trades. For example, Maug and Naik (1996) show that portfolio managers' compensation schemes provide a reason for them to
imitate benchmark portfolios. In this section, I explore the impact of current deviations of institutional portfolios from the market portfolio on institutional future trading decisions. I show that institutions exhibit strong tendency to target the market portfolio proxied by all stocks in the CRSP universe.

In a CAPM world investors hold the market portfolio. In reality, they could significantly deviate from the market portfolio but independently of their trading strategies, institutional investors might have the tendency to allocate their funds "close" to the market index. One reason is diversification. An additional reason is performance evaluation — the investment performance of most portfolio managers is evaluated relative to a stock index. Managers increase their holdings in stocks for which they have favorable information and decrease their holdings in stocks for which they have unfavorable information. Although private information will induce managers to deviate from the index, the structure of their compensation contracts will make large deviations very costly (Maug and Naik (1996)).

In order to explore these questions, for each institution-quarter I estimate the probabilities for an increase, $p^a$, and a decrease, $p^d$, of institutional holdings in a stock as the fraction of stocks in which the institution increases (decreases) its holdings over the total number of stocks in which it trades. The first two columns of Table 28 report averages of the estimated probabilities for buys and sells across all institution-quarters and across the institutional types of banks (Bnk.), insurance companies (Ins.), mutual funds (Mut.), Investment Advisors (Iadv.), and all remaining institutions (Othr.). In every trade, the average institution faces a 54% probability for buying a stock and a 46% probability for
selling a stock. The difference in the estimated probabilities is intuitive since institutions substantially increase their market share over the sample period (Figure 1), and as a result are net buyers. Similar pattern is observed for all major institutional types.

Next, I estimate the probabilities for buy (sell) conditional on the current level of institutional stock-ownership. Each quarter the stocks in every institutional portfolio are split into two groups depending on whether the institutional allocation in the stock is below or above the market weight of the stock at the beginning of the quarter. Afterwards, for both groups of stocks, the conditional probabilities for an increase, $p^{a}$, and decrease, $p^{d}$, of institutional holdings in the groups are estimated. Averages of the above probabilities across all institution-quarters and across the major institutional types are presented in Table 28.

The average institution faces substantially larger probability to increase its holding in a stock if its current holding is below the market weight, 77%, versus an unconditional probability of 54%. It further faces substantially smaller probability to increase its holdings in a stock if its weight is above the market weight, 45%. The fact that institutions tend to converge toward market weights is probably related to the fact that institutional managers are evaluated with stock market indices and their compensation depends strongly on their standing relative to the index.

3.7 Conclusions

This dissertation essay investigates the intertemporal trading patterns of US institutional investors based on quarterly disclosures of their equity portfolio holdings. The analysis on
stock level reveals that institutions tend to increase (decrease) their holdings in a stock after periods of significant institutional net buys (sells). They are also more likely to open a position in a stock after periods of increased institutional buys. Institutional types differ in their trading decisions – banks, insurance companies, and investment advisors are more likely to act in conformity with their peers, corporate and state pension funds are not significantly influenced by previous institutional trades, while mutual funds exhibit contrarian behavior.

There is a substantial variation in the tendency of institutional investors to follow aggregate trades across stocks. Institutions pay more attention to their peers' trades in small volatile stocks and in stocks experiencing significant price decreases. The tendency of institutional investors to follow their peers' trades in small volatile stocks suggests that institutional imitative behavior is largely driven by a search of investment information, which is more scarce for those securities.

Institutions with the highest tendency to follow aggregate institutional trades do not outperform significantly all remaining institutions. They further underperform the group of contrarian institutions, betting against the trend in aggregate institutional trades. However, the fact that all herding institutions underperform their peers questions the rationality of this type of behavior. It also suggests that the explanation of institutional imitative behavior lies beyond the reputation-based herding theories.

Compensation structures could significantly affect institutional trading decisions. I demonstrate that institutional investors exhibit the tendency to reverse their trades around market weights. This pattern is probably related to the fact that managerial compensation
is often tied to the performance of the fund relative to a stock index. This aspect of institutional trading behavior could have important implications for capital markets and further analysis in this direction would be worthwhile.
CHAPTER 4

CONCLUSION

This dissertation investigates the investment performance and trading behavior of U.S. institutional investors. I find that financial institutions demonstrate considerable ability to manage portfolios of stocks. This result is robust with respect to several conditional and unconditional performance measures based on factor- and characteristic-benchmarks. I further demonstrate that the various institutional types do not contribute equally to this superior performance: banks, independent investment advisors, and mutual funds outperform significantly insurance companies and state pension funds while corporate pension funds do not perform significantly different from all remaining institutions. In order to shed more light on the performance results, I investigate the relation between investment performance and characteristics of the evaluated portfolios. I establish that institutional performance is related to the size of the managed portfolio, its stock characteristics, and its flows.

Good investment performance is determined by both better information and better managerial incentives. I presume that the top-performers in the study exhibit both characteristics, while the bottom performers exhibit none. The results are further consistent with the predictions of agency theory and support the “transparency” hypothesis of Ross. Banks, investment advisors, and mutual funds are more transparent than insurance companies and
pension funds. In addition, banks and independent investment advisors, due to their concentrated investor base and performance-sensitive compensation contracts, provide stronger incentives for managers to perform better.

I further investigate the intertemporal trading patterns of US institutional investors. The analysis reveals that institutions tend to increase (decrease) their holdings in a stock after periods of significant institutional net buys (sells). They are also more likely to open a position in a stock after periods of increased institutional buys. Institutional types differ in their trading decisions – banks, insurance companies, and investment advisors are more likely to act in conformity with their peers, corporate and state pension funds are not significantly influenced by previous institutional trades, while mutual funds exhibit contrarian behavior.

There is a substantial variation in the tendency of institutional investors to follow aggregate institutional trades across stocks. Institutions pay more attention to their peers' trades in small volatile stocks and in stocks experiencing significant price decreases. The tendency of institutional investors to follow their peers' trades in small volatile stocks suggests that institutional imitative behavior is largely driven by a search of investment information, which is more scarce for those securities.

Institutions with the highest tendency to follow aggregate institutional trades do not outperform significantly all remaining institutions. They further underperform the group of contrarian institutions, betting against the trend in aggregate institutional trades. However,
the fact that all herding institutions underperform their peers questions the rationality of this type of behavior. It also suggests that the explanation of institutional imitative behavior lies beyond the reputation-based herding theories.

Compensation structures could significantly affect institutional trading decisions. Institutional investors further exhibit the tendency to reverse their trades around market weights. This pattern is probably related to the fact that managerial compensation is often tied to the performance of the fund relative to a stock index. This aspect of institutional trading behavior could have important implications for capital markets and further analysis in this direction would be worthwhile.
LIST OF REFERENCES


Badrinath, S.G. and S. Wahal, 1999, Momentum trading by institutions, working paper, Emory University.


Chen H., Jegadeesh N., and R. Wermers, 1999, The value of active mutual fund management:


Compensation survey of investment management professionals 1999, AIMR and Russell Reynolds Associates


Del Guercio, Diane, and Paula Tkac 2000, The determinants of the flow of funds of managed portfolios: mutual funds versus pension funds, working paper 2000-21, Federal Reserve Bank of Atlanta


Gervais, S., and T. Odean, 1999, Learning to be overconfident, working paper, UC Davis


94


Mitchell, Mark and Erik Stafford, 2000, Managerial decisions and long-term stock price performance, *Journal of Business* 73, July


Pástor, L., and R. Stambaugh, 2000, Evaluating and investing in equity mutual funds, working paper, University of Chicago and University of Pennsylvania


Securities industry fact book 1999, Securities Industry Association


Wylie, Sam, 2000, Fund manager herding: a test of the accuracy of empirical results using UK data, working paper, Dartmouth College.


APPENDIX A

TABLES

Panel A: Number of Stocks and Institutions

<table>
<thead>
<tr>
<th>Year</th>
<th># Stocks</th>
<th># Inst.</th>
<th>in Portf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>3186</td>
<td>620</td>
<td>142</td>
</tr>
<tr>
<td>1985</td>
<td>4139</td>
<td>818</td>
<td>164</td>
</tr>
<tr>
<td>1988</td>
<td>4765</td>
<td>958</td>
<td>185</td>
</tr>
<tr>
<td>1991</td>
<td>4943</td>
<td>1099</td>
<td>194</td>
</tr>
<tr>
<td>1994</td>
<td>6521</td>
<td>1237</td>
<td>234</td>
</tr>
<tr>
<td>1996</td>
<td>7518</td>
<td>1437</td>
<td>250</td>
</tr>
</tbody>
</table>

Panel B: Number of Institutions by Type

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>232</td>
<td>66</td>
<td>52</td>
<td>182</td>
<td>28</td>
<td>11</td>
<td>49</td>
</tr>
<tr>
<td>1985</td>
<td>241</td>
<td>72</td>
<td>57</td>
<td>354</td>
<td>28</td>
<td>12</td>
<td>54</td>
</tr>
<tr>
<td>1988</td>
<td>227</td>
<td>69</td>
<td>61</td>
<td>495</td>
<td>33</td>
<td>13</td>
<td>60</td>
</tr>
<tr>
<td>1991</td>
<td>230</td>
<td>75</td>
<td>60</td>
<td>631</td>
<td>34</td>
<td>16</td>
<td>53</td>
</tr>
<tr>
<td>1994</td>
<td>209</td>
<td>78</td>
<td>57</td>
<td>801</td>
<td>29</td>
<td>15</td>
<td>48</td>
</tr>
<tr>
<td>1996</td>
<td>197</td>
<td>75</td>
<td>93</td>
<td>978</td>
<td>30</td>
<td>16</td>
<td>49</td>
</tr>
</tbody>
</table>

Table 1: Sample Characteristics

Panel A: For selected years are presented the total number of stocks, the total number of institutions, and the average number of stocks in each institutional portfolio in the sample.

Panel B: For selected years are presented the number of institutions in the sample by institutional type: banks (Bnk.), insurance companies (Ins.), mutual funds (Mut.), independent investment advisors (Iadv.), corporate pension funds (CoPens.), state pension funds (StPens.), and all remaining institutions (Rest.). The group of Rest. covers the largest university endowments, foundations, etc.
Table 2: Performance of Aggregate Institutional Portfolios

Constructed are equally- and value-weighted portfolios of institutions. In Panels A, B and C, the resulting time-series are regressed on the market model, Eq.1, the Fama and French three-factor model, Eq.2, and the Carhart four-factor model, Eq.3, respectively. In Panels D, E and F, the portfolio returns are regressed on the conditional market model, Eq.4, the conditional Fama and French three-factor model, Eq.5, and the conditional Carhart four-factor model, Eq.6. The coefficients α are the estimated intercepts from the regressions and the coefficients β, σ, h, and m are the estimated loadings on the market factor, Rmrf, size factor, Smb, book-to-market factor, Hml, and momentum factor, Mom, respectively. Reported are the estimates of all coefficients and their t-statistics (the loadings on the interaction terms between the factors and the information variables are not presented in the table). All intercepts are annualized to percent per year.
Table 3: Performance of Aggregate Institutional Portfolios Based on Portfolio Weights

The GT (Own Benchmark), CS (Characteristic Selectivity), and CT (Characteristic Timing) measures, introduced in Section 2.3.3, are presented for equally-weighted and value-weighted portfolios of institutions. The quarterly component of the GT measure is calculated by subtracting the time t return of the portfolio held at month t-4 from the time t return of the portfolio held at t-1. The quarterly component of the CS measure is the difference between the time t return of the portfolio held at time t-1 and the time t return of the time t-1 matching control portfolio. The quarterly component of the CT measure is computed, for each institution, by matching stocks held at time t-4 and at time t-1 with the corresponding control portfolios at time t-4 and at time t-1, respectively. Next, the portfolio-weighted return of the time t-4 matching portfolio, at time t, is subtracted from the portfolio-weighted return of the time t-1 control portfolio, also at time t. All portfolios are rebalanced quarterly. The table presents annual, as well as whole-period averages of the quarterly measures (returns) and their t-statistics.
For each institutional type, banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (ladv.), corporate pension funds (Corp. Pens.), and state pension funds (State Pens.), are constructed equally- and value-weighted portfolios of institutions. In Panels A, B and C, the resulting time-series are regressed on the market model, Eq.1, the Fama and French three-factor model, Eq.2, and the Carhart four-factor model, Eq.3, respectively. In Panels D, E and F, the portfolio returns are regressed on the conditional market model, Eq.4, the conditional Fama and French three-factor model, Eq.5, and the conditional Carhart four-factor model, Eq.6. The coefficients \( \alpha_p \) are the estimated intercepts from the regressions. Reported are the estimates of model alphas and their t-statistics. All intercepts are annualized to percent per year.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equally-weighted</strong></td>
<td><strong>Value-weighted</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( Bnk. )</td>
<td>( Bnk. )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estim. 1.35</td>
<td>Estim. 1.37</td>
<td>Estim. 1.28</td>
<td>Estim. 1.37</td>
<td>Estim. 1.37</td>
<td>Estim. 1.37</td>
</tr>
<tr>
<td>t-stat. 2.89</td>
<td>t-stat. 3.65</td>
<td>t-stat. 2.78</td>
<td>t-stat. 3.27</td>
<td>t-stat. 3.03</td>
<td>t-stat. 3.03</td>
</tr>
<tr>
<td>( Ins. )</td>
<td>( Ins. )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estim. 0.21</td>
<td>Estim. 0.25</td>
<td>Estim. 0.34</td>
<td>Estim. 0.34</td>
<td>Estim. 0.34</td>
<td>Estim. 0.34</td>
</tr>
<tr>
<td>t-stat. 0.47</td>
<td>t-stat. 0.57</td>
<td>t-stat. 0.53</td>
<td>t-stat. 0.75</td>
<td>t-stat. 0.75</td>
<td>t-stat. 0.75</td>
</tr>
<tr>
<td>( Mut. )</td>
<td>( Mut. )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estim. -0.19</td>
<td>Estim. -0.04</td>
<td>Estim. -0.07</td>
<td>Estim. -0.07</td>
<td>Estim. -0.07</td>
<td>Estim. -0.07</td>
</tr>
<tr>
<td>t-stat. -0.32</td>
<td>t-stat. -0.07</td>
<td>t-stat. -0.07</td>
<td>t-stat. 0.21</td>
<td>t-stat. -0.11</td>
<td>t-stat. -0.11</td>
</tr>
<tr>
<td>( ladv. )</td>
<td>( ladv. )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estim. 0.06</td>
<td>Estim. 0.12</td>
<td>Estim. 0.15</td>
<td>Estim. 0.12</td>
<td>Estim. 0.15</td>
<td>Estim. 0.15</td>
</tr>
<tr>
<td>t-stat. 0.11</td>
<td>t-stat. 0.95</td>
<td>t-stat. 1.00</td>
<td>t-stat. 0.95</td>
<td>t-stat. 1.00</td>
<td>t-stat. 1.00</td>
</tr>
<tr>
<td>( Co.Pens )</td>
<td>( Co.Pens )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estim. 0.86</td>
<td>Estim. 1.16</td>
<td>Estim. 1.06</td>
<td>Estim. 0.76</td>
<td>Estim. 0.57</td>
<td>Estim. 0.57</td>
</tr>
<tr>
<td>t-stat. 1.27</td>
<td>t-stat. 1.32</td>
<td>t-stat. 1.44</td>
<td>t-stat. 0.37</td>
<td>t-stat. 0.95</td>
<td>t-stat. 0.95</td>
</tr>
<tr>
<td>( St.Pens. )</td>
<td>( St.Pens. )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estim. 0.41</td>
<td>Estim. 0.78</td>
<td>Estim. 1.18</td>
<td>Estim. 0.69</td>
<td>Estim. 0.82</td>
<td>Estim. 0.82</td>
</tr>
<tr>
<td>t-stat. 0.89</td>
<td>t-stat. 1.97</td>
<td>t-stat. 1.18</td>
<td>t-stat. 0.89</td>
<td>t-stat. 1.81</td>
<td>t-stat. 1.81</td>
</tr>
</tbody>
</table>

Table 4: Performance Evaluation by Institutional Type
Table 5: Performance Evaluation by Institutional Type Based on Portfolio Weights

The GT (Own Benchmark), CS (Characteristic Selectivity), and CT (Characteristic Timing) measures are presented for equally-weighted and value-weighted portfolios within each institutional type: banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (Iadv.), corporate pension funds (Corp. Pens.), and state pension funds (State Pens.). The quarterly component of the GT measure is calculated by subtracting the time t return of the portfolio held at month t-4 from the time t return of the portfolio held at t-1. The quarterly component of the CS measure is the difference between the time t return of the portfolio held at time t-1 and the time t return of the time t-1 matching control portfolio. The quarterly component of the CT measure is computed, for each institution, by matching stocks held at time t-4 and at time t-1 with the corresponding control portfolios at time t-4 and at time t-1, respectively. Next, the portfolio-weighted return of the time t-4 matching portfolio, at time t, is subtracted from the portfolio-weighted return of the time t-1 control portfolio, also at time t. All portfolios are rebalanced quarterly. The table presents time-series averages of the quarterly measures (returns) and their t-statistics.
Table 6: Characteristics of Institutional Portfolios

Average characteristics of institutional portfolios for the following institution types: banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (ladv.), corporate pension funds (Co.Pns.), and state pension funds (St.Pns.). PSZ is the market capitalization of the portfolio, No.Stck. is the average number of stocks per portfolio, Beta is the sensitivity to the market portfolio, SZ is the value-weighted size of the stocks in the portfolio, BM is the value-weighted book-to-market ratio of the stocks in the portfolio, Mom is the value-weighted momentum (past 6 months return, lagged one month) of the stocks in the portfolio, HI is the concentration of the portfolio allocation across two-digit industries, TO is the quarterly portfolio turnover, and FL is the quarterly flow of funds to the portfolio. Medians of the above characteristics are presented in parentheses. The F-value (in column 7) results from a test of the null-hypothesis that all intergroup means are identical.
<table>
<thead>
<tr>
<th></th>
<th>BM1 (Low)</th>
<th>BM2 (Low)</th>
<th>BM3 (High)</th>
<th>BM4 (High)</th>
<th>BM5 (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SZ1</td>
<td>0.88</td>
<td>-0.09</td>
<td>0.18</td>
<td>0.30</td>
<td>0.45</td>
</tr>
<tr>
<td>(Small)</td>
<td>-3.52</td>
<td>-0.52</td>
<td>1.22</td>
<td>2.17</td>
<td>2.96</td>
</tr>
<tr>
<td>SZ2</td>
<td>-0.51</td>
<td>-0.04</td>
<td>0.09</td>
<td>0.14</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>-4.46</td>
<td>-0.67</td>
<td>1.23</td>
<td>1.72</td>
<td>-0.65</td>
</tr>
<tr>
<td>SZ3</td>
<td>-0.26</td>
<td>-0.01</td>
<td>0.04</td>
<td>0.14</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td>-2.41</td>
<td>-0.10</td>
<td>0.51</td>
<td>1.73</td>
<td>-0.81</td>
</tr>
<tr>
<td>SZ4</td>
<td>0.07</td>
<td>0.00</td>
<td>-0.07</td>
<td>-0.06</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>0.68</td>
<td>0.00</td>
<td>-0.78</td>
<td>-0.64</td>
<td>0.86</td>
</tr>
<tr>
<td>SZ5</td>
<td>0.08</td>
<td>-0.01</td>
<td>0.12</td>
<td>-0.22</td>
<td>-0.07</td>
</tr>
<tr>
<td>(Big)</td>
<td>0.86</td>
<td>-0.06</td>
<td>1.46</td>
<td>-2.23</td>
<td>-0.47</td>
</tr>
</tbody>
</table>

Table 7: Performance of 25 SZ/BM Portfolios Based on the Fama and French Three Factor Model

Formed are 25 Size/BM equity portfolios based on independently constructed NYSE size and book-to-market quintiles. Afterwards, the resulting 25 return time-series are regressed on the Fama and French three-factor model

\[ R_{p,t} - R_{f,t} = \alpha + \beta_1 R_{m,t} + \beta_2 S_{mb,t} + \beta_3 H_{ml,t} + \epsilon \]

where \( R_{m,t} \) is the difference between the returns on the market portfolio and the risk-free security, \( S_{mb,t} \) is the difference between the returns on portfolios of "small" and "big" stocks, and \( H_{ml,t} \) is the difference between the returns of portfolios of "high" book-to-market and "low" book-to-market stocks. The table presents the estimated intercept terms and their t-statistics.
Table 8: Mispricing-adjusted Performance Measures based on the Fama and French Three Factor Model

The following models

\[ R_{pt}^{\text{bch}} = a_{\text{bch}} + b_p R_{mf} + s_p S_{mb} + h_p H_{ml} + \ell_p, \]

and

\[ R_{pt} = a_p + b_p R_{mf} + s_p S_{mb} + h_p H_{ml} + \ell_p, \]

are estimated for equally-weighted and value-weighted portfolios of financial institutions. \( R_{pt} \) is the return on the evaluated portfolio, \( R_{pt}^{\text{bch}} \) is the return on a benchmark portfolio with a similar Size/BM composition (its construction is described in Section 3), \( R_{mf} \) is the difference between the returns on the market portfolio and the risk-free security, \( S_{mb} \) is the difference between the returns on portfolios of “small” and “big” stocks, and \( H_{ml} \) is the difference between the returns of portfolios of “high” book-to-market and “low” book-to-market stocks. The table presents the estimated mispricing-adjusted intercept terms and their t-statistics:

\[ \delta_{\text{adj}} = \delta_p - \delta_{\text{bch}} \]

and

\[ t_{\text{adj}} = (\delta_p - \delta_{\text{bch}}) / \sigma_p. \]
Table 9: Mispricing-adjusted Performance Measures by Institutional Type based on the Fama and French Three Factor Model

The following models

\[ R_{\text{bench},p,t} = a_{\text{bench}} + b_{p} R_{\text{mrfi},t} + S_{\text{mb},t} + h_{p} H_{\text{ml},t} + \epsilon_{p,t}, \]

and

\[ R_{p,t} = a_{p} + b_{p} R_{\text{mrfi},t} + S_{\text{mb},t} + h_{p} H_{\text{ml},t} + \epsilon_{p,t}, \]

are estimated for equally-weighted and value-weighted portfolios of financial institutions within each institution type: banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (ladv.), corporate pension funds (Corp. Pens.), and state pension funds (State Pens.). \( R_{p,t} \) is the return on the evaluated portfolio, \( R_{\text{bench},p,t} \) is the return on a benchmark portfolio with a similar Size/BM composition (its construction is described in Section 3), \( R_{\text{mrfi},t} \) is the difference between the returns on the market portfolio and the risk-free security, \( S_{\text{mb},t} \) is the difference between the returns on portfolios of "small" and "big" stocks, and \( H_{\text{ml},t} \) is the difference between the returns of portfolios of "high" book-to-market and "low" book-to-market stocks. The table presents the estimated mispricing-adjusted intercept terms and their t-statistics:

\[ \Delta_{\text{adj}}^{\epsilon_p} = \Delta_{\text{adj}}^{\epsilon_{\text{bench}}} , \text{ and } t_{\text{adj}}^{\epsilon_p} = (\Delta_{\text{adj}}^{\epsilon_p} - \Delta_{\text{adj}}^{\epsilon_{\text{bench}}}) / p \]
Table 10: Variation in Performance across Institutional Types: Pair-wise Comparison

For each institutional type, banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (Adv.), corporate pension funds (Corp. Pens.), and state pension funds (State Pens.), are constructed value-weighted portfolios of financial institutions. Afterwards, the differences in the performance across institutional types is tested for statistical significance based on the adjusted three-factor model

\[ R_{p}^{i} - R_{p}^{j} = \alpha_{p} + b_{p} \text{Rmrf}_{i} + c_{p} \text{Smb}_{i} + d_{p} \text{Hml}_{i} + e_{p} \]

where \( R_{p}^{i} \) is the return on portfolio \( i \) and \( R_{p}^{j} \) is the return on portfolio \( j \). The test is performed against the Null hypothesis \( H0: \alpha_{p} = \alpha_{p}^{\text{bench,i}} - \alpha_{p}^{\text{bench,j}} \), where \( \alpha_{p}^{\text{bench,i}} \) is the intercept on a benchmark portfolio with a similar Size/BM composition to portfolio \( i \) and \( \alpha_{p}^{\text{bench,j}} \) is the intercept on a benchmark portfolio with a similar Size/BM composition to portfolio \( j \) (their construction is described in Section 3). \( \text{Rmrf}_{i} \) is the difference between the returns on the market portfolio and the risk-free security, \( \text{Smb}_{i} \) is the difference between the returns on portfolios of "small" and "big" stocks, and \( \text{Hml}_{i} \) is the difference between the returns of portfolios of "high" book-to-market and "low" book-to-market stocks. The above-diagonal elements of the table present the difference between the estimated alphas of the institutional types in the corresponding columns and rows. The below-diagonal elements present symmetrically their t-statistics.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Bnk.</td>
<td>-</td>
<td>0.59</td>
<td>0.03</td>
<td>0.07</td>
<td>0.97</td>
<td>0.79</td>
</tr>
<tr>
<td>Ins.</td>
<td>2.19</td>
<td>-</td>
<td>-0.56</td>
<td>-0.53</td>
<td>0.38</td>
<td>0.20</td>
</tr>
<tr>
<td>Mut.</td>
<td>0.07</td>
<td>-1.65</td>
<td>-</td>
<td>0.03</td>
<td>0.94</td>
<td>0.76</td>
</tr>
<tr>
<td>Adv.</td>
<td>0.18</td>
<td>-1.80</td>
<td>0.10</td>
<td>-</td>
<td>0.91</td>
<td>0.73</td>
</tr>
<tr>
<td>Corp. Pens.</td>
<td>1.15</td>
<td>0.46</td>
<td>1.04</td>
<td>1.08</td>
<td>-</td>
<td>-0.18</td>
</tr>
<tr>
<td>State Pens.</td>
<td>2.43</td>
<td>0.67</td>
<td>1.79</td>
<td>2.25</td>
<td>-0.20</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 11: Performance of Institutional Portfolios Stratified by Portfolio Characteristics
Based on the Adjusted Three-factor Model

At the end of each quarter (1982-1996), all institutional portfolios are sorted into five
groups according to their market capitalization (portfolio size). Afterward, five portfolios
of institutions within each of the corresponding quintiles are constructed. Similarly are
constructed five portfolios within each institution type. Afterwards, the performance of
the top-quintile portfolio (quintile 5) and the bottom quintile portfolio (quintile 1) are
compared by estimating the adjusted three-factor model:

\[ R^5_{pt} - R^1_{pt} = \alpha + \beta \cdot Rmft + \gamma \cdot Smbf + \delta \cdot Hmft \]

where \( R^5_{pt} \) is the return on the top-quintile (highest) portfolio and \( R^1_{pt} \) is the return on
the bottom-quintile (lowest) portfolio. Panel A reports the estimated intercepts and their
t-statistic. Panels B through G report the estimated intercepts from stratifications with
respect to average stock size, stock book-to-market ratio, stock momentum, portfolio
turnover, and preceding and subsequent capital flows.
Table 12: Performance of Institutional Portfolios Stratified by Portfolio Characteristics Based on the Characteristic Selectivity Measure

At the end of each quarter (1982-1996), all institutional portfolios are sorted into five groups according to their market capitalization (portfolio size). Afterward, five portfolios of institutions within each of the corresponding quintiles are constructed. Similarly are constructed five portfolios within each institution type. Afterwards, the performance of the top-quintile portfolio (quintile 5) and the bottom quintile portfolio (quintile 1) are compared with the characteristic selectivity measure, CS*. Panel A reports the differences of the corresponding selectivity measures and their t-statistics. Panels B through G report the estimated differences from stratifications with respect to average stock size, stock book-to-market ratio, stock momentum, portfolio turnover, and preceding and subsequent capital flows.
<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Banks</th>
<th>Insurance Companies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TOT BMS IBMS NB</td>
<td>TOT BMS IBMS NB</td>
<td>TOT BMS IBMS NB</td>
</tr>
<tr>
<td>Mean</td>
<td>31.09 0.076 -0.04 0.194</td>
<td>6.91 0.01 -0.007 0.028</td>
<td>2.51 0.002 -0 0.009</td>
</tr>
<tr>
<td>t-stat.</td>
<td>628 67.1 -1.01 254</td>
<td>409 22.5 -40.3 110</td>
<td>255 9.97 -26.9 69.4</td>
</tr>
<tr>
<td>St.Dev.</td>
<td>21.00 0.51 0.17 0.34</td>
<td>7.46 0.19 0.08 0.11</td>
<td>4.34 0.10 0.05 0.06</td>
</tr>
<tr>
<td>Median</td>
<td>27.00 0.64 0.00 0.07</td>
<td>4.45 0.00 0.00 0.00</td>
<td>0.89 0.00 0.00 0.00</td>
</tr>
<tr>
<td>Skew.</td>
<td>0.54 2.69 -5.81 7.71</td>
<td>2.18 1.25 -17.10 22.30</td>
<td>5.68 28.10 -24.40 40.70</td>
</tr>
<tr>
<td>Kurt.</td>
<td>-0.58 121 204 312</td>
<td>8.12 156 1123 901</td>
<td>60.80 5082 1847 3800</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Mutual Funds</th>
<th>Investment Advisors</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TOT BMS IBMS NB</td>
<td>TOT BMS IBMS NB</td>
<td>TOT BMS IBMS NB</td>
</tr>
<tr>
<td>Mean</td>
<td>3.79 0.015 -0.01 0.025</td>
<td>15.61 0.048 -0.022 0.125</td>
<td>2.27 0.002 -0 0.007</td>
</tr>
<tr>
<td>t-stat.</td>
<td>306 39.5 -40.1 105</td>
<td>556 55.2 -81 224</td>
<td>238 9.88 -26.5 75.1</td>
</tr>
<tr>
<td>St.Dev.</td>
<td>5.47 0.17 0.05 0.11</td>
<td>12.4 0.04 0.12 0.25</td>
<td>4.21 0.08 0.05 0.04</td>
</tr>
<tr>
<td>Median</td>
<td>1.69 0.00 0.00 0.00</td>
<td>0.12 0.00 0.00 0.03</td>
<td>0.61 0.00 0.00 0.00</td>
</tr>
<tr>
<td>Skew.</td>
<td>2.86 4.62 -5.83 14.91</td>
<td>0.99 0.93 -4.47 7.19</td>
<td>7.82 -11.80 -52.80 31.80</td>
</tr>
<tr>
<td>Kurt.</td>
<td>15.69 199 542 919</td>
<td>0.87 169 239 172</td>
<td>117 1330 6788 2792</td>
</tr>
</tbody>
</table>

Table 13: Summary Statistics of Institutional Trades

Presented are summary statistics of quarter-end total institutional ownership in a stock (TOT), quarterly changes of total institutional ownership in a stock – net buys (BMS), quarterly changes of the ownership of all institutions with constant holding in the stock over the previous quarter – induced net buys (IBMS), and the aggregate buys of all institutions which did not hold the stock before – new buys (NB). All institutional trades are normalized with the total number of shares outstanding. In addition to aggregate institutional trades, the table summarizes also the trades of the following institutional types: trust departments of banks, insurance companies, mutual funds, investment advisors, and all remaining institutions.
<table>
<thead>
<tr>
<th></th>
<th>BMS</th>
<th>IBMS</th>
<th>NB</th>
<th>RET</th>
<th>BMS</th>
<th>IBMS</th>
<th>NB</th>
<th>RET</th>
</tr>
</thead>
<tbody>
<tr>
<td>k = 0</td>
<td>1.00</td>
<td>0.39</td>
<td>0.45</td>
<td>0.15</td>
<td>0.06</td>
<td>0.05</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>k = 1</td>
<td>1.00</td>
<td>-0.11</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.08</td>
<td>-0.04</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>k = 2</td>
<td>1.00</td>
<td>0.16</td>
<td>0.05</td>
<td>-0.03</td>
<td>0.23</td>
<td>0.02</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>k = 3</td>
<td>1.00</td>
<td>0.10</td>
<td>0.05</td>
<td>0.08</td>
<td>-0.01</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 14: Cross-autocorrelations of Institutional Trades

Presented are correlations and cross-autocorrelations of quarterly stock returns (RET) and the following components of aggregate institutional trades: changes of total institutional ownership in a stock – net buys (BMS), quarterly changes of the ownership of all institutions with constant holding in the stock over the previous quarter – induced net buys (IBMS), and the aggregate buys of all institutions which did not hold the stock over the previous quarter – new buys (NB). All institutional trades are normalized with the total number of shares outstanding.
Table 15: Cross-autocorrelations of Institutional Trades by Institutional Type

For all institutional types are presented correlations and cross-autocorrelations of quarterly stock returns (RET) and the following components of aggregate institutional trades: changes of total institutional ownership in a stock — net buys (BMS), quarterly changes of the ownership of all institutions with constant holding in the stock over the previous quarter — induced net buys (IBMS), and the aggregate buys of all institutions which did not hold the stock before — new buys (NB). All institutional trades are normalized with the total number of shares outstanding.
Table 15 (cont): Cross-autocorrelations of Institutional Trades by Institutional Type

<table>
<thead>
<tr>
<th>Panel C: Mutual Funds</th>
<th>BMS&lt;sub&gt;k&lt;/sub&gt;</th>
<th>IBMS&lt;sub&gt;k&lt;/sub&gt;</th>
<th>NB&lt;sub&gt;k&lt;/sub&gt;</th>
<th>RET&lt;sub&gt;k&lt;/sub&gt;</th>
<th>BMS&lt;sub&gt;k&lt;/sub&gt;</th>
<th>IBMS&lt;sub&gt;k&lt;/sub&gt;</th>
<th>NB&lt;sub&gt;k&lt;/sub&gt;</th>
<th>RET&lt;sub&gt;k&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>k=0</td>
<td>k=1</td>
<td></td>
<td></td>
<td>k=0</td>
<td>k=1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>0.21</td>
<td>0.55</td>
<td>0.10</td>
<td>0.07</td>
<td>0.00</td>
<td>0.10</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.00)</td>
<td>(0.53)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>IBMS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>-0.12</td>
<td>0.01</td>
<td></td>
<td>0.00</td>
<td>0.02</td>
<td>-0.02</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.02)</td>
<td></td>
<td></td>
<td>(0.71)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>NB&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>0.07</td>
<td></td>
<td></td>
<td>0.08</td>
<td>-0.02</td>
<td>0.16</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>RET&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td>0.05</td>
<td>0.01</td>
<td>0.05</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Panel D: Investment Advisors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>0.31</td>
<td>0.49</td>
<td>0.14</td>
<td>0.03</td>
<td>0.02</td>
<td>0.09</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>IBMS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>-0.17</td>
<td>0.00</td>
<td></td>
<td>-0.02</td>
<td>0.03</td>
<td>-0.04</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.34)</td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>NB&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>0.16</td>
<td></td>
<td></td>
<td>0.02</td>
<td>-0.04</td>
<td>0.24</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>RET&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td>0.09</td>
<td>0.03</td>
<td>0.07</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Panel E: Other</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>0.64</td>
<td>0.37</td>
<td>-0.03</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.00)</td>
<td>(0.05)</td>
<td>(0.00)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>IBMS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>-0.11</td>
<td>-0.02</td>
<td></td>
<td>-0.01</td>
<td>0.01</td>
<td>-0.01</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.78)</td>
</tr>
<tr>
<td>NB&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td>0.00</td>
<td></td>
<td></td>
<td>0.01</td>
<td>-0.02</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td></td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>RET&lt;sub&gt;k&lt;/sub&gt;</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.43)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

113
## Table 16: Intertemporal Patterns in Aggregate Institutional Investors' Trades

For each stock $i$, the change in the fraction of total institutional ownership over quarter $t$, $BMS_{i,t}$, is regressed on the change over the previous quarter.

$$BMS_{i,t+1} = a_i + b_i BMS_{i,t} + u_{i1} TOTI_{i,t} + u_{i2} TOTI_{i,t}^2 + u_{i3} R_{i,t} + u_{i4} M_{i,t} + u_{i5},$$

where $TOTI_{i,t}$ is the percentage of institutional ownership in the stock at the end of period $t$, $TOTI_{i,t}^2$ is $TOTI_{i,t}$ squared, $R_{i,t}$ is the return of the stock over period $t$, and $M_{i,t}$ is a dummy variable equal to 1 if $R_{i,t}$ is within the top decile across all stocks, -1 if $R_{i,t}$ is within the bottom decile, and 0 otherwise. Summary statistics of the estimated coefficients and t-statistics of the mean values across all stocks are presented in Panel A. In Panels B and C, induced net buys – $IBMS_{i,t}$ defined as the percentage of net buys over period $t$ of institutions with constant holdings over period $t-1$, and new buys – $NB_{i,t}$ are regressed on the same set of dependent variables.
Table 17: Intertemporal Patterns in Aggregate Institutional Investors' Trades: Multiperiod Analysis

For each stock i, the change in the fraction of total institutional ownership over quarter t+1, BMS_{it+1}, is regressed on the changes in total institutional ownership over the previous three quarters - BMS_{it}, BMS_{it-1}, and BMS_{it-2}

\[ BMS_{it+1} = a + h_1 BMS_{it} + h_2 BMS_{it-1} + h_3 BMS_{it-2} + \mu_1 TOT_{it} + \mu_2 TOT^2_{it} + \mu_3 R_{it} + \mu_4 M_{it} + \epsilon, \]

where TOT_{it} is the percentage of institutional ownership in the stock at the end of period t, TOT^2_{it} is TOT_{it} squared, R_{it} is the return of the stock over period t, and M_{it} is a dummy variable equal to 1 if R_{it} is within the top decile across all stocks, -1 if R_{it} is within the bottom decile, and 0 otherwise. Summary statistics of the estimated coefficients and t-statistics of the mean values across all stocks are presented in Panel A. In Panels B and C, induced net buys - IBMS_{it} defined as the percentage of net buys over period t of institutions with constant holdings over period t-1, and new buys - NB_{it}, are regressed on the same set of dependent variables.

<table>
<thead>
<tr>
<th></th>
<th>(a)</th>
<th>(h_1)</th>
<th>(h_2)</th>
<th>(h_3)</th>
<th>(\mu_1)</th>
<th>(\mu_2)</th>
<th>(\mu_3)</th>
<th>(\mu_4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Net Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.05</td>
<td>0.024</td>
<td>-0.032</td>
<td>-0.005</td>
<td>-0.072</td>
<td>-0.581</td>
<td>0.014</td>
<td>0.001</td>
</tr>
<tr>
<td>t-stat.</td>
<td>2.44</td>
<td>5.03</td>
<td>-6.92</td>
<td>-1.12</td>
<td>-1.08</td>
<td>-2.71</td>
<td>13.07</td>
<td>1.38</td>
</tr>
<tr>
<td>Panel B: Induced Net Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.020</td>
<td>0.010</td>
<td>0.004</td>
<td>0.000</td>
<td>0.035</td>
<td>-0.152</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>t-stat.</td>
<td>-0.98</td>
<td>6.83</td>
<td>-2.36</td>
<td>0.00</td>
<td>0.83</td>
<td>-1.53</td>
<td>4.61</td>
<td>1.90</td>
</tr>
<tr>
<td>Panel C: New Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.050</td>
<td>0.009</td>
<td>-0.008</td>
<td>-0.001</td>
<td>-0.115</td>
<td>0.274</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td>t-stat.</td>
<td>8.96</td>
<td>2.83</td>
<td>-2.97</td>
<td>-0.31</td>
<td>-5.02</td>
<td>2.01</td>
<td>8.61</td>
<td>-0.18</td>
</tr>
</tbody>
</table>
Table 18: Intertemporal Patterns in Aggregate Institutional Investors' Trades: Buys vs. Sells

For each stock \( i \), the change in the total institutional ownership over quarter \( t \), \( BMS_{it} \), is regressed on the positive and negative changes of total institutional ownership over the previous quarter:

\[
BMS_{it} = \alpha_i + h_{1i} BMS_{it-1} + h_{2i} BMS_{it-1}^2 + h_{3i} BMS_{it-1} (BMS_{it-1} < 0) + h_{4i} BMS_{it-1} (BMS_{it-1} > 0) + \beta_1 \text{TOT}_{it-1} + \beta_2 \text{TOT}^2_{it-1} + \beta_3 R_{it} + \beta_4 M_{it} + \epsilon_i,
\]

where \( \text{TOT}_{it} \) is the percentage of institutional ownership in the stock at the end of period \( t \), \( \text{TOT}^2_{it} \) is \( \text{TOT}_{it} \) squared, \( R_{it} \) is the return of the stock over period \( t \), and \( M_{it} \) is a dummy variable equal to 1 if \( R_{it} \) is within the top decile across all stocks, -1 if \( R_{it} \) is within the bottom decile, and 0 otherwise. Summary statistics of the estimated coefficients and t-statistics of the mean values across all stocks are presented in Panel A. In Panels B and C, induced net buys – \( IBMS_{it} \) defined as the percentage of net buys over period \( t \) of institutions with constant holdings over period \( t-1 \), and new buys – \( NB_{it} \) are regressed on the same set of dependent variables.
### Table 19: Intertemporal Patterns in Trades of Institutional Types Subsequent to Aggregate Institutional Trades

For each stock $i$, the change of the fraction of institutional ownership of institutional type $J$ over quarter $t+1$, $BMS_{t+1}$, is regressed on the change of aggregate institutional ownership of the same institutional type, $BMS_t$, and of all remaining institutions, $BMS_{t,TOT}^{J}$, over the previous quarter.

$$BMS_{t+1} = a + BMS_t + BMS_{t,TOT}^{J} + \text{TOT}_{t+1}^{J} + \text{TOT}_{t+1}^{J} + \text{R}_{t+1} + \text{M}_{t+1} + \epsilon,$$

where $\text{TOT}_{t}^{J}$ is the percentage of institutional ownership of institutional type $J$ in the stock at the end of period $t$, $\text{TOT}_{t}^{J}$ is $\text{TOT}_{t}$ squared, $\text{R}_{t}$ is the return of the stock over period $t$, and $\text{M}_{t}$ is a dummy variable equal to 1 if $\text{R}_{t}$ is within the top decile across all stocks, -1 if $\text{R}_{t}$ is within the bottom decile, and 0 otherwise. Summary statistics of the estimated coefficients and t-statistics of the mean values across all stocks are presented in Panel A. In Panels B and C, induced net buys $-IBMS_{t}$ defined as the percentage of net buys over period $t$ of institutions of type $J$ with constant holdings over period $t-1$, and new buys of institutional type $J - NB_{t}$ are regressed on the same set of dependent variables.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
</tr>
<tr>
<td>Mean</td>
<td>0.054</td>
<td>0.02</td>
<td>0.012</td>
<td>0.016</td>
<td>0.035</td>
</tr>
<tr>
<td>t-stat.</td>
<td>6.95</td>
<td>0.72</td>
<td>1.39</td>
<td>2.11</td>
<td>2.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
</tr>
<tr>
<td>Mean</td>
<td>0.012</td>
<td>0.005</td>
<td>-0.015</td>
<td>0.007</td>
<td>-0.005</td>
</tr>
<tr>
<td>t-stat.</td>
<td>6.45</td>
<td>0.65</td>
<td>-2.32</td>
<td>2.02</td>
<td>-0.47</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
<td>$h_1$</td>
<td>$h_1^{100}$</td>
</tr>
<tr>
<td>Mean</td>
<td>0.011</td>
<td>0.051</td>
<td>-0.09</td>
<td>0.016</td>
<td>0.112</td>
</tr>
<tr>
<td>t-stat.</td>
<td>1.48</td>
<td>2.01</td>
<td>-0.96</td>
<td>3.68</td>
<td>1.02</td>
</tr>
</tbody>
</table>
Table 20: Intertemporal Patterns in Aggregate Institutional Investors' Trades Following Trades of Institutional Types

For each stock i, the change of the fraction of total institutional ownership over quarter t+1, BMS_{i,t+1}, is regressed on the change of institutional ownership of institutional type J over the previous quarter, BMS_{J,t}:

\[ BMS_{i,t+1} = \alpha_i + h_1 BMS_{i,t} + \eta_1 TOT_{i,t}^1 + \eta_2 TOT_{i,t}^2 + \eta_3 R_i + \eta_4 M_i + \epsilon_i \]

where TOT_{i,t}^1 is the percentage of institutional ownership of institutional type J in the stock at the end of period t, TOT_{i,t}^2 is TOT_{i,t}^1 squared, R_i is the return of the stock over period t, and M_i is a dummy variable equal to 1 if R_i is within the top decile across all stocks, -1 if R_i is within the bottom decile, and 0 otherwise. Summary statistics of the estimated coefficients and t-statistics of the mean values across all stocks are presented in Panel A. In Panels B and C, induced net buys – IBMS_{i,t} defined as the percentage of net buys over period t of institutions with constant holdings over period t-1, and new buys – NB_{i,t} are regressed on the same set of dependent variables.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Net Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.165</td>
<td>-3.239</td>
<td>0.476</td>
<td>0.06</td>
<td>1.375</td>
</tr>
<tr>
<td>t-stat.</td>
<td>1.42</td>
<td>-1.12</td>
<td>0.87</td>
<td>4.23</td>
<td>1.16</td>
</tr>
<tr>
<td>Panel B: Induced Net Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.006</td>
<td>0.703</td>
<td>-0.038</td>
<td>0.002</td>
<td>-0.047</td>
</tr>
<tr>
<td>t-stat.</td>
<td>0.42</td>
<td>1.57</td>
<td>-0.48</td>
<td>2.16</td>
<td>-0.87</td>
</tr>
<tr>
<td>Panel C: New Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.013</td>
<td>-3.75</td>
<td>0.029</td>
<td>0.002</td>
<td>0.25</td>
</tr>
<tr>
<td>t-stat.</td>
<td>1.51</td>
<td>-1.05</td>
<td>0.28</td>
<td>2.49</td>
<td>1.09</td>
</tr>
</tbody>
</table>
Table 21: Herding and Stock Characteristics

Estimated is the following regression

\[ \text{BMS}_{it+1} = a_t + h_t \text{BMS}_{it} + \lambda_1 \text{TOTI}_{it} + \lambda_2 \text{TOTI}_{it}^2 + \lambda_3 \text{RETI}_{it} + \lambda_4 \text{M_{it}} + \epsilon_t, \]

for all stocks over the first five years of the sample period (1982-1986). Afterwards, the estimated trade-sensitivity coefficients \( h_t \) (one for each stock) are regressed on stock characteristics:

\[ h_t = a + \lambda_1 \text{RET}_t + \lambda_2 \text{SZ}_t + \lambda_3 \text{BM}_t + \epsilon_t, \]

where \( \epsilon_t \) is the estimated standard deviation of monthly stock returns over the period, \( \text{RETI}_t \) is the stock average cumulative return, \( \text{SZ}_t \) is the market capitalization of firm's equity at the end of the period, and \( \text{BM}_t \) is the book-to-market ratio of firm's equity at the end of the period. The same two-step procedure is estimated subsequently rolling forward the estimation window by a quarter. Time-series averages of the estimated coefficients and their t-statistics are presented in Panel A. Panels B and C report similar estimates for the determinants of induced net buys and new buys, respectively.
<table>
<thead>
<tr>
<th></th>
<th>SZ1 (Small)</th>
<th>SZ2</th>
<th>SZ3</th>
<th>SZ4</th>
<th>SZ5</th>
<th>SZ5 - SZ1 (Big)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Net Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.573</td>
<td>0.202</td>
<td>0.126</td>
<td>0.247</td>
<td>-0.012</td>
<td>-0.585</td>
</tr>
<tr>
<td>t-stat.</td>
<td>3.45</td>
<td>1.44</td>
<td>0.82</td>
<td>1.80</td>
<td>-0.10</td>
<td>-3.02</td>
</tr>
<tr>
<td>Panel B: Induced Net Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.043</td>
<td>0.726</td>
<td>0.024</td>
<td>-0.12</td>
<td>0.014</td>
<td>-0.029</td>
</tr>
<tr>
<td>t-stat.</td>
<td>0.63</td>
<td>1.90</td>
<td>0.62</td>
<td>-0.40</td>
<td>0.47</td>
<td>-0.26</td>
</tr>
<tr>
<td>Panel C: New Buys</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.559</td>
<td>-0.036</td>
<td>0.043</td>
<td>0.162</td>
<td>-0.046</td>
<td>-0.605</td>
</tr>
<tr>
<td>t-stat.</td>
<td>3.09</td>
<td>-0.25</td>
<td>0.27</td>
<td>1.32</td>
<td>-0.67</td>
<td>-2.45</td>
</tr>
</tbody>
</table>

Table 22: Intertemporal Patterns in Aggregate Institutional Investors' Trades in Stock Portfolios Stratified by Size

All stocks are sorted into five portfolios according to their market capitalization. Afterwards, for each portfolio the value-weighted change in the fraction of total institutional ownership over quarter t, $BMS_{t+1}$, is regressed on the change over the previous quarter.

$$BMS_{t+1} = a + h BMS_t + \gamma \text{TOT}_t + \delta \text{TOT}_t^2 + \rho R_t + \omega M_t + \epsilon,$$

where $\text{TOT}_t$ is the percentage of institutional ownership in the stock at the end of period t, $\text{TOT}_t^2$ is $\text{TOT}_t$ squared, $R_t$ is the value-weighted average of $R_t$ - the returns of the stocks in the portfolio over period t, and $M_t$ is the average of $M_t$ a dummy variable equal to 1 if $R_{t,i}$ is within the top decile across all stocks, -1 if $R_{t,i}$ is within the bottom decile, and 0 otherwise. Estimated coefficients and their t-statistics are presented in Panel A. In Panel B, the averages of induced net buys, $IBMS_{t+1}$, defined as the percentage of net buys over period t of institutions with constant holdings over period t-1; in Panel C, the average new buys - $NB_{t+1}$ are regressed on the same set of dependent variables. The last column compares the difference between the estimated coefficients in the first and the fifth quintiles.
Table 23: Intertemporal Patterns in Aggregate Institutional Investors’ Trades in Stock Portfolios Stratified by Book-to-Market Ratio

All stocks are sorted into five portfolios according to their book-to-market ratios. Afterwards, for each portfolio the value-weighted change in the fraction of total institutional ownership over quarter t, $BMS_{it}$, is regressed on the change over the previous quarter.

$$BMS_{it+1} = a + hBMS_{i} + TOT_{it} + TOT_{it}^2 + R_{it} + M_{it} + \epsilon,$$

where $TOT_{it}$ is the percentage of institutional ownership in the stock at the end of period t, $TOT_{it}^2$ is $TOT_{it}$ squared, $R_{it}$ is the value-weighted average of $R_{it}$ – the returns of the stocks in the portfolio over period t, and $M_{it}$ is the average of $M_{it}$, a dummy variable equal to 1 if $R_{it}$ is within the top decile across all stocks, -1 if $R_{it}$ is within the bottom decile, and 0 otherwise. Estimated coefficients and their t-statistics are presented in Panel A. In Panel B, the averages of induced net buys, $IBMS_{it+1}$, defined as the percentage of net buys over period t of institutions with constant holdings over period t-1; in Panel C, the average new buys – $NB_{it+1}$ are regressed on the same set of dependent variables. The last column compares the difference between the estimated coefficients in the first and the fifth quintiles.

<table>
<thead>
<tr>
<th></th>
<th>BM1 (Low)</th>
<th>BM2</th>
<th>BM3</th>
<th>BM4</th>
<th>BM5</th>
<th>BM5 - BM1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Net Buys</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.141</td>
<td>-0.065</td>
<td>0.293</td>
<td>0.204</td>
<td>0.024</td>
<td>0.165</td>
</tr>
<tr>
<td>t-stat.</td>
<td>-1.21</td>
<td>-0.49</td>
<td>1.82</td>
<td>1.69</td>
<td>0.21</td>
<td>0.64</td>
</tr>
<tr>
<td><strong>Panel B: Induced Net Buys</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.006</td>
<td>-0.003</td>
<td>0.059</td>
<td>0.032</td>
<td>-0.01</td>
<td>-0.004</td>
</tr>
<tr>
<td>t-stat.</td>
<td>-0.27</td>
<td>-0.14</td>
<td>1.75</td>
<td>0.73</td>
<td>-0.39</td>
<td>-0.28</td>
</tr>
<tr>
<td><strong>Panel C: New Buys</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.055</td>
<td>-0.060</td>
<td>0.058</td>
<td>0.000</td>
<td>0.084</td>
<td>0.139</td>
</tr>
<tr>
<td>t-stat.</td>
<td>-1.14</td>
<td>-0.98</td>
<td>0.63</td>
<td>0.01</td>
<td>1.58</td>
<td>1.34</td>
</tr>
</tbody>
</table>
### Table 24: Intertemporal Patterns in Aggregate Institutional Investors' Trades in Stock Portfolios Stratified by Change in Stock Volatility

We estimated stock volatility for each stock-quarter based on stock daily returns. All stocks are further sorted into five portfolios according to the changes in their quarterly volatility. Afterwards, for each portfolio the value-weighted change in the fraction of total institutional ownership over the same quarter, BMS_{it}, is regressed on the change over the previous quarter

$$BMS_{it} = a + h BMS_{i,t-1} + R_t + M_t + \epsilon_t,$$

where TOT_t is the percentage of institutional ownership in the stock at the end of period t, TOT_t^2 is TOT_t squared, R_t is the value-weighted average of R_{it} — the returns of the stocks in the portfolio over period t, and M_t is the average of a dummy variable equal to 1 if R_{it} is within the top decile across all stocks, -1 if R_{it} is within the bottom decile, and 0 otherwise. Estimated coefficients and their t-statistics are presented in Panel A. In Panel B, the averages of induced net buys, IBMS_{i,t+1}, defined as the percentage of net buys over period t of institutions with constant holdings over period t-1; in Panel C, the average new buys — NB_{i,t+1} are regressed on the same set of dependent variables. The last column compares the difference between the estimated coefficients in the first and the fifth quintiles.

<table>
<thead>
<tr>
<th>Panel A: Net Buys</th>
<th>DSIG1 (Small)</th>
<th>DSIG2</th>
<th>DSIG3</th>
<th>DSIG4</th>
<th>DSIG5</th>
<th>SIG5 - DSIG1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.145</td>
<td>-0.003</td>
<td>0.056</td>
<td>0.053</td>
<td>-0.027</td>
<td>-0.172</td>
</tr>
<tr>
<td>t-stat.</td>
<td>1.53</td>
<td>-0.04</td>
<td>0.61</td>
<td>0.67</td>
<td>-0.17</td>
<td>-1.41</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Induced Net Buys</th>
<th>DSIG1 (Small)</th>
<th>DSIG2</th>
<th>DSIG3</th>
<th>DSIG4</th>
<th>DSIG5</th>
<th>SIG5 - DSIG1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.024</td>
<td>0.018</td>
<td>-0.003</td>
<td>0.038</td>
<td>-0.017</td>
<td>-0.041</td>
</tr>
<tr>
<td>t-stat.</td>
<td>1.05</td>
<td>0.80</td>
<td>-0.15</td>
<td>1.63</td>
<td>-0.42</td>
<td>-0.67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: New Buys</th>
<th>DSIG1 (Small)</th>
<th>DSIG2</th>
<th>DSIG3</th>
<th>DSIG4</th>
<th>DSIG5</th>
<th>SIG5 - DSIG1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.017</td>
<td>-0.086</td>
<td>0.049</td>
<td>-0.019</td>
<td>-0.054</td>
<td>-0.037</td>
</tr>
<tr>
<td>t-stat.</td>
<td>-0.26</td>
<td>-1.24</td>
<td>0.84</td>
<td>-0.43</td>
<td>-0.73</td>
<td>-0.41</td>
</tr>
</tbody>
</table>
Table 25: Performance of Financial Institutions Following Aggregate Institutional Trades

For each institution j, the change in the fraction of institutional ownership in a stock over quarter t, $\Delta BMS_{t, j}$, is regressed on the change of aggregate institutional ownership in the stock over the previous quarter, $\Delta BMS_{t-1}$:

$$BMS_{t, j} = a + b BMS_{t-1} + \epsilon$$

where $R_{t-1}$ is the return of the stock over period t-1. Afterwards, all institutions are sorted into five quintile portfolios according to their estimated herding measure $\hat{H}$ over the previous quarter. Based on the same stratification, five portfolios for banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (Iadv.), and all remaining institutions (Othr.) are constructed. For each one of the above quintile-portfolios is estimated the Characteristic Selectivity (CS) measure

$$CS_{j} = \sum_{j=1}^{N} \omega_{j} \left( R_{j,t} - R_{t}^{\text{b},j-1} \right)$$

Time-series averages of the measures and their t-statistics are presented in the table below. The last two rows present the difference between the performance measures in the fifth (highest) and the first (lowest) quintiles and their t-statistics.
<table>
<thead>
<tr>
<th></th>
<th>Bnk.</th>
<th>Ins.</th>
<th>Mut.</th>
<th>Iadv.</th>
<th>Othr.</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>1.02</td>
<td>-0.10</td>
<td>1.12</td>
<td>1.29</td>
<td>-0.29</td>
<td>1.03</td>
</tr>
<tr>
<td>t-stat.</td>
<td>(3.35)</td>
<td>(-0.18)</td>
<td>(1.57)</td>
<td>(2.62)</td>
<td>(-0.53)</td>
<td>(2.72)</td>
</tr>
<tr>
<td>L2</td>
<td>0.40</td>
<td>0.56</td>
<td>0.51</td>
<td>0.73</td>
<td>1.47</td>
<td>0.59</td>
</tr>
<tr>
<td>t-stat.</td>
<td>(1.51)</td>
<td>(1.35)</td>
<td>(0.78)</td>
<td>(1.65)</td>
<td>(2.15)</td>
<td>(1.83)</td>
</tr>
<tr>
<td>L3</td>
<td>0.25</td>
<td>0.82</td>
<td>1.05</td>
<td>0.67</td>
<td>0.58</td>
<td>0.57</td>
</tr>
<tr>
<td>t-stat.</td>
<td>(0.75)</td>
<td>(1.69)</td>
<td>(1.99)</td>
<td>(1.78)</td>
<td>(1.06)</td>
<td>(2.02)</td>
</tr>
<tr>
<td>L4</td>
<td>0.74</td>
<td>0.24</td>
<td>0.49</td>
<td>0.64</td>
<td>0.87</td>
<td>0.57</td>
</tr>
<tr>
<td>t-stat.</td>
<td>(2.03)</td>
<td>(0.37)</td>
<td>(0.74)</td>
<td>(1.61)</td>
<td>(1.40)</td>
<td>(2.07)</td>
</tr>
<tr>
<td>L5</td>
<td>0.74</td>
<td>0.61</td>
<td>1.32</td>
<td>1.39</td>
<td>0.54</td>
<td>1.02</td>
</tr>
<tr>
<td>t-stat.</td>
<td>(2.11)</td>
<td>(0.71)</td>
<td>(1.39)</td>
<td>(2.65)</td>
<td>(0.65)</td>
<td>(2.76)</td>
</tr>
<tr>
<td>L5 - L1</td>
<td>-0.28</td>
<td>0.71</td>
<td>0.20</td>
<td>0.10</td>
<td>0.83</td>
<td>-0.01</td>
</tr>
<tr>
<td>t-stat.</td>
<td>(-0.79)</td>
<td>(0.78)</td>
<td>(0.18)</td>
<td>(0.29)</td>
<td>(0.98)</td>
<td>(-0.07)</td>
</tr>
</tbody>
</table>

Table 26: Performance of Financial Institutions Leading Aggregate Institutional Trades

For each institution $j$, the change in the fraction of institutional ownership in a stock over quarter $t$, $BMS_{it}^{j}$, is regressed on the change of aggregate institutional ownership in the stock over the following quarter, $BMS_{it+1}$

$$BMS_{it}^{j} = \alpha + \beta BMS_{it}^{j} + \gamma R_{it} + \epsilon$$

where $R_{it}$ is the return of the stock over period $t-1$. Afterwards, all institutions are sorted into five quintile portfolios according to their estimated leading measure $^j$ over the previous quarter. Based on the same stratification, five portfolios for banks ($Bnk.$), insurance companies ($Ins.$), investment companies ($Mut.$), independent investment advisors ($Iadv.$), and all remaining institutions ($Othr.$) are constructed. For each one of the above quintile-portfolios is estimated the Characteristic Selectivity (CS) measure

$$CS_{it} = \sum_{j=1}^{n} \omega_{j} (R_{it} - R_{it}^{j})$$

Time-series averages of the measures and their t-statistics are presented in the table below. The last two rows present the difference between the performance measures in the fifth (highest) and the first (lowest) quintiles and their t-statistics.
Table 27: Past Performance of Financial Institutions Leading Aggregate Institutional Trades

For each institution \( j \), the change in the fraction of institutional ownership in a stock over quarter \( t \), \( BMS_{i,t} \), is regressed on the change of aggregate institutional ownership in the stock over the following quarter, \( BMS_{i,t+1} \)

\[
BMS_{i,t} = a^j + b^j BMS_{i,t+1} + c^j R_{i,t-1} + \varepsilon_{i,t},
\]

where \( R_{i,t-1} \) is the return of the stock over period \( t-1 \). Afterwards, all institutions are sorted into five quintile portfolios according to their estimated leading measure \( j \) over the following quarter. Based on the same stratification, five portfolios for banks (Bnk.), insurance companies (Ins.), investment companies (Mut.), independent investment advisors (Iadv.), and all remaining institutions (Othr.) are constructed. For each one of the above quintile-portfolios is estimated the Characteristic Selectivity (CS) measure

\[
CS_t = \sum_{j=1}^{N} \omega_{j,t-1} (R_{j,t} - R_{t}^{j,t-1})
\]

Time-series averages of the measures and their t-statistics are presented in the table below. The last two rows present the difference between the performance measures in the fifth (highest) and the first (lowest) quintiles and their t-statistics.
<table>
<thead>
<tr>
<th></th>
<th>Unconditional</th>
<th>Below Market</th>
<th>Above Market</th>
<th>Ho: $p^u = p^d$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p^u$</td>
<td>$p^d$</td>
<td>$bp^u$</td>
<td>$bp^d$</td>
</tr>
<tr>
<td>Panel A: All Institutions</td>
<td>0.54</td>
<td>0.46</td>
<td>0.77</td>
<td>0.23</td>
</tr>
<tr>
<td>Estim.</td>
<td>0.21</td>
<td>0.21</td>
<td>0.22</td>
<td>0.22</td>
</tr>
<tr>
<td>Panel B: Banks</td>
<td>0.53</td>
<td>0.47</td>
<td>0.65</td>
<td>0.35</td>
</tr>
<tr>
<td>Estim.</td>
<td>0.19</td>
<td>0.19</td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>Panel C: Insurance Companies</td>
<td>0.58</td>
<td>0.42</td>
<td>0.84</td>
<td>0.16</td>
</tr>
<tr>
<td>Estim.</td>
<td>0.21</td>
<td>0.21</td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>Panel D: Mutual Funds</td>
<td>0.57</td>
<td>0.43</td>
<td>0.85</td>
<td>0.15</td>
</tr>
<tr>
<td>Estim.</td>
<td>0.18</td>
<td>0.18</td>
<td>0.17</td>
<td>0.17</td>
</tr>
<tr>
<td>Panel E: Investment Advisors</td>
<td>0.53</td>
<td>0.47</td>
<td>0.79</td>
<td>0.21</td>
</tr>
<tr>
<td>Estim.</td>
<td>0.21</td>
<td>0.21</td>
<td>0.21</td>
<td>0.21</td>
</tr>
<tr>
<td>Panel F: Other Institutions</td>
<td>0.57</td>
<td>0.43</td>
<td>0.84</td>
<td>0.16</td>
</tr>
<tr>
<td>Estim.</td>
<td>0.26</td>
<td>0.26</td>
<td>0.22</td>
<td>0.22</td>
</tr>
</tbody>
</table>

**Table 28: Probabilities for Up- and Down-changes of Institutional Portfolio Weights**

For each institution-quarter are estimated the probabilities for an increase, $p^u$, and a decrease, $p^d$, of institutional holdings in a stock as the fraction of stocks in which the institution increases/decreases its holdings over the total number of stocks in which it trades. Further, each quarter the stocks in each institutional portfolio are split into two groups depending on whether the institutional allocation in the stock is below or above the market weight of the stock at the beginning of the quarter. Afterwards, for both groups of stocks, the conditional probabilities for increase, $p^u$, and decrease, $p^d$, of institutional holdings in the groups are estimated. Averages of the above probabilities across all institution-quarters and across the institutional types of banks (Bnk.), insurance companies (Ins.), mutual funds (Mut.), Investment Advisors (Iadv.), and all remaining institutions (Othr.) are presented in the table below.
APPENDIX B

FIGURES
Figure 1: Distribution of Institutional Ownership. For each stock is calculated the fraction of total number of shares held by institutional investors and total number of shares outstanding based on the CDA\Spectrum database. Charts 1A, 1B, and 1C show the value-weighted average fraction of institutional ownership in a stock at the end of years 1982, 1989, and 1996. Tables 2A, 2B, and 2C further present the distribution of institutional ownership across bank trust departments (Bnk), insurance companies (Ins), mutual funds (Mut), investment advisors (Iadv), and all remaining institutions (Othr).