Essays on the performance and trading strategies of institutional investors

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Essays on the Performance and Trading Strategies of Institutional Investors

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This thesis consists of three stand-alone studies relating to the performance and trading strategies of institutional investors.

The first study examines information sharing among delegated portfolio managers through networks connected by investment mandates between plan sponsors and their sub-advisers. Specifically, this study identifies similarity in returns, holdings and trading between mutual funds operated by sub-advisers, and tests whether such similarity is stronger when two funds share a mandate network. The empirical results provide evidence consistent with information sharing among these delegated portfolio managers. A mutual fund on average shares more similar returns, holdings and trading with funds in mandate networks than with funds outside the networks. Preliminary evidence suggests that information about both general investment styles and individual firms is transferred within mandate networks.

The second study investigates to what extent institutional investors engage in socially responsible investing by examining institutional trading behavior on four stocks targeted by the Sudan divestment campaign from 2001 to 2012. The empirical results provide evidence of a negative relationship between the intensity of the campaign and the institutional ownership breadth of the stocks. However, selling by institutional investors is only observed in the U.S., the original home of the campaign. Further, higher campaign intensity is associated with depressed stock prices and thus higher future returns. In summary, the evidence is consistent with institutional investors engaging in socially responsible investing, and supports the effectiveness of the stock boycott.

The third study examines the attribution of mutual fund performance between fund companies and individual fund managers. The empirical results suggest that manager fixed effects play a more significant role than fund, firm or advisor fixed effects in explaining the variations in fund performance. Further, manager skills appear to dominate fund performance. When a fund replaces its manager, the fund's performance after the manager replacement can be forecast by the manager's past performance at other funds, rather than the fund's past performance with the previous manager. However, there is only modest evidence that manager skills are appreciated by investors. Taken together, the evidence is consistent with fund managers being more important than fund companies for fund performance.

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Abstract

This thesis consists of three stand-alone studies relating to the performance and trading strategies of institutional investors.

The first study examines information sharing among delegated portfolio managers through networks connected by investment mandates between plan sponsors and their sub-advisers. Specifically, this study identifies similarity in returns, holdings and trading between mutual funds operated by sub-advisers, and tests whether such similarity is stronger when two funds share a mandate network. The empirical results provide evidence consistent with information sharing among these delegated portfolio managers. A mutual fund on average shares more similar returns, holdings and trading with funds in sub-advisory mandate networks than with funds outside the networks. Preliminary evidence suggests that information about both general investment styles and individual firms is transferred within mandate networks.

The second study investigates to what extent institutional investors engage in socially responsible investing by examining the trading behavior of a large group of institutional investors on four emerging market stocks targeted by the Sudan divestment campaign from 2001 to 2012. The empirical results provide evidence of a negative relationship between the intensity of the campaign and the institutional ownership breadth of the stocks. However, selling by institutional investors is only observed in the U.S., the original home of the campaign. Further, higher campaign intensity is associated with depressed stock prices and thus higher future returns. In summary, the evidence is consistent with institutional investors engaging in socially responsible investing, and supports the effectiveness of the stock boycott.

The third study examines the attribution of mutual fund performance between fund companies and individual fund managers. Specifically, this study explores the relative importance of the personal skills of the fund manager compared with the supporting personnel and resources of the fund company in determining a fund's performance outcomes. The empirical results suggest that manager fixed effects play a more significant role than fund, firm or advisor fixed effects in explaining the variations in fund performance. Further, manager skills appear to dominate fund performance, especially in sole-managed funds. When a fund replaces its manager, the fund's performance after the manager replacement is positively and significantly correlated with the manager's past performance at other funds, rather than the fund's past performance with the previous manager. However, there is only modest evidence that manager skills are appreciated by investors. Taken together, the evidence is consistent with fund managers being more important than fund companies for fund performance.

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Chapter 1

Introduction

Institutional investors, including mutual funds, exchange traded funds, pension funds, insurance companies, hedge funds, and a variety of separately managed accounts, have become increasingly important in global capital markets. Assets managed by these professional investors have exceeded US$60 trillion, which is about 170% of global gross domestic product (GDP) and almost triple the assets in 1995 (International Monetary Fund (IMF), 2011). In developed markets, the role of institutional investors is even more significant. For instance, the U.S. has seen institutional ownership of common equities rise from approximately 7% to 67% over the period 1950-2010. In the largest 1,000 corporations, shares owned by institutions have reached as much as 73% of total shares outstanding in the late 2000s (Aguilar, 2013).

The rapid growth of institutional investors has attracted great attention from the academic community, with mutual funds being most extensively studied due to best data availability. There is a large literature examining the performance, including persistence in performance, as well as the holdings and trades of institutional investors. The examination on the performance of institutional investors has great implications, as it can be viewed as a straightforward way to test the efficient markets hypothesis. If the efficient markets hypothesis holds, one would expect that even these professional investors earn no more than a fair compensation for the risk they choose to take. Starting with Jensen (1968), studies based on mutual fund returns consistently find that mutual funds on average underperform the market on a risk-adjusted basis, net of fees. While there is some evidence that past winning funds continue to outperform over short horizons (e.g., Hendricks, Patel and Zeckhauser, 1993; Goetzmann and Lbbotson, 1994; Brown and Goetzmann, 1995), it seems that the persistence in performance is largely driven by the momentum effect documented by Jegadeesh and Titman (1993) (Carhart, 1997). Recent studies on mutual fund performance increasingly rely on new datasets and sophisticated econometric approaches to estimate risk-adjusted performance. Some studies document evidence of persistent outperformance by some funds (e.g., Bollen and Busse, 2005; Kosowski, Timmermann, Wermers and White, 2006; Avramov and Wermers, 2006), while others are unable to detect such evidence (e.g., Fama and French, 2010; Barras, Scaillet and Wermers, 2010). Using data on the investment products managed by investment management companies for plan sponsors such as retirement plans, endowments and foundations, Busse, Goyal and Wahal (2010) also find little evidence of superior performance or performance persistence. There seems to be some evidence of superior skills in hedge fund returns (e.g., Kosowski, Naik and Teo, 2007; Fung, Hsieh, Naik and Ramadorai, 2008; Jagannathan, Malakhov and Novikov, 2010). However, studies on hedge fund performance generally suffer from various data biases and the lack of appropriate risk-adjustment models.

The aims of studies examining the holdings and trades of institutional investors have been twofold. First, holdings and trades provide another way to investigate the ability of institutional investors. In fact, recent studies using institutional stock-holdings data seem to support the existence of stock-picking skills. For example, Wermers (2000) finds that stocks held by mutual funds significantly outperform the market. Chen, Jegadeesh and Wermers (2000) show that stocks that mutual funds buy significantly outperform stocks that mutual funds sell. Cremers and Petajisto (2009) find that mutual funds deviating more from benchmark holdings deliver better performance. Second, given the large percentage of shares held by institutional investors, it is important to examine how institutional investors trade, and how their trades impact security prices. Previous studies find that institutional investors have a preference for stocks with certain characteristics (e.g., Falkenstein, 1996; Gompers and Metrick, 2001; Bennett, Sias and Starks, 2003), stocks purchased by other institutions in the same city (Hong, Kubik and Stein, 2005), stocks issued by firms to which the portfolio managers have personal connections (Cohen, Frazzini and Malloy, 2008), and stocks from the home states of the portfolio managers (Pool, Stoffman and Yonker, 2012). Studies also find that institutional investors follow each other's trades into and out of the same stocks and industries, known as herding (Sias, 2004; Choi and Sias, 2008). The relationship between institutional trading and stock returns has attracted even more attention. It has been well documented that institutional trading is positively correlated with contemporaneous stock returns (e.g., Nofsinger and Sias, 1999; Wermers, 1999; Griffin, Harris and Topaloglu, 2003). Several studies report evidence that institutional investors enter stocks after stock prices go up (e.g., Cai and Zheng, 2004; Badrinath and Wahal, 2002). However, Cohen, Gompers and Vuolteenaho (2002) show that institutional investors only enter stocks whose prices go up due to good cash flow news. When stock prices rise without such news, institutional investors sell the stocks. Evidence on the relationship between institutional trading and future stock returns is also mixed. Some studies find that institutional trading positively predicts stock returns (e.g., Nofsinger and Sias, 1999; Wermers, 1999; Gompers and Metrick, 2001), while others find a negative relationship between the two (e.g., Cai and Zheng, 2004).

This thesis contributes to the literature on the performance and trading strategies of institutional investors by investigating three important issues that have received only limited attention. The three issues are examined in Chapter 2, 3 and 4, respectively. Each chapter contains a dedicated introduction, data, empirical results, and conclusion for each issue. Chapter 2 investigates information sharing among delegated portfolio managers through networks created by investment mandates. Previous studies provide considerable evidence that personal networks facilitate information sharing and thus contribute to investment decision making (e.g., Hong, Kubik and Stein, 2004, 2005; Ivković and Weisbenner, 2007; Cohen, Frazzini and Malloy, 2008, 2010). This study focuses on institutional networks that are connected by investment mandates between plan sponsors and their hired investment companies (or sub-advisors), referred to as "mandate networks".[1] This study hypothesizes that mandate networks facilitate information sharing among delegated portfolio managers that are connected. As the actual information flow is unobservable, indirect evidence is provided by examining the similarity in the performance, holdings and trades of investment products managed by investment companies sharing mandate networks. If investment companies in a mandate network have access to a common information pool and use such information in decision making, one would expect that the investment products managed by these investment companies share more similarity in their investments and performance with each other than with those managed by investment companies outside the mandate network. Due to the data availability, this prediction is empirically tested using data on actively managed U.S. equity mutual funds managed by these investment companies.[2] The empirical results suggest that a mutual fund shares more similar returns, holdings and trades with funds managed by investment companies inside its mandate network, than with funds managed by investment companies outside its mandate network. Further, the returns, holdings and trades of a pair of mutual funds that are managed by two different investment companies become more similar after the two companies join the same mandate network than before. There is also preliminary evidence that information about both general investment styles and individual firms is shared within mandate networks. Overall, the evidence is consistent with the notion that networks connected by investment mandates between plan sponsors and their sub-advisors

[1] Throughout this thesis, plan sponsors and sub-advisors refer to institutions, rather than individuals.

[2] The rationale underlying the use of mutual fund data and the resultant implications for the inferences are discussed in detail in Section 2.2.2.

provide new channels for information sharing, which results in a higher level of similarity in the investments and performance of the investment products managed by delegated portfolio managers that share such networks.

Chapter 3 of this thesis explores to what extent institutional investors are engaged in socially responsible investing by examining the trading behavior of a large sample of institutional investors in four emerging market stocks that are targeted by the long-running and cross-country Sudan divestment campaign. This study departs from an event study framework that targets boycott announcement effects and, rather, focuses on the interaction between the changing intensity of the campaign over time and the breadth of institutional ownership, as well as the subsequent stock market outcomes. Specifically, two main hypotheses are tested in this study. First, the intensity of the boycott campaign is negatively related to the breadth of institutional ownership of the targeted stocks, after controlling for factors potentially related to breadth of institutional ownership. Second, after controlling for known predictors of returns, the increased intensity of the boycott campaign exerts selling pressure on the targeted stocks, and leads to depressed stock prices and higher expected returns. The empirical results support both hypotheses. First, there is a negative relationship between the intensity of the campaign and the breadth of institutional ownership. Higher campaign intensity prevents institutional investors from entering the targeted stocks. In the U.S., where the Sudan divestment campaign was initiated, higher campaign intensity also encourages existing holders of the targeted stocks to exit. Second, the intensity of the campaign positively predicts returns of the targeted stocks. The result is consistent with higher campaign intensity exerting higher selling pressure on the targeted stocks, which leads to depressed stock prices and higher future returns. Overall, the findings provide evidence consistent with institutional investors engaging in socially responsible investing, and support the effectiveness of the Sudan divestment campaign.

Chapter 4 of this thesis examines the attribution of mutual fund performance between fund companies and individual fund managers. Specifically, this study focuses on the relative importance of manager skills and fund skills, such as the personnel and resources of the fund company supporting the fund, in determining a fund's results. Previous mutual fund studies implicitly acknowledge that both fund companies and fund managers play a role in determining fund performance. However, to the best of our knowledge, there is no unifying study done yet to reconcile previous empirical findings about the determinants of fund performance, and answer the question "to whom should fund performance be attributed". Examining this question also sheds light on the debate about the portability of fund performance records by individual fund managers in practice. The empirical analysis of this study starts with a fixed effects regression analysis. The results show that, after controlling for time-varying fund and manager characteristics that may affect fund performance, a larger part of the unexplained variation in fund performance can be attributed to manager fixed effects than to fund, company or advisor fixed effects. The evidence is consistent with fund managers being more important than fund companies for fund performance. In the next step, further insights into this comparison are provided using the commonly used skill measure, performance persistence. The empirical results suggest that sole-managed funds exhibit stronger persistence in performance than team-managed funds. As manager skills should be fully exerted in sole-managed funds due to fewer coordination issues or investment restrictions, while fund skills should be better implemented in team-managed funds because of less idiosyncratic discretion of individuals, the evidence is consistent with manager skills playing a more important role than fund skills in driving fund performance. The portability of manager skills across different funds is also examined. The results show that after a fund replaces its manager, the fund's performance is positively correlated with the new manager's past performance at other funds, rather than the fund's own past performance with another manager. The evidence again supports the notion that fund performance is mainly driven by manager skills rather than fund skills. The final step of this study explores whether manager skills have a real effect on the investment decisions of investors. However, only modest evidence is documented that manager skills are appreciated by investors.

Finally, Chapter 5 concludes this thesis.

Chapter 2

Information Sharing within the Networks of Delegated Portfolio Managers: Evidence from Plan Sponsors and Their Sub-Advisors

2.1. Introduction

A growing literature indicates that personal networks, whether formal ones connected by business ties or informal ones due to social ties, facilitate information sharing and thus contribute to investment decision making. Communications within networks could convey valuable information which serves as an important input in the decision making process of relevant economic agents including corporate managers, financial analysts and professional investors. This chapter provides evidence on information sharing within the networks of delegated portfolio managers. Specifically, we identify a specific type of networks of delegated portfolio managers connected by investment mandates between plan sponsors and their hired investment companies (their sub-advisors), and study the influence of such networks on the similarity in investments and returns of connected sub-advisors.

A network is a structure consisting of a set of nodes, such as individuals or institutions, that are connected by various ties such as formal business ties or informal social ties. A prominent feature of human society is that people constantly communicate with each other through their personal networks. Despite the tenets of traditional finance theory that a stock's ownership should not affect its returns and risk, whether correlated ownership and trading have short-term and long-term effects on stock performance is a question of increasing popularity among researchers. There is now considerable evidence that communications within networks facilitate information transmission and affect investment decision making and asset returns (e.g., Hong, Kubik and Stein, 2004, 2005; Ivković and Weisbenner, 2007; Cohen, Frazzini and Malloy, 2008, 2010).

This chapter focuses on information sharing among networks of delegated portfolio managers created by investment mandates between plan sponsors and their sub-advisors (referred to as "mandate networks" hereafter).[3] Institutional plan sponsors, such as public and corporate pension plans, endowments, foundations, and some fund organizations, routinely outsource large pools of assets to professional investment companies. The asset class, investment style and specific dollar amount of the outsourced assets are formalized by investment mandates. We hypothesize that the mandate networks facilitate information sharing among delegated portfolio managers connected by these networks. There is anecdotal evidence that plan sponsors could obtain investment-related information from their sub-advisors. A perusal of representative Requests for Proposals (RFPs) released by large public plan sponsors shows that such information exchange could take place via several channels.[4] One channel is through monthly reports from the sub-advisors. These reports commonly summarize portfolio-specific metrics such as investment performance, portfolio characteristics, top holdings and major transactions, and sometimes even the future market and economic outlook.[5] Many plan sponsors also request additional reports

[3] Throughout this chapter, plan sponsors and sub-advisors refer to institutions, rather than individuals.

[4] Once a plan sponsor has decided the amount and asset class of an investment mandate, it puts out a request for proposals (RFP) and the search for investment companies begins. The RFP usually introduces the plan sponsor and the specific mandate, and also specifies the services to be provided by the hired investment company and the minimum qualifications of the hired investment company.

[5] For example, the Chicago Teachers' Pension Fund (CTPF) requested their hired investment companies "to report to the Board monthly, in writing on the composition and relative performance of the investments in the designated portfolio; the economic and investment outlook for the near and long term; significant changes in the portfolio during the month; and the reasons for any significant differences between the performance of the portfolio and the appropriate market indices or other performance benchmarks established by CTPF and the investment manager". A similar case is presented in the RFPs by the Teachers' Retirement System of Louisiana. Please refer to Part 3 of the RFP by the Chicago Teachers' Pension Fund and Appendix B (I) of the RFP by the Teachers' Retirement System of Louisiana. Available from: https://www.callan.com/about/rfp/ctpf/em_market/Emerging%20Markets%20CTPF%20rfp%20draft%203-13-12.pdf and http://trsl.org/uploads/File/SFPs/SFP_Mid%20Cap%20Growth%202013.pdf (accessed on August 5, 2013).

and face-to-face meetings when necessary. Another channel is to request advice on various investment-related issues from the sub-advisors.[6] Further, some plan sponsors even request their sub-advisors to train their internal investment staff.[7] Through all these channels, valuable investment information could be exchanged between the sub-advisors and plan sponsors. A rational plan sponsor would naturally pass such information to its other hired investment companies in the hope of improving investment performance. Similarly, a rational investment company would also use such information for all its investment decisions as long as it is valuable and relevant. As such, a plan sponsor could act as an information hub for its network of sub-advisors.

The information shared within mandate networks could be value relevant and have an economically significant effect on investment decisions of sub-advisors. There are good reasons to suspect that sub-advisors may be unwilling to share highly valuable investment information with their plan sponsors, and thus, when they act as information recipients, they may not apply the information obtained from plan sponsors seriously in their

[6] For example, the California Public Employees' Retirement System (CalPERS) requested their hired investment companies to "provide advice on market conditions, including positive and/or negative trends and various security-related issues". The New Mexico State Investment Council (SIC) specified in their RFP that their hired investment companies should "advise the SIC and appropriate staff on equity-related issues" and "advise the SIC when specific segments of the equity markets are particularly attractive and be willing to manage an opportunistic portfolio in those segments for the SIC as part of this RFP". Please refer to section III of the RFP by the California Public Employees' Retirement System and section V of the RFP by the New Mexico State Investment Council. Available from: http://www.calpers.ca.gov/eip-docs/business/opportunities/2005-3865/rfp-2005-3865.pdf and http://www.sic.state.nm.us/PDF%20files/20111107%20RFP%2012-0020%20Large-Cap%20Domestic%20Equity.pdf (accessed on August 5, 2013).

[7] For example, the Firefighters' Retirement System of Louisiana specified in their RFP that the hired investment company should "provide on-going education to trustees and staff if requested". The University of Kentucky Endowment also requests that "the successful Contractor(s) will also be required to provide educational and ongoing advisory services to Investment Committee members and investment staff". Please refer to section B of the RFP by the Firefighters' Retirement System of Louisiana and section 7.1 of the RFP by the University of Kentucky Endowment. Available from: http://www.lafirefightersret.com/pdf/RFPRiskParity080613.docx (accessed on August 5, 2013). The second RFP is no longer available online. The document is available on request.

investment decisions. However, there are also reasons to believe that sub-advisors might do so. They may share valuable information with their plan sponsors, especially large ones, to retain them as clients. There is also evidence from both the academic literature and the popular financial press that some investment managers do share sensitive information from time to time with each other. For example, Hong, Kubik and Stein (2005) show that mutual funds in the same city tend to buy (or sell) the stock of a particular firm together even when the funds and the firm are located far apart. The authors interpret the results as evidence of investors spreading information about stocks to one another by word of mouth. Further, a *Wall Street Journal* article by Strasburg and Pulliam (2011) points out that "Many hedge-fund managers freely share investment ideas with one another. … Fund managers, traders and hedge-fund chiefs exchange ideas through instant messages, emails and private chats". The authors also note that after gatherings of portfolio managers, some portfolio managers would purchase a specific stock because other attendees owned it. As the mandate relationship is a formal business relationship, it is probable that plan sponsors and their sub-advisors exchange ideas from time to time, and these ideas might contain valuable investment information. This chapter is an empirical test of these conjectures.

Since the actual information flow within the mandate networks is unobservable, we make indirect inferences about information sharing from similarities in investment products managed by investment companies sharing mandate networks. If investment companies in a mandate network have access to a common information pool and use such information in making investment decisions, it is likely that they share more similarity in their investments and performance with the network members than with non-members.

To empirically test this hypothesis, we first obtain data on investment mandates between plan sponsors and their sub-advisors from the iiSEARCHES database created by

Institutional Investor Publications, based on which we identify mandate networks of these investment companies connected via plan sponsors. The information sharing mechanism proposed above suggests that information shared within networks could affect the investment decisions of any asset class within a hired investment company, to the extent that the information is value relevant for that asset class. However, due to the data availability, we focus only on the actively managed U.S. equity mutual funds managed by these hired investment companies whose returns and holdings data are available in the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database and the CDA Spectrum Mutual Fund Holdings Database.[8] We discuss the rationale underlying the use of mutual fund data and the resultant implications for our inferences in detail when describing the mutual fund data in Section 2.2.2. To be consistent, we also include only mandates invested in the U.S. equity market in the analyses. The final sample includes 360 plan sponsors, 112 investment companies, and more than 1,300 unique U.S. equity funds managed by these companies over the period 1995-2010.

We then explore the commonality in returns, asset holdings and asset trading between mutual funds to infer correlated information flow. Commonality in returns of a pair of funds is measured by the correlation coefficient of two funds' returns. To measure commonality in the holdings and trading of individual stocks by pairs of mutual funds, we follow the method of Elton, Gruber and Green (2007). First, for each stock, we calculate its weights in the pair's portfolios, and take the minimum of the two weights as the

[8] Most plan sponsors, such as public and corporate pension plans, endowments and foundations, normally do not manage mutual funds. In the final sample, there are 4 plan sponsors that manage equity mutual funds. Thus, we focus only on mutual funds managed by the hired investment companies for the analyses and only use plan sponsor information to identify mandate networks.

common holding on the stock. Second, we aggregate the common holdings of all stocks in the funds' portfolios to obtain the overall commonality in holdings between the funds. The commonality in quarterly trading between two funds is identified in a similar way, requiring overlapping trading by the funds on the same stock in the same direction. We provide more details of this procedure in Section 2.3.2. Complementing the return correlation analysis, the examination of commonality in holdings and trading of assets between pairs of funds helps shed light on specific types of information, for example, investment style-related information versus firm-specific information, transferred within mandate networks. With that aim, we extend the above method to identify commonality in holdings and trading of style portfolios. Specifically, we classify stocks into 125 styles based on market capitalization, book-to-market equity ratio, and the intermediate-term past return according to the methodology of Daniel, Grinblatt, Titman and Wermers (1997). We then calculate individual mutual funds' holdings and trading of a style portfolio by aggregating the holdings and trading of component stocks in that style portfolio. Finally, we calculate the commonality in holdings and trading of style portfolios in the same way as for individual stocks.

We find supporting evidence for our hypothesis. First, a mutual fund on average has a higher correlation in returns with another fund managed by an investment company inside its mandate network, than with a fund managed by a company outside its mandate network. Second, a mutual fund tends to hold and trade both individual stocks and style portfolios more in common with another fund when the management companies of the two funds share a mandate network. Both findings are consistent with funds inside a mandate network utilizing more correlated information flows for their investment decisions than those not sharing a mandate network.

However, the inside-network versus outside-network comparison could be contaminated by the endogenous choice of plan sponsors and investment companies in the mandate contracting process. For example, it is possible that funds in a mandate network tend to be alike due to similarities in the selection criteria of the plan sponsors, which could bias for finding commonality between the funds. On the other hand, it is also possible that plan sponsors may deliberately select as dissimilar investment companies as possible within their strategic constraints for diversification benefits, which could bias against finding commonality between funds sharing a mandate network. To address the potential endogeneity issue, we further compare the similarity in returns, holdings and trading of the same pair of funds before and after they were connected by investment mandates, and find evidence consistent with mandate networks facilitating information sharing among network members. Specifically, a pair of mutual funds managed by two different investment companies tends to have more correlated returns after the two companies join the same mandate network than before. Similarly, the commonality in holdings and trading between two funds also increases after their management companies join the same mandate network. Overall, our findings based on both return correlation and commonality in holdings and trading of assets are consistent with the hypothesis that delegated portfolio managers share information within mandate networks and use the information in their investment decisions, generating correlated investments and returns.

Our work is closely related to recent developments in the finance literature on the role of networks and connections in the financial decision making of individuals and institutions. For example, Hong, Kubik and Stein (2004) find that individual investors are more likely to invest in the stock market when they socialize with people participating in the stock market. Similarly, Ivković and Weisbenner (2007) show that individual investors are more likely to purchase stocks from an industry if their neighbors do so. Similar network effects are found in mutual funds' investment decisions. Hong, Kubik and Stein (2005) document that mutual funds headquartered in the same city tend to buy (or sell) a particular stock together. Cohen, Frazzini and Malloy (2008) show that fund managers prefer to invest in firms with board members who are in their education networks and achieve superior performance on such bets. In a related study, Cohen, Frazzini and Malloy (2010) also find evidence that analysts obtain superior access to information through their connection with executives of firms sharing their education networks. We identify a specific type of network connected by investment mandates, and find evidence that such networks facilitate information transmission, which leads to stronger commonality in investment and performance of investment companies sharing a mandate network.

This study also contributes to a growing literature that examines the increasingly popular practice of outsourcing of investment mandates by plan sponsors. According to a recent survey by Pensions & Investments (2013), about US$955 billion has been outsourced globally as of March 2013. Existing studies focus mainly on the cost-benefit analysis of outsourcing assets by plan sponsors (e.g., Dyck and Pomorski, 2011; Blake, Rossi, Timmermann, Tonks and Wermers, 2013), the investment company hiring and firing process (e.g., Parwada and Faff, 2005; Heisler, Knittel, Neumann and Stewart, 2007; Goyal and Wahal, 2008), and the agency issues in the management of outsourced assets by the hired investment companies (e.g., Duong, 2010; Chuprinin, Massa and Schumacher, 2011; Chen, Hong, Jiang and Kubik, 2013). Rather than focusing only on the two parties involved in an investment mandate, this study explores the effect of information transmission among investment companies connected via their investment mandates with the same plan sponsor. The findings suggest a potential reduction in diversification benefit for plan sponsors, especially large and powerful ones, due to the information sharing within mandate networks and the consequently increasing commonality in investments by the sub-advisors.[9] The results should capture the attention of practitioners who, according to a Bank for International Settlements (BIS) (2003) survey, report that investment mandates are increasingly stringent, with little scope for external managers of the outsourced assets to take advantage of opportunities outside their mandates, a phenomenon modelled formally by He and Xiong (2013). We argue that increased correlations in holdings and trading among investment companies linked by mandate networks exacerbate this problem.

The findings of this study also have implications for the debate on the increasing similarity among delegated portfolio managers and the consequently elevated comovement of asset returns. With the increasing amount of assets being outsourced over time, the information sharing mechanism studied in this chapter could also contribute to herding and increasing similarity across investment managers in general.[10] Given the importance of those investment companies gaining mandates, the information sharing and thus similarity in investment decisions among them could also have an asset pricing implication – the increased comovement of asset returns and systematic risks.[11]

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[9] For a sample of 56 public defined-benefit plans covered by both the mandate database and the annual performance data made available by the Center for Retirement Research at Boston College, we find that higher commonality in asset holdings among investment companies hired by a plan sponsor is associated with increased volatility in the plan's investment returns. However, the reliability of the finding and the causality inference is an issue due to the very small sample size and weak power of the test.

[10] The amount of outsourced assets grew spectacularly over time. According to the two surveys conducted by Pensions & Investments in 2011 and 2013, the sector grew by 59% over the two-year period, from $586 billion to $955 billion. We find a similar trend of increasing commonality in mutual funds' returns over time – the average R-squared of a time-series regression of fund returns on Fama-French three-factors (market excess return, small minus big size return, and high minus low book-to-market return) and Carhart's momentum factor increased from about 0.83 in 1995 to more than 0.95 in 2010 for all actively managed U.S. equity funds in our mutual fund sample.

[11] The correlated trading and its effect on return comovement attract attention from both academics and practitioners. For example, in a recent *Financial Analysts Journal* article, Greenwood and Sosner (2007) examine the excessive correlated trading and return comovement around the redefinition of Nikkei 255 index. It is also speculated that the significant losses of some high-profile and highly successful quantitative long/short

The chapter proceeds as follows. Section 2.2 describes the data and sample construction. Section 2.3 presents methodology and empirical results. Finally Section 2.4 concludes.

2.2. Data and Sample

2.2.1. Data on Investment Mandates

We obtain data on investment mandates between plan sponsors and their sub-advisors from the iiSEARCHES database created by Institutional Investor Publications. The database provides detailed information for more than 50,000 mandate records since 1995.[12] For each mandate, iiSEARCHES records the type of the mandate, the hiring/firing date, the name, type and key contacts of the plan sponsor, the name and key contacts of the hired/fired investment company, the name of the consultant if used, and other mandate characteristics such as dollar amount and asset class. However, iiSEARCHES does not contain information about the actual person managing the delegated assets or the investment product in which the delegated assets are managed.

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equity hedge funds during the week of August 6, 2007 were caused by similarity in portfolio holdings of the sector and the liquidation series triggered by the fire-sale of only one or few funds (Khandani and Lo, 2011).

[12] The mandate records fall into four categories: Potential, New, Completed, and Discontinued. A potential mandate is an expression of intent that a plan sponsor might award a mandate in the future. A new mandate is created when there is an outstanding Request for Proposal. A completed mandate is a confirmed hiring decision of specific investment companies. The hiring decision can take one of the following three forms: 1) a new hiring, in which a new company is hired without replacing any existing company; 2) a rehiring, in which a new asset allocation is awarded to an existing company and no existing company is replaced; or 3) a replacement, in which a newly hired company or another current company replaces an existing company and takes over its asset allocation. A discontinued mandate can also involve one of the following three situations. First, the selection process for a potential new company is completed but no mandate is awarded. Second, an existing investment company is fired but no new company is hired. Third, part of the asset allocated to an existing company is withdrawn but no new company is hired to take over the withdrawn asset allocation.

The empirical analysis requires identifying connected investment companies managing assets for the same plan sponsor at a given point of time. Ideally we want to track the life of an investment mandate from hiring to termination date if applicable. However, although the iiSEARCHES database records the termination of investment companies, the termination data are sparse and there is no reliable way to identify the date for a termination decision. As a result, we include in this study only completed mandates which identify hiring decisions. We assume that an investment mandate is in effect for a period of three years, starting from the hiring date. We discuss the rationale underlying this assumption and how it may influence our inferences in detail when we describe our identification of mandate networks in Section 2.2.3.

The iiSEARCHES database includes mandates allocated by plan sponsors from all over the world. The targeted market can be a single country or globally oriented. The asset classes include traditional investments, such as public equity, fixed-income security and real estate, and alternative investments, such as private equity, commodities and hedge funds. In this study, we focus on mandates allocated by U.S. plan sponsors and invested in the U.S. equity market, for which the data on returns and holdings of the hired investment companies, more specifically, the mutual funds managed by these investment companies, are commonly available. This selection criterion results in a sample of 8,005 hiring decisions made by 2,911 plan sponsors for a total of 7,301 investment mandates between 1995 and 2010.[13] Panel A of Table 2.1 provides summary statistics about the plan sponsors

[13] It is possible that multiple investment managers are hired under one investment mandate, and thus the total number of hiring decisions is larger than that of investment mandates. Some plan sponsors have missing values for assets under management. Similarly, some investment mandates have missing values for the size of mandated assets. As such, the number of plan sponsors and investment mandates reported here differs from Table 2.1 which counts only the plan sponsors and investment mandates with non-missing assets. However,

and the investment mandates. The total assets under management for these plan sponsors sum to about US$9.91 trillion, and the assets allocated under the covered investment mandates sum to about US$685 billion, outsourced to 977 investment companies. Public pension plans offer the most mandates, representing about 47% of the hiring decisions. They are also the most important players in terms of the size of outsourced assets, contributing about 63% to all assets allocated to investment mandates. Other important types of plan sponsors include manager of managers, corporate pension plans, endowments and foundations, and union pension plans, with decreasing importance in terms of the total assets outsourced.

we do not exclude those plan sponsors and investment mandates with missing assets from the sample because they are used only for the identification of mandate networks.

Table 2.1 Summary Statistics for Plan Sponsors and Investment Mandates

This table reports summary statistics for plan sponsors and investment mandates over the period 1995-2010. Panel A reports summary statistics for all investment mandates allocated by U.S. plan sponsors and invested in the U.S. equity market. Panel B reports summary statistics for investment mandates that are included in the final sample. Plan sponsors are grouped into six types: "Manager of Managers" refers to professional investment managers that hire other professional investment managers to oversee some or all of a client's assets. "Others" include Banks, Health Plans, Hospital Plans, Insurances, Money Purchase Plans, Non-Profit Organizations, Nuclear Decommissioning Trusts, Operating Funds, Trust Funds, and 529 Plans.

Panel A: Summary statistics for all investment mandates

	Number of	Plan Sponsor Size ($M)			Mandate Size ($M)		
Plan Sponsor Type	Hiring Decisions	Mean	Median	N	Mean	Median	N
Corporate Pensions	1,829	1,442	280	917	64	23	1,011
Endowments & Foundations	1,144	1,016	180	532	29	12	935
Manager of Managers	309	48,146	9,500	81	786	90	149
Public Pensions	3,753	5,470	312	667	159	40	2,729
Union Pensions	633	768	215	335	46	17	560
Others	337	1,671	200	145	54	20	274
All	8,005	3,702	260	2,677	121	25	5,658

Panel B: Summary statistics for sample investment mandates

	Number of	Plan Sponsor Size ($M)			Mandate Size ($M)		
Plan Sponsor Type	Hiring Decisions	Mean	Median	N	Mean	Median	N
Corporate Pensions	290	1,514	354	108	60	30	99
Endowments & Foundations	108	1,301	260	41	54	15	82
Manager of Managers	52	39,194	26,500	12	533	275	13
Public Pensions	631	13,562	1,900	155	271	100	493
Union Pensions	53	1,437	620	22	57	36	42
Others	44	7,355	685	12	117	40	34
All	1,178	8,312	800	350	206	61	763

2.2.2. Data on Mutual Funds

We use the investment and performance data of mutual funds managed by investment companies hired under mandates for our tests. We start with the sample of mutual funds in the CRSP Survivorship Bias Free Mutual Fund Database and the CDA Spectrum Mutual Fund Holdings Database. From the CRSP Database, we obtain information on fund returns, total net assets, investment objectives, expense ratios, turnover ratios and other fund characteristics. From the CDA Spectrum Database, we obtain information on fund holdings, fund management companies, and investment objectives. We merge the two databases using the linking information in the Mutual Fund Links (MFLINKS) dataset obtained from Wharton Research Data Services (WRDS). For funds with different share classes but sharing the same portfolio of holdings, we eliminate all classes but the one with the largest average total net assets. We restrict our analysis to actively managed U.S. equity funds. For details of our fund sample selection process, see Appendix 2.1.

We include all the actively managed U.S. equity mutual funds of a sub-advisor in our empirical analyses based on both the hypothesized information sharing mechanism and data availability. First, we hypothesize that a plan sponsor would serve as an information hub in its mandate network, soliciting information from each of its hired investment companies and sharing such information with other network members so as to improve the performance of outsourced assets. We further hypothesize that a hired investment company would naturally use the shared information for all its investments as long as it is value relevant. The previous literature provides some support for the close interaction and the use of common information within an investment company. For example, Evans and Fahlenbrach (2012) show that there are no significant differences in the factor loadings on the market, size and value factor across retail mutual funds and their institutional twins (i.e., separate accounts and institutional mutual funds) managed by the same individual fund manager(s). The authors further find that the after-expense performance of retail and institutional twins are quite similar. Further, Elton, Gruber and Green (2007) show that mutual funds managed by the same fund management company share more correlated returns, which is primarily due to common stock holdings.

Second, it would be ideal to have the data on all investments managed by the hired investment companies to test the hypothesized information sharing mechanism. In particular, we would expect the information shared through the plan sponsors to be most relevant for the assets covered by mandates. However, we only have access to data on the performance and investment details of mutual funds managed by these investment companies. It is also natural to expect the shared information to be more relevant for investment products with the same investment styles as the mandated assets, and thus we could have sharpened our inferences by focusing on these investments. Though theoretically appealing, such a requirement would achieve very few matches, significantly reducing the number of observations and the statistical power of tests. Further, to test the sharing of information relevant only to the mandated assets or investments of similar styles, we would need to examine pairs of hired investment companies with mandates of similar styles with the same plan sponsor, which is absent from the data. With all these data limitations, the existing identification strategy – conducting tests based on all mutual funds managed by hired investment companies – biases against finding evidence for information sharing. It is reasonable to believe that the effect documented using all mutual funds managed by hired investment companies only provides a lower-bound estimate for the full effect of information sharing within mandate networks.

2.2.3. Identification of Mandate Networks and Final Sample Construction

A. Identification of Mandate Networks

With the information sharing model discussed in the introduction section in mind, we identify mandate networks 'coordinated' by plan sponsors. Specifically, for each plan sponsor, we define its mandate network as including the plan sponsor itself and all its hired investment companies. It is worth noting that some large investment companies, such as Fidelity, usually work for multiple plan sponsors at the same time. In this instance, these sub-advisors belong to multiple mandate networks and are assumed to participate in information sharing in each of them.

The identification of mandate networks ideally requires knowledge of the life span of an investment mandate – the starting and terminating dates of the mandate. However, as discussed in the description of mandate data above, the information on mandate terminations in the iiSEARCHES database is very sparse. As such, following Goyal and Wahal (2008), we adopt a rule of thumb, assuming that an investment mandate is in effect for the three-year period starting from the hiring date.[14] In other words, at a specific point of time T, two investment companies are deemed to share a mandate network only if they both start an investment mandate with a same plan sponsor in the three-year period preceding time T. However, for a given investment company M, when we try to identify its non-connected investment companies at time T, we exclude those companies that had managed assets for the plan sponsor before, including times dated more than three years

[14] The assumption of a three-year effective period for an investment mandate may appear arbitrary. However, based on the 176 hiring decisions for which we could obtain terminating dates, the mean (median) effective period is 4.7 (4.5) years. Thus, this assumption seems to be conservative.

before time T, in case the previously awarded mandates might be still in effect at time T. Assuming a fixed effective period for mandates potentially introduces two types of noise in identifying network connections: first, some actual connections via investment mandates lasting for more than three years may be excluded from the sample of identified connections, which reduces the sample size; and second a pair of companies may be mistakenly identified as connected at a specific point of time T in the sample because both of them started an investment mandate with a same plan sponsor in the past three years, but one or both of the mandates were terminated before time T. Our tests focus on the difference between connected managers and non-connected managers. Both types of noise should reduce the power of our tests and work against finding a significant difference.

B. Construction of the Final Sample

Following our identification rule, we first create panel data on connected investment companies. In each period, we identify all pairs of investment companies sharing mandate networks. For each pair of investment companies, we create time series for periods when they share mandate networks. Next, we obtain the data of mutual funds managed by these companies in the connection panel data.[15] This process results in some loss of observations on connected companies and the related investment mandates for two reasons. First, some hired investment companies, for example, hedge fund companies, do not manage any mutual fund. Second, we use pairs of funds managed by two different companies in a mandate network for our tests, which requires a minimum of two hired companies with

[15] We match the investment companies in the panel data with the fund management companies in the mutual fund data by company names. For each investment company, we first apply an algorithm to find a small list of fund management companies with close names, and then manually check each matched pair to pick up correct matches.

mutual fund data for a mandate network. After these screens, we are left with 1,178 hiring decisions made under 1,108 investment mandates, involving over US$157 billion delegated by 360 plan sponsors to 112 investment companies.[16]

Panel B of Table 2.1 reports some key statistics about the plan sponsors and investment mandates included in the final sample. The statistics are comparable with those for all U.S. equity mandates reported in Panel A of Table 2.1. Public pension plans still contribute most to the final sample, in terms of both the frequency of hiring decisions (54%) and the outsourced assets (85%).

Finally, for all hiring decisions in the final sample, we obtain data on mutual funds managed by the sub-advisors over the three-year post-hiring period. We present the summary statistics of fund data in Table 2.2. The mutual fund sample includes 1,303 distinct funds. The mutual funds in the sample have an average total net asset value of about US$2 billion, and an average monthly return of 0.5%. The average expense ratio and turnover ratio are 1.07% and 77.38%, respectively. The last three rows of Table 2.2 report holdings-based style characteristics. Following Daniel, Grinblatt, Titman and Wermers (1997), in each month t, we group all CRSP stocks into quintiles according to their market capitalization at the end of month t-1, book-to-market equity ratio at the end of month t-1, where the fiscal year end for the book equity precedes the end of month t-1 by at least 5 months, and cumulative return over the period month t-12 to month t-2, and assign a score 1 for the lowest quintile and 5 for the highest quintile. Then for each fund month, we

[16] Again, the total numbers of plan sponsors and investment mandates included in the final sample are different from the numbers presented in Panel B of Table 2.1 because of missing values for plan sponsor size and mandate size.

calculate the value-weighted size, value, and momentum scores across all stocks in the fund's portfolio. As shown in the table, mutual funds in the sample tend to hold mainly large stocks (average size score = 4.74), slightly more of growth stocks (average value score = 2.01), and relatively more of past winners (average momentum score = 3.38).

Table 2.2 Summary Statistics for Mutual Funds

This table presents summary statistics for mutual fund data. The last three rows report holding-based style characteristics. Following Daniel, Grinblatt, Titman and Wermers (1997), in each month t, we group all CRSP stocks into quintiles according to their market capitalization at the end of month t-1, book-to-market equity ratio at the end of month t-1, where the fiscal year end for the book equity precedes the end of month t-1 by at least 5 months, and cumulative return over the period month t-12 to month t-2, and assign a score 1 for the lowest quintile and 5 for the highest quintile. Then for each fund each month, we calculate the value-weighted size, value, and momentum scores across all stocks in the fund's portfolio.

	Mean	Median	Standard Deviation
Number of Distinct Funds	1,303		
Number of Fund-Months	54,280		
Monthly Total Net Assets (TNA) ($M)	1,935	244	6,091
Monthly Return (%)	0.50	0.87	4.91
Expense Ratio (%)	1.07	0.98	1.30
Turnover Ratio (%)	77.38	57.10	88.56
Size Score	4.74	4.90	0.47
Value Score	2.01	1.98	0.49
Momentum Score	3.38	3.34	0.57

2.3. Empirical Analysis

2.3.1. Methodology

We measure information sharing within mandate networks by comparing the commonalities in returns, holdings and trading between funds. In the first test, we compare commonalities between pairs of funds, managed by different investment companies, in a common mandate network and those between pairs of funds not sharing any mandate network. Following the logic discussed in Section 2.2.3.A, for two funds at a specific point of time, we identify the pair as sharing a mandate network if they both entered into an investment mandate with an outsourcing plan sponsor in the preceding three-year period, and as not sharing any mandate network if they had never worked for the same plan sponsor before. We hypothesize that a fund would share more commonalities in returns, holdings and trading with another fund in its network than with one outside its network.

However, such inside-network versus outside-network comparison could be contaminated by the endogenous choice of plan sponsors and investment companies in the mandate contracting process. For example, it is possible that funds in a mandate network tend to be more similar due to similar selection criteria applied by the plan sponsor, which could bias the analysis towards finding commonality between funds sharing a mandate network. On the other hand, it is also possible that plan sponsors may select as differentiated investment companies as possible within their strategic constraints for diversification purposes, which could bias against finding commonality between funds sharing a mandate network. To address this potential endogeneity issue, we further adopt an event time framework and compare the similarity in returns, holdings and trading of the same pair of funds before and after they were connected by investment mandates. For a pair of funds ever sharing a mandate network, we identify the post-joining period as all overlapped mandate-effective windows for their mandates contracted with a same plan sponsor, where we similarly assume a three-year mandate-effective period following the commencement date of the mandate contract. For the pre-joining period, we use the three-year period prior to the time when the pair of funds first shared a mandate network. We hypothesize that the commonalities in returns, holdings and trading would be higher after they shared common networks.

2.3.2. Comparison of Commonality of Connected Funds versus Unconnected Funds

A. Commonality in Fund Returns

We follow Elton, Gruber and Green (2007) to measure commonality in returns. For each fund, we first calculate its correlations in returns with all funds managed by a different investment company, and then obtain the average correlations for mandate-connected (Inside Network) and non-connected pairs (Outside Network) separately.[17] Panel A of Table 2.3 presents the summary statistics of fund-level return correlations and the comparison of inside-network versus outside-network correlations.[18] The standard errors are clustered by investment companies to account for the intra-family correlations.

[17] We conduct the tests about return correlations using net fund returns. Theoretically, gross fund returns should be the performance variable to examine. However, we report the results based on net fund returns due to two considerations: first, occasionally expense ratios are missing in the data, which causes unnecessary loss of observations; second, the results are similar whether using gross or net fund returns. The results using gross fund returns are available on request.

[18] We require at least 12 monthly observations to calculate pair-wise correlations. To mitigate the impact of outliers, we winsorize both the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. The winsorization of variables only improves the statistical significance of estimated coefficients, but does not change the sign or the magnitude of the coefficients qualitatively. Results without winsorization are available upon request.

Table 2.3 Comparison of Similarity Inside versus Outside Mandate Networks

This table presents comparisons of return correlations, common holdings and common trading for pairs of funds inside versus outside mandate networks. Following Elton, Gruber and Green (2007), for each fund, we first calculate its correlations in returns with all funds managed by a different investment company, and then obtain the average correlations for inside-network and outside-network funds separately. We require at least 12 monthly observations to calculate pair-wise correlations. Risk-free excess return is calculated as the fund return in excess of the 1-month T-bill rate. Style excess return is calculated as the fund return in excess of the value-weighted average return of funds in the respective investment style group. Risk-adjusted return is calculated by subtracting from the fund return the expected return due to the exposures to Fama-French three-factors and Carhart's momentum factor. We follow Elton, Gruber and Green (2007) to measure common holdings between a pair of funds *i* and *j* at time *t* in the following way:

$$Common\ Holdings\ (F_{it}, F_{jt}) = \sum_{k=1}^{N} min(H_{it}^{k}, H_{jt}^{k}),$$

where H_{it}^{k} and H_{jt}^{k} are the fractions of asset k in the portfolios of funds i and j at time t respectively, and N is the total number of assets commonly held by both funds. We measure common trading between a pair of funds *i* and *j* in a similar way:

$$Common\ Trading\ (F_{it}, F_{jt}) = \sum_{k=1}^{N} max(0, TSign_{it}^{k} * TSign_{jt}^{k}) * min(T_{it}^{k}, T_{jt}^{k}),$$

where $TSign_{it}^{k}$ and $TSign_{jt}^{k}$ are the indicators for trading direction, +1 for buying and -1 for selling, in asset k by funds i and j between time t-1 and t respectively, T_{it}^{k} and T_{jt}^{k} are the fractions of asset k's turnover in the total turnovers of funds i and j between time t-1 and t respectively, and N is the total number of assets commonly traded by both funds. For each fund, we first calculate its common holdings (trading) at the end of each quarter with all funds managed by a different investment manager, and then calculate the average common holdings (trading) for any pair of this fund and another fund from the time-series data. We further average the pair-wise common holdings (trading) to obtain the inside- and outside-network common holdings (trading) for each fund separately. To mitigate the impact of outliers, we winsorize the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. We also winsorize the quarterly common holdings (trading) and the fund-level average common holdings (trading) at the 95th percentile values. The standard errors (in parentheses) are clustered by investment companies to account for the intra-family correlations. ***, ** and * indicate 1%, 5% and 10% statistical significance levels respectively.

	N	Inside Network (I)	Outside Network (O)	Difference (I-O)
Panel A: Return correlations				
Risk-Free Excess Return	336	0.863	0.848	0.015***
		(0.006)	(0.005)	(0.004)
Style Excess Return	336	0.033	0.017	0.016**
		(0.008)	(0.004)	(0.008)
Risk-Adjusted Return	331	0.098	0.062	0.036***
		(0.009)	(0.004)	(0.007)
Panel B: Common holdings				
Common Stock Holdings (%)	418	13.9	12.8	1.1***
		(0.007)	(0.006)	(0.004)
Common Style Holdings (%)	418	47.5	45.2	2.3***
		(0.012)	(0.011)	(0.006)
Panel C: Common trading				
Common Stock Trading (%)	388	3.4	3.0	0.4***
		(0.001)	(0.001)	(0.001)
Common Style Trading (%)	388	9.7	9.2	0.5***
		(0.002)	(0.001)	(0.002)

We first measure commonality in risk-free excess return, calculated as the fund return in excess of the 1-month T-bill rate. As can be seen in the first row of Panel A in Table 2.3, the average correlation between two funds is 0.863 if they share mandate networks and 0.848 if they do not. The difference between inside-network and outside-network correlations is 0.015, which is statistically significant at the 1% level according to a simple difference in means *t*-test. While such a difference may seem small relative to the level of average return correlations, the narrow magnitude is mainly because most mutual funds benchmark to a specific investment style and deviate slightly from the targeted investment style for their investments.

To show this effect, we further examine commonality in two alternative return measures – style-excess return and risk-adjusted return. We calculate style-excess return as the fund return in excess of the value-weighted average return of funds in the respective investment style group. As described in Appendix 2.1, we classify funds into seven investment styles according to their investment objective codes: Aggressive Growth, Growth, Growth & Income, Income, Value, Core and Balanced. As presented in the second row of Panel A in Table 2.3, two funds inside a mandate network have an average correlation of 0.033, while two funds from separate mandate networks have an average correlation of only 0.017. The difference in correlations is not only statistically significant, but also economically significant compared with the level of return correlations.

The results are qualitatively similar when we examine the commonality in risk-adjusted returns. We subtract the fund returns by the expected returns due to the exposures to Fama-French three-factors and Carhart's momentum factor (Fama and French, 1993; Carhart, 1997),

$$\alpha_{it} = \left(R_{it} - R_{ft}\right) - (\hat{\beta}_{it,1} * MKTRF_t + \hat{\beta}_{it,2} * SMB_t + \hat{\beta}_{it,3} * HML_t + \hat{\beta}_{it,4} * UMD_t) \quad (2.1),$$

where R_{it} is the return of fund i in month t, R_{ft} is the risk-free return in month t, and $\hat{\beta}_{it1}$ - $\hat{\beta}_{it4}$ are factor loadings estimated over month t-37 to month t-2, requiring a minimum of 24 observations. As shown in the third row of Panel A in Table 2.3, the average inside-network correlation is 0.098, which is significantly higher than the average outside-network correlation.

B. Commonality in Holdings and Trading

In this section, we provide more direct evidence about investment decisions based on funds' holdings and trading. We follow Elton, Gruber and Green (2007) to measure commonality in holdings between a pair of funds i and j:

$$Common\ Holdings\ (F_{it}, F_{jt}) = \sum_{k=1}^{N} min(H_{it}^{k}, H_{jt}^{k}) \qquad (2.2),$$

where H_{it}^{k} and H_{jt}^{k} are the fractions of asset k in the portfolios of funds i and j at time t respectively, and N is the total number of assets commonly held by both funds. We measure the commonality in trading in a similar way:

$$Common\ Trading\ (F_{it}, F_{jt}) = \sum_{k=1}^{N} max(0, TSign_{it}^{k} * TSign_{jt}^{k}) * min(T_{it}^{k}, T_{jt}^{k}) \qquad (2.3),$$

where $TSign_{it}^{k}$ and $TSign_{jt}^{k}$ are the indicators for trading direction, +1 for buying and -1 for selling, in asset k by funds i and j between time t-1 and t respectively, T_{it}^{k} and T_{jt}^{k} are the fractions of asset k's turnover in the total turnovers of funds i and j between time t-1 and t respectively, and N is the total number of assets commonly traded by both funds. For each quarter t, we compare the holding of asset k at the end of the quarter with that at the end of quarter t-1 (after taking account of share splits and stock dividends if there are any). We determine an increase in holding as a BUY and a decrease in holding as a SELL. We multiply the change in the number of shares held between the ends of quarter t-1 and t

by the share price at the end of quarter t-1 to obtain the quarterly turnover in each security. The total turnover for a fund in quarter t is calculated as the sum of turnovers in all securities held by the fund. As can be seen from equation (2.3), only when two funds trade in a security in the same direction is an instance of common trading counted.

To understand the potential types of information shared within mandate networks, we also examine the commonality in holdings and trading on style portfolios in addition to that on individual stocks. We follow Daniel, Grinblatt, Titman and Wermers (1997) to classify individual stocks into style portfolios using the following steps. First, in each month t, we group all CRSP stocks into quintiles according to their market capitalization at the end of month t-1, book-to-market equity ratio at the end of month t-1, where the fiscal year end for the book equity precedes the end of month t-1 by at least 5 months, and cumulative return over the period month t-12 to month t-2 respectively. We then form 125 style portfolios across all stocks using the quintile information. We construct style holdings by aggregating stock holdings in each style portfolio. We define style trading as the net turnover on individual stocks in each style portfolio. Finally, we calculate the common holdings and trading on style portfolios according to equations (2) and (3). When calculating common trading, the total turnover for a fund is calculated as the aggregate turnover across all individual stocks, following exactly the same procedure used to calculate common trading on individual stocks.[19]

[19] We also try an alternative measure of total turnover – the sum of net turnovers on style portfolios – which makes the common trading measures larger (due to smaller total turnover measures) and more importantly, results in more discernible differences in common trading measures between inside-network fund pairs and outside-network fund pairs.

Panels B and C of Table 2.3 present the results for commonalities in holdings and trading respectively. For each fund, we first calculate its commonality measures at the end of each quarter t with all funds managed by a different investment company, and then calculate the average commonality for any pair of this fund and another fund from the time-series data. We further average the pair-wise commonality measures to obtain the mandate-connected (inside-network) commonality and non-connected (outside-network) commonality for each fund separately. Finally, we present the summary statistics of fund-level commonality measures and the comparison of inside-network versus outside-network commonalities.[20] The standard errors are clustered by investment companies to account for the intra-family correlations.

On average, funds within a mandate network have 13.9% of the portfolio in common when we look at holdings in individual stocks. The percentage of common holdings decreases to 12.8% when a fund is compared to another fund outside its mandate network. When we look at the commonalities in holding stocks in the same style, we find that funds within a mandate network hold 47.5% of the portfolio in common styles, which is 2.3% higher than funds from different mandate networks do. All differences are statistically significant.

Turning to commonality in trading, on average, funds inside a mandate network have 3.4% of their trading in individual stocks in common, while the corresponding proportion for funds from different mandate networks is 3.0%. When we examine the trading of style

[20] Similarly, to mitigate the impact of outliers, we winsorize both the quarterly commonality measures and the fund-level average commonalities at the 95th percentile values. Again, the winsorization of variables only improves the statistical significance of estimated coefficients, but does not change the sign or the magnitude of the coefficients qualitatively. Results without winsorization are available upon request.

portfolios, we find a similar difference in commonality in trading between connected funds and non-connected ones. One limitation of our analysis of commonality in trading is that we infer the trading from the holdings at the end of quarters and thus miss interim trading activities. This could cause a downward bias in estimating fund turnovers and also the commonality in trading.

Collectively, the results of inside-network versus outside-network comparison indicate that funds are more similar if they are managed by investment companies within the same mandate networks, which is consistent with these delegated portfolio managers sharing information within mandate networks. Further, there is preliminary evidence that information related to both individual stocks and style portfolios is shared within mandate networks.

2.3.3. Comparison of Commonality of Funds Before versus After Joining Shared Mandate Networks

The results of inside-network versus outside-network comparison presented in the previous section could be contaminated by the endogenous choice of plan sponsors and investment companies in the mandate contracting process. In this section, we compare the similarity in returns, holdings and trading of the same pair of funds before and after they were connected by investment mandates, which is less subject to the endogeneity concern.

We present the results of such comparison in Table 2.4. The results in Panel A indicate a significant increase in return correlation after two funds join a network. The average correlation in risk-free excess returns increases from 0.815 in the pre-joining period to 0.873 in the post-joining period. The increase in return correlation is more salient when we use style excess returns, from -0.003 to 0.020 after two funds shared a network for the first time. Both differences in return correlations are statistically significant. We do not conduct a similar analysis using risk-adjusted returns because the significant overlapping in three-year periods statistically confounds the estimation of factor loadings for both pre-joining and post-joining windows.

Panel B of Table 2.4 presents the percentages of common holdings before and after two funds share a mandate network for the first time. When we look at holdings in individual stocks, the average percentage of common holdings between funds increases from 12.0% in the pre-joining period to 14.0% in the post-joining period. When we aggregate holdings in individual style portfolios, we find that on average the percentage of common holdings increases from 44.5% to 47.7% after two funds share a mandate network for the first time. Again, all the changes are statistically significant. Similarly, as presented in Panel C of Table 2.4, the commonality in trading between two funds increases significantly after they share a mandate network for the first time, whether the trading is measured at the stock level or the style portfolio level.

Overall, the comparison of commonality between fund pairs before versus after joining the same mandate networks indicates that a pair of funds tends to share more similarity in investments and performance after the pair of funds is connected by mandate networks. Corroborating the findings on inside network versus outside mandate network commonality comparison, these results are consistent with mandate networks facilitating information sharing among network members, possibly through plan sponsors connecting them.

Table 2.4 Comparison of Similarity Before and After Sharing Mandate Networks

This table presents comparisons of return correlations, common holdings and common trading for the same pair of funds managed by two different investment companies before and after they were connected by investment mandates. For a pair of funds ever sharing a mandate network, we identify the post-joining period as all overlapping mandate-effective windows for their mandates contracted with a same plan sponsor, where we similarly assume a three-year mandate-effective period following the commencement date of the mandate contract. For the pre-joining period, we use the three-year period prior to the time when they first shared a mandate network. We require at least 12 monthly observations to calculate pair-wise return correlations both before and after funds' sharing of mandate networks. Risk-free excess return is calculated as the fund return in excess of the 1-month T-bill rate. Style excess return is calculated as the fund return in excess of the value-weighted average return of funds in the respective investment style group. We follow Elton, Gruber and Green (2007) to measure common holdings between a pair of funds *i* and *j* at time *t* in the following way:

$$Common\ Holdings\ (F_{it}, F_{jt}) = \sum_{k=1}^{N} min(H_{it}^{k}, H_{jt}^{k}),$$

where H_{it}^{k} and H_{jt}^{k} are the fractions of asset k in the portfolios of funds i and j at time t respectively, and N is the total number of assets commonly held by both funds. We measure common trading between a pair of funds *i* and *j* in a similar way:

$$Common\ Trading\ (F_{it}, F_{jt}) = \sum_{k=1}^{N} max\left(0, TSign_{it}^{k} * TSign_{jt}^{k}\right) * min(T_{it}^{k}, T_{jt}^{k}),$$

where $TSign_{it}^{k}$ and $TSign_{jt}^{k}$ are the indicators for trading direction, +1 for buying and -1 for selling, in asset k by funds i and j between time t-1 and t respectively, T_{it}^{k} and T_{jt}^{k} are the fractions of asset k's turnover in the total turnovers of funds i and j between time t-1 and t respectively, and N is the total number of assets commonly traded by both funds. To mitigate the impact of outliers, we winsorize the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. We also winsorize the quarterly common holdings (trading) and the fund-level average common holdings (trading) at the 95th percentile values. The standard errors (in parentheses) are clustered by investment companies to account for the intra-family correlations. ***, ** and * indicate 1%, 5% and 10% statistical significance levels respectively.

	N	Before (B)	After (A)	Difference (A-B)
Panel A: Return correlations				
Risk-Free Excess Return	285	0.815	0.873	0.058***
		(0.010)	(0.007)	(0.009)
Style Excess Return	285	-0.003	0.020	0.022***
		(0.010)	(0.008)	(0.008)
Panel B: Common holdings				
Common Stock Holdings (%)	388	12.0	14.0	1.9***
		(0.007)	(0.007)	(0.004)
Common Style Holdings (%)	388	44.5	47.7	3.1***
		(0.014)	(0.012)	(0.009)
Panel C: Common trading				
Common Stock Trading (%)	342	2.7	3.4	0.7***
		(0.002)	(0.002)	(0.001)
Common Style Trading (%)	342	9.2	9.7	0.5**
		(0.002)	(0.002)	(0.002)

2.3.4. Robustness Checks

In this section, we provide additional analyses and discussion on the robustness of our findings. For each robustness test, we report only the results of comparing return correlations inside networks versus outside networks for simplicity. The inferences are qualitatively similar if we compare commonalities of holdings and trading or commonalities before versus after joining mandate networks.

A. Comparison of Commonality Inside versus Outside Consultant Networks

Plan sponsors may hire professional consultants to assist with selecting investment companies. These consultants could actually select the winning investment companies and thus may influence the behaviour of the investment companies through the selection process. To alleviate concerns that the mandate network effect is a by-product of consultant activity, we obtain information on plan consultants from iiSEARCHES and construct consultant networks in the same way as for mandate networks. At a given time point, we group all fund pairs into three categories: 1) sharing both consultant networks and mandate networks, 2) sharing only consultant networks, or 3) sharing neither type of networks. We compare the return correlations of fund pairs in these three categories and present the results in Table 2.5. We find that pairs of funds sharing consultant networks, even if they do not share mandate networks, have more correlated returns compared with those not sharing any type of networks, which is consistent with the argument that consultants may influence the investment activities of investment companies, and thus induce investment similarity. More importantly, when we compare pairs of funds sharing both types of networks with those sharing only consultant networks, we find a much more significant increase in return correlations, suggesting that the mandate network effect goes beyond and is even more significant than the consultant network effect.

Table 2.5 Comparison of Return Correlations Inside versus Outside Consultant Networks

This table presents the comparison of return correlations for pairs of funds sharing both consultant networks and mandate networks (IB), pairs of funds only sharing consultant networks (IC), and pairs of funds sharing neither type of networks (O). Following Elton, Gruber and Green (2007), for each fund, we first calculate its correlations in returns with all funds managed by a different investment company, and then obtain the average correlations within each group separately. We require at least 12 monthly observations to calculate pair-wise correlations. Risk-free excess return is calculated as the fund return in excess of the 1-month T-bill rate. Style excess return is calculated as the fund return in excess of the value-weighted average return of funds in the respective investment style group. Risk-adjusted return is calculated by subtracting from the fund return the expected return due to the exposures to Fama-French three-factors and Carhart's momentum factor. To mitigate the impact of outliers, we winsorize both the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. The standard errors (in parentheses) are clustered by investment companies to account for the intra-family correlations. ***, ** and * indicate 1%, 5% and 10% statistical significance levels respectively.

	N	Inside Both Networks (IB)	Only inside Consultant Network (IC)	Outside both Networks (O)	Difference (IB-IC)	Difference (IC-O)
Risk-Free Excess Return	271	0.865	0.844	0.835	0.021***	0.009**
		(0.006)	(0.005)	(0.006)	(0.004)	(0.004)
Style Excess Return	271	0.030	0.012	0.018	0.018*	-0.006
		(0.008)	(0.005)	(0.005)	(0.010)	(0.006)
Risk-Adjusted Return	268	0.101	0.086	0.073	0.015*	0.013***
		(0.009)	(0.007)	(0.004)	(0.009)	(0.004)

B. Comparison of Commonality Inside versus Outside Mandate Networks after Excluding D.C. Plans

We include both defined benefit plans (D.B. plans) and defined contribution plans (D.C. plans) in our previous analyses. All investment mandates delegated by D.B. plans are once-off asset delegations, while some investment mandates delegated by D.C. plans could potentially list one or more funds managed by the hired investment company as investment options for the pension plan beneficiaries. Thus, it is possible that correlated cash flows received from common D.C. plans could induce correlated investment decisions and returns of funds listed on the menu, which has nothing to do with common information flow within mandate networks. To address this issue, we exclude all D.C. plans, which account for about 19% of the final sample of plan sponsors, and redo the return correlation comparison. The results, reported in Table 2.6, are very similar to those including both D.B. and D.C. plans, indicating that the results are not driven by D.C. plans.

Table 2.6 Comparison of Return Correlations Inside versus Outside Mandate Networks: Excluding D.C. Plans

This table presents the comparison of return correlations for pairs of funds inside versus outside mandate networks, after excluding mandate networks connected via D.C. plans. Following Elton, Gruber and Green (2007), for each fund, we first calculate its correlations in returns with all funds managed by a different investment company, and then obtain the average correlations for inside-network and outside-network funds separately. We require at least 12 monthly observations to calculate pair-wise correlations. Risk-free excess return is calculated as the fund return in excess of the 1-month T-bill rate. Style excess return is calculated as the fund return in excess of the value-weighted average return of funds in the respective investment style group. Risk-adjusted return is calculated by subtracting from the fund return the expected return due to the exposures to Fama-French three-factors and Carhart's momentum factor. To mitigate the impact of outliers, we winsorize both the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. The standard errors (in parentheses) are clustered by investment companies to account for the intra-family correlations. ***, ** and * indicate 1%, 5% and 10% statistical significance levels respectively.

	N	Inside Network (I)	Outside Network (O)	Difference (I-O)
Risk-Free Excess Return	298	0.865	0.834	0.031***
		(0.006)	(0.006)	(0.005)
Style Excess Return	298	0.044	0.016	0.027***
		(0.010)	(0.004)	(0.009)
Risk-Adjusted Return	292	0.110	0.072	0.038***
		(0.011)	(0.004)	(0.009)

C. Comparison of Commonality Inside versus Outside Mandate Networks by Types of Plan Sponsors

In this section, we examine whether the mandate network effect is driven by a specific type of plan sponsor. We classify all plan sponsors into three types, specifically public pension plans, corporate pension plans and others, and conduct the return correlation comparison separately for each type of plan sponsor. The results, as presented in Table 2.7, suggest that the incremental return correlation associated with mandate networks is modestly bigger for pairs of funds connected by public plan sponsors relative to those connected by the other two types of plan sponsors. It seems that the information sharing effect is more relevant for mandate networks connected by public pension plans which may be attributed to their size and consequent market power.

Table 2.7 Comparison of Return Correlations Inside versus Outside Mandate Networks: Public Pension Plans, Corporate Pension Plans and Other Types of Plans

This table presents the comparison of return correlations for pairs of funds inside versus outside mandate networks, differentiating different types of networks connected by public pension plans, corporate pension plans and other types of plans. We separate investment mandates in our sample into three groups: mandates delegated by public pension plans, mandates delegated by corporate pension plans, and mandates delegated by other types of plans, and then calculate return correlations for pairs of funds inside and outside networks separately for these three groups of mandate networks. Following Elton, Gruber and Green (2007), for each fund, we first calculate its correlations in returns with all funds managed by a different investment company, and then obtain the average correlations for each group separately. We require at least 12 monthly observations to calculate pair-wise correlations. Risk-free excess return is calculated as the fund return in excess of the 1-month T-bill rate. Style excess return is calculated as the fund return in excess of the value-weighted average return of funds in the respective investment style group. Risk-adjusted return is calculated by subtracting from the fund return the expected return due to the exposures to Fama-French three-factors and Carhart's momentum factor. To mitigate the impact of outliers, we winsorize both the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. The standard errors (in parentheses) are clustered by investment companies to account for the intra-family correlations. ***, ** and * indicate 1%, 5% and 10% statistical significance levels respectively.

	N	Inside Network (I)	Outside Network (O)	Difference (I-O)
Panel A: Networks connected by public pension plans				
Risk-Free Excess Return	298	0.865	0.834	0.031***
		(0.006)	(0.006)	(0.005)
Style Excess Return	298	0.044	0.016	0.027***
		(0.010)	(0.004)	(0.009)
Risk-Adjusted Return	267	0.130	0.082	0.049***
		(0.013)	(0.005)	(0.010)
Panel B: Networks connected by corporate pension plans				
Risk-Free Excess Return	225	0.863	0.836	0.026***
		(0.007)	(0.008)	(0.007)
Style Excess Return	225	0.018	0.014	0.004
		(0.012)	(0.005)	(0.012)
Risk-Adjusted Return	218	0.075	0.072	0.003
		(0.010)	(0.005)	(0.08)
Panel C: Networks connected by other types of plans				
Risk-Free Excess Return	209	0.863	0.825	0.038***
		(0.005)	(0.007)	(0.006)
Style Excess Return	209	0.025	0.018	0.007
		(0.016)	(0.003)	(0.015)
Risk-Adjusted Return	204	0.079	0.075	0.004
		(0.012)	(0.006)	(0.011)

D. Comparison of Commonality Inside versus Outside Mandate Networks after Controlling for Fund Size

Fund size has been shown to be an important factor in mutual fund performance (see e.g., Chen, Hong, Huang and Kubik, 2004). In our context, it is possible that successful funds grow their assets and are also more likely to win mandates. These funds could become more similar in their investment strategies; for example, loading more on common risk factors, due to their growing size, which could partly contribute to our findings. Accordingly, we conduct a robustness check of our results, controlling for the fund size effect. Specifically, for a fund managed by an investment company in a mandate network, when we select a control fund for each of its network member fund to calculate the benchmark measures, we only select among funds outside its mandate network and with fund size close to the corresponding member fund. We repeat the return correlation comparison and present the results in Table 2.8. The results are very similar to those reported in Table 2.3.

Table 2.8 Comparison of Return Correlations Inside versus Outside Mandate Networks: Controlling for Fund Size

This table presents the comparison of return correlations for pairs of funds inside versus outside mandate networks, after controlling for fund size. For a fund managed by an investment company in a mandate network, when we select a control fund for each of its network member fund to calculate the benchmark correlation coefficients, we only select among funds outside its mandate network and with fund size close to the corresponding member fund. Following Elton, Gruber and Green (2007), for each fund, we calculate its correlations in returns with its network member funds and the corresponding control funds, and then obtain the average correlations for each group separately. We require at least 12 monthly observations to calculate pair-wise correlations. Risk-free excess return is calculated as the fund return in excess of the 1-month T-bill rate. Style excess return is calculated as the fund return in excess of the value-weighted average return of funds in the respective investment style group. Risk-adjusted return is calculated by subtracting from the fund return the expected return due to the exposures to Fama-French three-factors and Carhart's momentum factor. To mitigate the impact of outliers, we winsorize both the pair-wise correlations and the fund-level average correlations at the 5th and the 95th percentile values. The standard errors (in parentheses) are clustered by investment companies to account for the intra-family correlations. ***, ** and * indicate 1%, 5% and 10% statistical significance levels respectively.

	N	Inside Network (I)	Outside Network (O)	Difference (I-O)
Risk-Free Excess Return	336	0.863	0.853	0.010**
		(0.006)	(0.005)	(0.004)
Style Excess Return	336	0.033	0.021	0.012
		(0.008)	(0.006)	(0.009)
Risk-Adjusted Return	330	0.099	0.065	0.034***
		(0.009)	(0.005)	(0.008)

2.4. Conclusion

This study suggests that networks connected by investment mandates between plan sponsors and their hired investment companies provide new channels for information sharing. Mutual funds managed by investment companies sharing mandate networks are more closely correlated in terms of returns, holdings and trading than those not connected by investment mandates. After two investment companies first join the same mandate network, their fund returns, holdings and trading become more similar. Our results also provide preliminary evidence that information about both individual firms and general investment styles is shared within mandate networks.

This study offers a new perspective to explore information transmission through networks in order to improve our understanding of the possible effects of asset outsourcing from plan sponsors to their sub-advisors. The results indicate that investment companies connected by a plan sponsor share information with each other via the plan sponsor, which could induce correlated investments and performances among these companies and may increase the risk of the plan sponsor. The findings may also provide potential explanations for such phenomena as institutional correlated trading and herding. Given the large percentage of assets managed by these delegated portfolio managers, the correlations among them may lead to return comovements and even market anomalies. For this reason, it is important to take into account such interactions among market participants when dealing with pricing issues. These findings are of potential interest to practitioners who see evidence of the information sharing implications of their participation in the mandate market for the first time. The results also present practitioners an additional antecedent to the phenomenon of the increasing stringency in the investment discretion for the delegated assets, which curtails portfolio managers' ability to differentiate their actions from others.

This study opens up at least two avenues for related future research. Because of data limitations, we are unable to observe the terminating dates of most investment mandates. With improvements in mandate termination data over time, it would be useful to examine whether or not delegated portfolio managers who are no longer connected by investment mandates stop sharing information with each other. Future studies could also explore to what extent different types of information are shared through mandate networks and how information sharing through mandate networks eventually affects security prices.

Appendix 2.1: The Filter of Mutual Funds Based on Classified Investment Objectives

For each investment company hired under a specific mandate, we include all actively managed U.S. equity mutual funds managed by the company in our analysis. We match the investment companies in the mandate data with the fund management companies in the mutual fund data by company names. To be included in the sample, a mutual fund must be identified as an actively managed U.S. equity fund in both the CRSP Mutual Fund Database and the CDA Spectrum Holdings Database. Specifically, a fund is identified as an actively managed U.S. equity fund in the CRSP Mutual Fund Database if it carries one of the following Strategic Insight Objective Codes: AGG, BAL, GMC, GRI, GRO, ING, or SCG. If the Strategic Insight Objective Code is not available for a fund, we refer to one of the following Wiesenberger Fund Type Codes: BAL, G, G-I, G-I-S, GCI, I, I-G, I-G-S, I-S, IEQ, LTG, MCG, S, S-G-I, S-I-G, or SCG. If neither of the above two objective codes is available, we require the fund to belong to one of the following Lipper Objective Code categories: B, BT, EI, EIEI, G, GI, I, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. A fund in the CDA Spectrum Holdings Database is deemed as an actively managed U.S. equity fund if its Investment Objective Code belongs to one of the following: Aggressive Growth (code 2), Growth (code 3), Growth & Income (code 4), and Balanced (code 7). After merging the identified actively managed U.S. equity funds in two databases, we remove index funds because they follow a passive indexing strategy. We identify index funds as those with a Lipper Objective Code of SP or SPSP or with the word "index" in the name.

We further classify all funds in the sample into seven different styles based on various investment objective codes in the CRSP Mutual Fund Database. The details are as follows:

1) Aggressive Growth: funds with Strategic Insight Objective Code of AGG.
2) Growth: funds with one of the following Strategic Insight Objective Codes: GMC, GRO or SCG. If the Strategic Insight Objective Code is missing, we then refer to the following Wiesenberger Fund Type Codes: G, LTG, SCG, or MCG, and finally to the following Lipper Objective Codes if the Wiesenberger code is also missing: G, LCGE, MCGE, MLGE, or SCGE.
3) Growth & Income: funds with Strategic Insight Objective Code of GRI or ING. If the Strategic Insight Objective Code is missing, we then refer to the following Wiesenberger Fund Type Codes: G-I, G-I-S, I-G, I-G-S, S-G-I, S-I-G, or GCT. If the Wiesenberger Fund Type Code is also missing, a fund is classified into this type if its Lipper Objective Code is GI.
4) Income: funds with one of the following Wiesenberger Fund Type Codes: I, I-S, or OEQ. If the Wiesenberger Fund Type Code is missing, we then refer to the following Lipper Objective Codes: EI, EIEI, or I.
5) Value: funds with one of the following Lipper Objective Codes: LCVE, MCVE, MLVE, or SCVE.
6) Core: funds with one of the following Lipper Objective Codes: LCCE, MCCE, MLCE, or SCCE.
7) Balanced: funds with Strategic Insight Objective Code of BAL. If the Strategic Insight Objective Code is missing, a fund is classified into this type if its Wiesenberger Fund Type Code is S or BAL. If the Wiesenberger Fund Type Code is also missing, a fund is classified into this type if its Lipper Objective Code is B or BT.

Chapter 3

When Does a Stock Boycott Work? Evidence from a Clinical Study of the Sudan Divestment Campaign

3.1. Introduction

According to traditional finance theory, a stock's ownership does not affect its return and risk since investors' decisions to buy or sell equity stakes occur as part of broader portfolio optimization that is informed by observing returns, variances and covariances. Yet the socially responsible investing (SRI) movement often works on the premise that influencing stock ownership may influence managers into acting in ways that ultimately affect stock returns and risk. Stock divestment campaigns are a typical example of such actions by socially conscious investors. The effectiveness of stock boycotts against firms perceived to violate social norms is still an open empirical question. The standard approach to examining the issue is an event study of the stock price reaction to announcements of shareholder divestments. While this approach would help understand the aggregate effects of stock boycotts, it would shed little light on the effects of this type of social activism on the trading activities of investors. In fact, the only study in the finance literature on the apartheid era boycott of U.S. stocks that invested in South Africa – Teoh, Welch and Wazzan (1999) – shows indiscernible stock price reaction to either legislative or shareholder pressure announcements.

In this chapter, we report the first empirical examination of the buying and selling of shares in stocks targeted by the long-running and cross-country Sudan divestment campaign. For much of the past decade, institutional investors in the U.S. and other countries have been subjected to a well-coordinated campaign to encourage the selling or avoidance of stocks deemed to be involved in operations in Sudan. The divestment campaign is mainly a form of protest against alleged human rights abuses by the Sudan government against inhabitants of the country's western region of Darfur, and the north-south civil war that preceded the formation of South Sudan in 2011. We trace the trading behavior of 4,555 institutional investors from 69 countries in four stocks that are named in the various boycott initiatives that comprise the campaign. The four stocks comprise two Chinese companies, China Petroleum & Chemical Corporation (Sinopec) and PetroChina Company Limited (PetroChina), one Indian firm, Oil and Natural Gas Corporation Limited (ONGC), and one Malaysian corporation, Petroliam Nasional Berhad (Petronas). These stocks had a combined market capitalization in 2012 of more than US$300 billion.

We address two economically important issues. First, does the divestment campaign induce shareholder exit? Second, does the boycott campaign affect stock prices and, hence, expected returns? The innovation of our study is to depart from an event study framework targeting boycott announcement effects and concentrate on the interaction between the changing intensity of the campaign over time and stock market outcomes. Following the sociology and politics literatures (e.g., Baron, 2003; King and Soule, 2007), we measure the intensity of the campaign by coverage of the boycott in the media. The outcome variables are several measures of shareholder breadth and stock returns, which we use to test two main hypotheses:

H1: The intensity of the boycott campaign is negatively related to the breadth of institutional ownership of the targeted stocks, after controlling for factors potentially related to breadth of institutional ownership.

H2: After controlling for known predictors of returns, the increased intensity of the boycott campaign exerts selling pressure on the targeted stocks, and leads to depressed stock prices and higher expected returns.

The intuition behind our hypotheses regarding the campaign intensity and price effects of the boycott campaign is provided, first, by Miller (1977):

> Since all existing stock must be held by someone, any decrease in the fraction of investors interested in the stock of a company must be offset by an equivalent increase in the fraction of those interested who decide to include it in their portfolio. The price of the stock must fall to increase the fraction of the investors who, after evaluation, include it in their portfolio. (pp. 1164–1165)

Second, following Hong and Kacperczyk (2009), our hypothesis on the price effects of the boycott campaign is based on Merton's (1987) model in which the prices of neglected stocks in segmented markets are depressed. If the boycott campaign leads targeted stocks to be neglected by an important segment of investors, their prices will be depressed due to limited risk sharing. This conjecture is also supported by Heinkel, Kraus and Zechner's (2001) model which, also in the spirit of Merton (1987), attributes the relatively lower stock prices of so-called "sin" stocks to limited risk sharing induced by neglect linked to social norms. While we do not view this clinical study of one divestment campaign as a strict test of the models, our analysis is in the spirit of asking whether the theories can be related to the empirical evidence. More generally, establishing whether stock boycotts have effects that contradict the theoretical literature, for example, should help theorists design new models of divestment campaigns.

Pitched against finding evidence in support of our hypotheses are several counterfactuals. First, as the quote from Miller (1977) above suggests, stock markets are two-sided. The selling of shares targeted by the campaign may be matched or even outpaced by buyers for reasons ranging from being indifferent to the aims of the boycott, to profit seeking arbitrage activities. In fact, the attention story (e.g., Gervais, Kaniel and Mingelgrin, 2001) contends that all attention paid to a stock is good. It is possible that the attention caused by the boycott causes investors to look more closely at the stock and then trade in the hope of realizing a sin-stock premium. Anecdotal evidence suggests there has been strong opposition to the boycott campaign from some major institutional investors.

For example, high profile investor Warren Buffett publicly opposed divestment and, in May 2007, led a vote against a shareholder resolution for Berkshire Hathaway Inc. to pull out of PetroChina.

Second, it is possible that the intensity of the divestment campaign is negatively related to expected returns because it proxies for a state variable that forecasts higher stock prices. One such phenomenon is the well-known result in Chordia, Subrahmanyam, and Anshuman (2001) showing that firms with higher variability of trading activity have lower expected returns, after controlling for size, book-to-market ratio, momentum, and the level of dollar volume or share turnover. To the extent the divestment campaign introduces variability in trading activity by existing and new investors, this effect could run counter to our second hypothesis on the boycott's influence on expected returns.

Third, there are several practical considerations that make it difficult to find results. Firstly, the stocks targeted by the campaign are majority owned by their home governments, diminishing the prospects of finding results in support of our hypotheses. Secondly, institutional investors such as large pension funds whose mandates require that only investment concerns must be taken into account in portfolio decisions may not be in a position to act in line with the boycott. Thirdly, a plethora of logistical issues hinder the spreading of accurate information about the boycott and the activities of the targeted firms in Sudan. For instance, the U.S. Government Accountability Office (2010) reports that while state and federal government controlled pension funds largely complied with the boycott, they "could benefit from increased disclosure regarding companies' ties to Sudan."

Consistent with our first prediction, we find that the intensity of the campaign is negatively related to the breadth of ownership in the targeted stocks. The results hold for both U.S. and non-U.S. based institutions. Further, higher campaign intensity decreases the number of new U.S. and non-U.S. domiciled investors that enter the stocks, and increases the number of existing U.S. domiciled investors that exit the stocks. This finding is consistent with the view that some investors may identify more with the campaign than others. We attribute the evidence to the effectiveness of coordinating the boycott such that any selling is likely to be coordinated despite the fiduciary concerns of investors wary of market impact, for example.

Regarding the divestment campaign's relationship to expected returns, the overwhelming evidence is that the intensifying of the boycott forecasts higher returns. This is consistent with our second hypothesis that higher campaign intensity induces depressed stock prices and thus higher expected returns through price pressure. In summary, our results support the effectiveness of the boycott campaign. We acknowledge a potential concern with identification in the interpretation of the findings of this study. One of the goals of the divestment campaign is to pressure companies to pull out of Sudan in a way that decreases foreign direct investment (FDI) and harms the Sudan government and makes the government willing to change its ways. Thus, if boycotts are successful, they would have real cash flow effects on the companies involved (whether they abandon investments or they stay in countries that are then growing more slowly). This possibility raises a concern at the outset about distinguishing between effects due to the real implications of a successful boycott versus the effects of changes in the ownership structure caused by the boycott. Not using an event study framework in our design may ameliorate this concern, since stock price reaction to divestment announcements and legislative pressure would indeed likely capture the cash flow implications of the campaign. Our analysis of the time varying effects of campaign intensity does not rely on the notion that the campaign has risk and return implications on the targeted stocks, although it is impossible to completely rule out that the findings of this research may reflect market concerns about cash flows.

This study is related to the socially responsible investing literature, in particular, the work of Hong and Kacperczyk (2009) who find that pension funds invest less in "sin" stocks that are involved in the alcohol, tobacco and gaming industries compared to less norm-constrained institutions such as hedge funds and mutual funds. Our contribution is to test whether, at the margin, the actions of social activists to convince other market participants to shun firms they have declared to be "sin" stocks are effective. The current study also contributes to the broader literature that now spans issues ranging from the causes and the impact of corporate social responsibility (CSR) on shareholder-value, the risk exposure and performance of socially responsible investment (SRI) funds and firms, as well as the behavior of SRI investors' money flows.[21] We add a new antecedent to this literature by focusing on the implications of coordinated SRI investors' buying and selling actions on firm value.

The study closest to ours is that of Teoh, Welch and Wazzan (1999) who investigate the shareholder boycott of the South African apartheid regime and find little stock price reaction to either legislative or shareholder pressure announcements. They attribute this result to the fact that corporate involvement in South Africa was minimal at the time.[22] As noted above, to complement Teoh, Welch and Wazzan's paper we do not examine boycott announcement effects. Moreover, our study focuses on shareholder exit from companies

[21] See Renneboog, Ter Horst and Zhang (2008) for a review.

[22] However, Teoh, Welch and Wazzan (1999) show weak evidence that institutional shareholdings increased in U.S. companies that complied with the boycott campaign and withdrew from operating in South Africa.

targeted by the campaign, rather than the withdrawal of the firms' operations from Sudan. In another related study, Grossman and Sharpe (1986) propose a South Africa-free (SAF) portfolio strategy for U.S. investors. While showing that, contingent on complete divestment from South Africa-related stocks, the SAF strategy would earn higher returns, Grossman and Sharpe do not show negative effects on the divested stocks, instead arguing that "the exclusion of South Africa-related stocks hurt portfolio performance, on average, while the small stock bias of the SAF strategy greatly increased portfolio return" (p. 15).

More broadly, this study is related to the literature on "private politics", a phrase popularized by Baron (2001) and (2003) to refer to the resolution of conflicts between economic agents through collective action rather than the application of the law. According to Baron, the evidence that has been recorded so far on the efficacy of divestment campaigns and consumer boycotts of certain products deemed socially unacceptable has been mixed, calling for more empirical studies in the area.

Finally, our study may be of interest to practitioners and researchers interested in factors that influence the composition of shareholders in a company. A new breed of theories posits that managers are concerned about the threat of exit by blockholders who may exert downward pressure on the stock price by raising the cost of capital (e.g., Admati and Pfleiderer, 2009; Edmans, 2009; Edmans and Manso, 2011). Some empirical studies also espouse the monitoring benefits of foreign institutional investors. In a study across 27 countries, Ferreira and Matos (2008) find higher valuations in corporations with higher ownership by foreign and independent institutions. Dewenter, Han and Malatesta (2010) show that stock prices respond positively (negatively) to announcements of investments (divestments) by sovereign wealth funds.

The remainder of the chapter is structured as follows. Section 3.2 provides the institutional background to the divestment campaign. Section 3.3 describes the data. Section 3.4 examines the relationship between the divestment campaign and breadth of institutional ownership. Section 3.5 analyses the relations between the divestment campaign and stock returns. Section 3.6 provides two robustness tests and Section 3.7 concludes.

3.2. The Sudan Divestment Campaign

The social movement in the U.S. aimed at pressuring money management firms to divest from Sudan is comprised of several informal and formal initiatives. Arguably, the precursor of the campaign was the declaration of economic sanctions against Sudan by the U.S. government in October 1997. Stories of investor campaigns to shun companies that invest in Sudan start to appear in major business publications in the early 2000s (see, e.g., Carlisle, 2000; Buchan, 2001). Since then some non-government organizations have formalized the Sudan divestment campaign, largely as a form of protest against alleged human rights abuses by the Sudan government against inhabitants of the country's western region of Darfur. The then U.S. President George Bush reportedly referred to deaths resulting from the Darfur civil war as 'genocide', terminology that has been adopted by activists associated with the Sudan divestment campaign. Although the north-south civil war in Sudan is also claimed as motivation by some activists, the divestment campaign has continued past the formation of the independent state of South Sudan on 9 July 2011.

For detailed accounts of the allegations made by the campaign and counterarguments by the Sudan government, as well as details of various stock boycott campaigns, see Patey (2009) and Westermann-Behaylo (2010). Here we briefly describe two of the major campaigns that comprise the Sudan divestment campaign. The Save Darfur Coalition, an umbrella group of more than 170 organizations, was formed to lobby large investment companies to dispose of portfolio investments linked to Sudan. Under the banner of the Save Darfur Coalition, the Sudan Divestment Task Force (SDTF) was formed by the Genocide Intervention Network (GIN) in 2004. The Investors Against Genocide (IAG) is a project of the Massachusetts Coalition to Save Darfur Inc., a registered charitable organization incorporated in the state of Massachusetts. The IAG sponsors shareholder resolutions for divestment by prominent mutual fund and money management firms.

The extensive reach of the boycott campaign has been aided by the passage of the Sudan Accountability and Divestment Act (SADA) in the U.S. on 31 December 2007. The effect of the SADA was to give U.S. federal government protection from lawsuits against divestment laws and boycott-compliant actions by U.S. state and local governments, as well as money managers. Between 2006 and 2010, 27 states and 23 cities in the U.S. passed legislation on divestment from Sudan. Also joining the campaign in that period were 61 universities and 11 religious organizations, according to the SDTF.[23] Further, according to the SDTF, 15 countries have initiated targeted Sudan divestment campaigns, including Australia, Belgium, Canada, Germany, Japan, Norway, Netherlands, New Zealand, Ireland, Italy, Sweden, Switzerland, South Africa, the U.S., and the U.K. Some major companies have ceased operations in Sudan or significantly changed their behavior in the country since the proliferation of the Sudan divestment movement.

The campaign has also permeated the socially responsible investment (SRI) management sector. For example, the SRI specialist firm Calvert regularly publishes analyses related to the divestment campaign in partnership with the SDTF. Several exchange traded funds, for example the Claymore/KLD Sudan Free Large-Cap Core ETF,

[23] See http://sudandivestment.org/statistics (accessed on December 19, 2011).

and indices screened of stocks targeted by the campaign are on offer to U.S. investors. Since 2006 the SDTF and several private investment firms have promoted a mutual fund screening tool for use by individuals seeking to ensure that their own investments comply with the boycott.

The U.S. Government Accountability Office (2010) reports survey evidence that fund managers from 23 U.S. states divested or froze almost US$3.5 billion in Sudan-related assets in the period 2006 to January 2010. The press reports that several firms have withdrawn from operating in Sudan, an outcome which activists have claimed credit for. All in all, the Sudan divestment campaign is perhaps the most important legislative and shareholder boycott at an international scale to date, second only to the apartheid era South African boycott. It therefore provides a rich context in which to address the questions raised in this study.

3.3. Data and Summary Statistics

Our empirical analysis primarily focuses on trading by institutional investors in four emerging market companies that have extensive operations in Sudan and are the focus of the major Sudan divestment campaigns. The sample comprises two Chinese companies, China Petroleum & Chemical Corporation (Sinopec) and PetroChina Company Limited (PetroChina), one Indian firm, Oil and Natural Gas Corporation Limited (ONGC), and one Malaysian corporation, Petroliam Nasional Berhad (Petronas). These are the only four companies that are named on the IAG's website (www.investorsagainstgenocide.org) and also among companies identified as boycott targets in publications either attributed to or reporting the activities of the GIN. The combined market capitalization of the four companies is almost US$300 billion at the end of 2012.

Our data on institutional ownership come from the Thomson One Banker's ownership database. This database contains information on shareholders and their positions at a quarterly frequency. Importantly for this study, the database reports the domicile country of the shareholders so that we can distinguish those based in the U.S., the original home of the campaign, from others. We start with a sample of institutions investing in the three emerging markets, China, India, and Malaysia, during the period 2001-2012. We then exclude Chinese, Indian, and Malaysian institutions that invest in their home countries for two reasons. First, we conjecture that domestic investors are not significantly influenced by the divestment campaigns given that the three countries are all developing countries with nationalistic tendencies among their investors. Second, our instrument for campaign intensity (see below) is based on counts of English language news articles about the boycott, which arguably justifies excluding China based investors from the computation of our response variables. The final sample includes 4,555 institutions from 69 countries, among which 2,524, or above 55% of the sample, are U.S. domiciled. Appendix 3.1 summarizes information on the institutions.

For each of the four companies mentioned above, we select the equity security that is the most liquid and open to foreign institutional investors. Over 40% (1,831 institutions) of the sample have invested in at least one of the four stocks during the sample period. Out of these institutions, over 46% (850 institutions) are incorporated in the U.S.

Following Chen, Hong, and Stein (2002), in each quarter t, we measure breadth of ownership for each stock, denoted BREADTH_t as the ratio of the number of institutions that hold a long position in the stock to the total number of institutions that hold a long position in stocks issued by companies incorporated in the same country as the issuer of that stock. The measure enters our analysis as the change in breadth from quarter t-1 to t, denoted ΔBREADTH$_t$. As in Chen, Hong, and Stein (2002), when defining ΔBREADTH$_t$, we look only at institutions that hold a long position in stocks issued by companies with the same country of domicile as the issuer of the stock we are interested in at both quarter t-1 and t. From this group, we subtract the number of institutions holding that stock at quarter t-1 from the number of institutions holding the stock at quarter t and divide the result by the total number of institutions in the group at quarter t-1 and t. Since the boycott campaign is specifically aimed at encouraging (discouraging) divestment (investment), we decompose ΔBREADTH$_t$ into IN$_t$ and OUT$_t$, where IN$_t$ is the proportion of institutions in the group that open new positions in the stock in quarter t when they previously had none in quarter t-1, and OUT$_t$ is the proportion of funds in the group that completely divest from the stock in quarter t.

We also compute another measure of institutional ownership, denoted HOLD$_t$. As in Chen, Jegadeesh, and Wermers (2000), this variable is defined as the aggregate stockholding of all foreign institutions at quarter t divided by the number of shares outstanding. We use ΔHOLD$_t$, the change in HOLD$_t$ from quarter t-1 to t, as a proxy for the change in institutional ownership in one of our robustness checks.

To measure the intensity or visibility of the divestment campaign in financial markets, we follow the sociology and politics literatures (e.g., Baron, 2003; King and Soule, 2007) and measure the intensity of the campaign by coverage of the boycott in the media. For each quarter t in our sample period, from Factiva we extract and count news articles published in English in which each of the four targeted stocks are mentioned along with reference to terms we deem unequivocally linked to the boycott theme.[24] The first measure is based on stories mentioning each firm and the word "genocide". We denote the measure $NEWS\_GENOCIDE_t$. The second measure is based on articles that mention the firms and both the terms "Sudan" and "divestment", denoted $NEWS\_SUDAN\_DIVEST_t$. We also compile the measure $NEWS\_SUDAN_t$ from counts of articles that mention the firms and just the country's name "Sudan" minus $NEWS\_GENOCIDE_t$ (or $NEWS\_SUDAN\_DIVEST_t$) and use it in one of our robustness tests. To control for non-campaign related coverage of the firms' operations, we define $NEWS\_FIRM_t$ as the number of articles that only mention the firms minus $NEWS\_GENOCIDE_t$ (or $NEWS\_SUDAN\_DIVEST_t$). By including the effect of non-campaign related firm coverage, we can more accurately distinguish the independent effect that the direct media coverage of the divestment campaign has on our outcome variables.

Data on stock prices (in U.S. dollars) and firm characteristics are obtained from the Thomson Datastream database. We follow standard convention and define the following stock level controls. $SIZE_t$ is the stocks' market capitalization calculated as share price times total shares outstanding at the end of quarter t. BM_t is the most recently available book-to-market ratio at the end of quarter t. MOM_t is the cumulative holding period return over quarter t-3 to t. $TURNOVER_t$ is the ratio of trading volumes to the total number of shares outstanding at quarter t. We use natural log for all the above variables except for the MOM_t.

[24] We include duplicates of news articles in all the tests reported in this research. After experimenting with news counts that exclude duplicates, we find that the results remain qualitatively unchanged.

Table 3.1 reports summary statistics for the variables used in our analysis. On average, nearly 22% of the institutions investing in the home countries of the stocks include the stocks in their portfolios. The rate at which institutional holders enter the stocks (2%) is slightly higher than the rate at which institutional holders exit the stocks (1.67%). Over 21% of the shares of the stocks are held by foreign institutions, out of which about 40% are held by U.S. institutions. The average market capitalization of the stocks is US$17.55 billion and they show over 28% in annual momentum.

The institutional holdings data distinguish U.S. and non-U.S. based firms. The average BREADTH for non-U.S. holders is larger than that of U.S. holders, as are the other breadth measures. On average, U.S. based institutions are net sellers (-0.02%) compared to the net buying (0.18%) by non-U.S. institutions as shown by the mean $\Delta HOLD_t$ measure.

Turning to our media coverage proxies for divestment campaign intensity, the data show that the firms' Sudan operations are closely followed by the press. On average, the firms each have 138 (8+130 or 5+133) stories published per quarter in connection to mentions of "Sudan". On average, each month eight stories mention campaign targeted stocks together with a reference to the genocide (NEWS_GENOCIDE), while five articles we denote NEWS_SUDAN_DIVEST are published. These statistics suggest that, at least according to our measures of the intensity of the campaign, the boycott, while visible, does not dominate the coverage of the firms' Sudan operations in the media.

Table 3.1 Summary Statistics

This table provides descriptive statistics on institutional ownership variables and firm characteristics. $BREADTH_t$ is the ratio of the number of foreign institutions holding a long position in a stock to the number of foreign institutions holding a long position in stocks with the same home country as the issuer of that stock in quarter t. $\Delta BREADTH_t$ is the change in BREADTH from quarter t-1 to t. IN_t is the fraction of foreign institutions opening a new position in the stock in quarter t. OUT_t is the fraction of foreign institutions selling off the position in the stock in quarter t. $HOLD_t$ is the ratio of aggregate foreign institutional shareholding to number of shares outstanding in quarter t. $\Delta HOLD_t$ is the change in HOLD from quarter t-1 to t. $SIZE_t$ is the market capitalization at the end of quarter t. BM_t is the most recent available book to market ratio at the end of quarter t-1. MOM_t is the cumulative return over quarter t-3 to t. $TURNOVER_t$ is the ratio of trading volume in quarter t to number of shares outstanding. $NEWS\_GENOCIDE_t$ is the number of news articles mentioning the firms and the word "genocide" in quarter t. $NEWS\_SUDAN\_DIVEST_t$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter t. $NEWS\_SUDAN_t$ 1 is the number of news articles mentioning the firms and the word "Sudan" in quarter t minus $NEWS\_GENOCIDE_t$. $NEWS\_SUDAN_t$ 2 is the number of news articles mentioning the firms and the word "Sudan" in quarter t minus $NEWS\_SUDAN\_DIVEST_t$. $NEWS\_FIRM_t$ 1 is the number of news articles mentioning the firms in quarter t minus $NEWS\_GENOCIDE_t$. $NEWS\_FIRM_t$ 2 is the number of news articles mentioning the firms in quarter t minus $NEWS\_SUDAN\_DIVEST_t$.

	All Holders		U.S. Holders		Non-U.S. Holders	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
$BREADTH_t$	21.81%	15.83%	16.54%	13.22%	25.78%	17.70%
$\Delta BREADTH_t$	0.32%	1.21%	0.28%	1.81%	0.35%	1.45%
IN_t	2.00%	1.69%	1.69%	1.90%	2.17%	1.84%
OUT_t	1.67%	1.37%	1.41%	1.51%	1.81%	1.54%
$HOLD_t$	21.66%	21.86%	8.56%	9.12%	13.10%	13.51%
$\Delta HOLD_t$	0.14%	4.02%	-0.02%	3.33%	0.18%	1.90%
$SIZE_t$ ($Billions)	17.55	15.61				
BM_t	0.62	0.29				
MOM_t	28.23%	42.39%				
$TURNOVER_t$	27.64%	32.34%				
$NEWS\_GENOCIDE_t$	8	17				
$NEWS\_SUDAN\_DIVEST_t$	5	11				
$NEWS\_SUDAN_t$ 1	130	96				
$NEWS\_SUDAN_t$ 2	133	97				
$NEWS\_FIRM_t$ 1	3,237	1,641				
$NEWS\_FIRM_t$ 2	3,240	1,643				

3.4. The Divestment Campaign and Breadth of Ownership

To test our first hypothesis, in Tables 3.2-3.4, we estimate panel regressions of breadth of ownership of the targeted stocks on divestment campaign intensity and other control variables. We organize the presentation of our results in each of Tables 3.2-3.4 using alternate measures of breadth as the dependent variables and two different proxies for divestment campaign intensity. To improve visibility of the coefficients, we use the percentage values of the breadth measures and the measures of divestment campaign intensity divided by 100 to estimate the regression models. We start by using data on all holders in Table 3.2 and then split the analysis between U.S. holders and non-U.S. institutions in Tables 3.3 and 3.4, respectively. In this way, we are able to report on the reach of the boycott beyond the U.S. where most of the public campaigning for and against divestment as well as legislative interventions originated. In our empirical tests here and throughout the rest of this chapter, we include firm fixed effects and cluster the standard errors at the stock level in each quarter.

Results in Table 3.2 indicate that higher divestment campaign intensity is associated with lower breadth of ownership even after controlling for relevant firm characteristics. In models with $\Delta\text{BREADTH}_t$ as the dependent variable, the estimated coefficients of the two measures of divestment campaign intensity are negative and statistically significant. The effect is also economically significant. For example, an interpretation of the coefficient on $\text{NEWS\_SUDAN\_DIVEST}_{t-1}$ suggests that an increase of 10 campaign related news articles in a quarter would decrease breadth of ownership by about 0.16% in the next quarter. Since there are close to 1,000 institutions investing in each country each quarter, this translates into a decrease of more than one in the number of institutions holding the stock.

Table 3.2 Divestment Campaign and Breadth of Ownership – All Holders

The table provides regression results where the dependent variables are measures of breadth of ownership for all holders. $\Delta BREADTH_t$ is the change in BREADTH from quarter t-1 to t times 100. IN_t is the fraction of foreign institutions opening a new position in the stock in quarter t times 100. OUT_t is the fraction of foreign institutions selling off the position in the stock in quarter t times 100. $NEWS\_CAMPAIGN_{t-1}$ equals $NEWS\_GENOCIDE_{t-1}$ in model (1) and $NEWS\_SUDAN\_DIVEST_{t-1}$ in model (2). $NEWS\_GENOCIDE_{t-1}$ is the number of news articles mentioning the firms and the word "genocide" in quarter t-1 divided by 100. $NEWS\_SUDAN\_DIVEST_{t-1}$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter t-1 divided by 100. $SIZE_{t-1}$ is the natural logarithm of market capitalization at the end of quarter t-1. BM_t is the natural logarithm of the most recent available book to market ratio at the end of quarter t-1. MOM_{t-1} is the cumulative return over quarter t-4 to t-1 times 100. $TURNOVER_{t-1}$ is the natural logarithm of the ratio of trading volume in quarter t-1 to number of shares outstanding. $NEWS\_FIRM_{t-1}$ equals the number of news articles mentioning the firms in quarter t-1 minus $NEWS\_GENOCIDE_{t-1}$ then divided by 100 in model (1) and the number of news articles mentioning the firms in quarter t-1 minus $NEWS\_SUDAN\_DIVEST_{t-1}$ then divided by 100 in model (2). All models include firm fixed effects. The standard errors are clustered at the stock level in each quarter and t-statistics are reported in parentheses. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively.

	$\Delta BREADTH_t$		IN_t		OUT_t	
	(1)	(2)	(1)	(2)	(1)	(2)
$NEWS\_CAMPAIGN_{t-1}$	-1.030***	-1.563***	-1.087***	-1.637***	-0.056	-0.074
	(-5.264)	(-3.398)	(-3.334)	(-2.890)	(-0.192)	(-0.240)
$SIZE_{t-1}$	-0.539**	-0.496**	-1.351***	-1.306***	-0.812***	-0.810***
	(-2.583)	(-2.331)	(-5.979)	(-5.781)	(-4.060)	(-3.992)
BM_{t-1}	-1.062	-1.016	-1.760**	-1.709**	-0.698	-0.693
	(-1.433)	(-1.376)	(-2.300)	(-2.244)	(-1.501)	(-1.540)
MOM_{t-1}	0.002	0.002	0.001	0.001	-0.001	-0.001
	(0.648)	(0.746)	(0.196)	(0.261)	(-0.454)	(-0.462)
$TURNOVER_{t-1}$	0.019	0.016	0.279*	0.277*	0.260*	0.261*
	(0.100)	(0.084)	(1.764)	(1.713)	(1.901)	(1.933)
$NEWS\_FIRM_{t-1}$	-0.004	-0.005	0.008	0.006	0.012***	0.011***
	(-0.414)	(-0.529)	(0.697)	(0.516)	(4.167)	(4.372)
Constant	4.975***	4.636***	14.081***	13.726***	9.106***	9.090***
	(3.081)	(2.800)	(6.951)	(6.689)	(4.437)	(4.384)
N	184	184	184	184	184	184
R^2	0.134	0.134	0.590	0.590	0.712	0.712

When we decompose $\Delta BREADTH_t$ into IN_t and OUT_t, we find that campaign intensity is negatively related to IN_t, but has little effect on OUT_t. Overall, the results indicate some success of the Sudan divestment campaign. Breadth of ownership decreases when the divestment campaign is more intense. The campaign affects the breadth mainly through preventing potential holders from entering the market.

In Table 3.3, which is based on the U.S. sub-sample of investors, measures of campaign intensity in models with $\Delta BREADTH_t$ and IN_t as the dependent variable again attract negative and statistically significant coefficients, indicating the effect of the divestment campaign on breadth of ownership through decreasing the number of new holders. When we use OUT_t as the dependent variable, we find that the estimated coefficients on proxies for campaign intensity are positive and statistically significant. This is consistent with the notion that the divestment campaign urges U.S. institutions to sell off their shares of Sudan-related companies.

Table 3.4 provides further evidence on the influence of the divestment campaign in countries beyond the U.S. The results are consistent with Table 3.2. We find that campaign intensity reduces breadth of ownership and the effects of the campaign mainly concentrate on potential investors.

Table 3.3 Divestment Campaign and Breadth of Ownership – U.S. Holders

The table provides regression results where the dependent variables are measures of breadth of ownership for U.S. holders. $\Delta BREADTH_t$ is the change in BREADTH from quarter t-1 to t times 100. IN_t is the fraction of foreign institutions opening a new position in the stock in quarter t times 100. OUT_t is the fraction of foreign institutions selling off the position in the stock in quarter t times 100. $NEWS\_CAMPAIGN_{t-1}$ equals $NEWS\_GENOCIDE_{t-1}$ in model (1) and $NEWS\_SUDAN\_DIVEST_{t-1}$ in model (2). $NEWS\_GENOCIDE_{t-1}$ is the number of news articles mentioning the firms and the word "genocide" in quarter t-1 divided by 100. $NEWS\_SUDAN\_DIVEST_{t-1}$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter t-1 divided by 100. $SIZE_{t-1}$ is the natural logarithm of market capitalization at the end of quarter t-1. BM_t is the natural logarithm of the most recent available book to market ratio at the end of quarter t-1. MOM_{t-1} is the cumulative return over quarter t-4 to t-1 times 100. $TURNOVER_{t-1}$ is the natural logarithm of the ratio of trading volume in quarter t-1 to number of shares outstanding. $NEWS\_FIRM_{t-1}$ equals the number of news articles mentioning the firms in quarter t-1 minus $NEWS\_GENOCIDE_{t-1}$ then divided by 100 in model (1) and the number of news articles mentioning the firms in quarter t-1 minus $NEWS\_SUDAN\_DIVEST_{t-1}$ then divided by 100 in model (2). All models include firm fixed effects. The standard errors are clustered at the stock level in each quarter and t-statistics are reported in parentheses. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively.

	$\Delta BREADTH_t$		IN_t		OUT_t	
	(1)	(2)	(1)	(2)	(1)	(2)
$NEWS\_CAMPAIGN_{t-1}$	-0.954***	-1.588***	-0.686***	-1.075**	0.269***	0.513***
	(-15.906)	(-4.467)	(-4.459)	(-2.410)	(3.107)	(3.683)
$SIZE_{t-1}$	-0.467***	-0.422***	-0.965***	-0.936***	-0.499**	-0.513**
	(-3.355)	(-2.736)	(-4.101)	(-3.995)	(-2.409)	(-2.476)
BM_{t-1}	-0.592	-0.570	-1.506**	-1.480**	-0.914*	-0.909*
	(-0.782)	(-0.742)	(-2.153)	(-2.111)	(-1.809)	(-1.747)
MOM_{t-1}	0.002	0.002	0.001	0.002	-0.001	-0.001***
	(0.712)	(0.819)	(0.380)	(0.426)	(-0.741)	(-3.153)
$TURNOVER_{t-1}$	0.091	0.084	0.151	0.149	0.061	0.064
	(0.425)	(0.384)	(0.739)	(0.708)	(0.747)	(0.796)
$NEWS\_FIRM_{t-1}$	0.001	-0.001	0.007	0.006	0.006	0.007
	(0.417)	(-0.404)	(0.911)	(0.697)	(0.814)	(0.907)
Constant	4.542***	4.175**	9.966***	9.726***	5.424***	5.551***
	(2.977)	(2.517)	(4.390)	(4.247)	(3.390)	(3.495)
N	184	184	184	184	184	184
R^2	0.044	0.045	0.501	0.501	0.731	0.732

Table 3.4 Divestment Campaign and Breadth of Ownership – Non-U.S. Holders

The table provides regression results where the dependent variables are measures of breadth of ownership for non-U.S. holders. ΔBREADTH$_t$ is the change in BREADTH from quarter t-1 to t times 100. IN$_t$ is the fraction of foreign institutions opening a new position in the stock in quarter t times 100. OUT$_t$ is the fraction of foreign institutions selling off the position in the stock in quarter t times 100. NEWS_CAMPAIGN$_{t\text{-}1}$ equals NEWS_GENOCIDE$_{t\text{-}1}$ in model (1) and NEWS_SUDAN_DIVEST$_{t\text{-}1}$ in model (2). NEWS_GENOCIDE$_{t\text{-}1}$ is the number of news articles mentioning the firms and the word "genocide" in quarter t-1 divided by 100. NEWS_SUDAN_DIVEST$_{t\text{-}1}$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter t-1 divided by 100. SIZE$_{t\text{-}1}$ is the natural logarithm of market capitalization at the end of quarter t-1. BM$_t$ is the natural logarithm of the most recent available book to market ratio at the end of quarter t-1. MOM$_{t\text{-}1}$ is the cumulative return over quarter t-4 to t-1 times 100. TURNOVER$_{t\text{-}1}$ is the natural logarithm of the ratio of trading volume in quarter t-1 to number of shares outstanding. NEWS_FIRM$_{t\text{-}1}$ equals the number of news articles mentioning the firms in quarter t-1 minus NEWS_GENOCIDE$_{t\text{-}1}$ then divided by 100 in model (1) and the number of news articles mentioning the firms in quarter t-1 minus NEWS_SUDAN_DIVEST$_{t\text{-}1}$ then divided by 100 in model (2). All models include firm fixed effects. The standard errors are clustered at the stock level in each quarter and t-statistics are reported in parentheses. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively.

	ΔBREADTH$_t$		IN$_t$		OUT$_t$	
	(1)	(2)	(1)	(2)	(1)	(2)
NEWS_CAMPAIGN$_{t\text{-}1}$	-1.011***	-1.406**	-1.385***	-1.928**	-0.374	-0.523
	(-3.033)	(-2.393)	(-3.029)	(-2.373)	(-0.818)	(-0.901)
SIZE$_{t\text{-}1}$	-0.625**	-0.588*	-1.540***	-1.488***	-0.915***	-0.901***
	(-2.042)	(-1.913)	(-5.086)	(-5.010)	(-5.027)	(-4.893)
BM$_{t\text{-}1}$	-1.297	-1.233	-1.850**	-1.761**	-0.553	-0.528
	(-1.598)	(-1.590)	(-2.218)	(-2.086)	(-0.593)	(-0.581)
MOM$_{t\text{-}1}$	0.002	0.003	0.001	0.001	-0.002	-0.002
	(0.728)	(0.844)	(0.185)	(0.269)	(-0.400)	(-0.387)
TURNOVER$_{t\text{-}1}$	0.015	0.016	0.408***	0.410***	0.393*	0.394*
	(0.061)	(0.066)	(2.785)	(2.788)	(1.762)	(1.774)
NEWS_FIRM$_{t\text{-}1}$	-0.003	-0.004	0.011	0.009	0.013***	0.013***
	(-0.206)	(-0.295)	(0.820)	(0.640)	(17.475)	(14.936)
Constant	5.641**	5.357*	16.232***	15.841***	10.592***	10.484***
	(1.999)	(1.911)	(6.340)	(6.310)	(4.570)	(4.451)
N	184	184	184	184	184	184
R^2	0.111	0.110	0.475	0.473	0.539	0.539

3.5. Effects of the Divestment Campaign on Expected Returns

The remaining empirical task is to examine the relationship between divestment campaign intensity and expected returns. We know from studies such as Parrino, Sias and Starks (2003), Chen, Hong and Stein (2002), and Nofsinger and Sias (1999) that breadth of ownership is related to expected returns. Therefore, we include lagged BREADTH (or lagged IN and lagged OUT) as one of the control variables in our regression models. In this section, we address whether campaign intensity is associated with depressed stock prices and, hence, higher expected return after accounting for relevant firm characteristics. The results are presented in Table 3.5.

Again, we find evidence consistent with the effectiveness of the divestment campaign. Lagged campaign intensity has a positive and statistically significant impact on stock returns, consistent with the notion that an increase in campaign intensity exerts higher selling pressure on the targeted stocks, leading to depressed stock prices and higher future returns. The results hold when we use different proxies for campaign intensity and different combinations of control variables. The economic significance is even higher. The estimated coefficients suggest that an increase of 10 news articles in a quarter decreases the stock return in the next quarter by 1.3% to 2.7% depending on the measure for campaign intensity and the control variables we choose.[25]

[25] One may expect positive and significant coefficients on $\Delta BREADTH_{t-1}$ when forecasting returns as in Chen, Hong, and Stein (2002). However, $\Delta BREADTH_{t-1}$ in Chen, Hong, and Stein (2002) is a measure of dispersion of opinions regarding the stocks' future returns when there are short-sell constraints. In our study, change in breadth is caused by the divestment campaign rather than differences of opinions about future returns. Thus, we do not expect the same relationship between $\Delta BREADTH_{t-1}$ and future returns as in Chen, Hong, and Stein (2002).

Table 3.5 Divestment Campaign and Stock Returns

The table provides regression results where the dependent variables are stock returns in quarter *t* expressed in percentage form. $\Delta BREADTH_t$ is the change in BREADTH from quarter *t*-1 to *t* times 100. IN_t is the fraction of foreign institutions opening a new position in the stock in quarter *t* times 100. OUT_t is the fraction of foreign institutions selling off the position in the stock in quarter *t* times 100. $NEWS\_CAMPAIGN_{t-1}$ equals $NEWS\_GENOCIDE_{t-1}$ in Model (1)-(3) and $NEWS\_SUDAN\_DIVEST_{t-1}$ in Model (4)-(6). $NEWS\_GENOCIDE_{t-1}$ is the number of news articles mentioning the firms and the word "genocide" in quarter *t*-1 divided by 100. $NEWS\_SUDAN\_DIVEST_{t-1}$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter *t*-1 divided by 100. $\Delta BREADTH_{t-1}$ (All) is the change in BREADTH calculated for all investors from quarter *t*-1 to *t* times 100. $\Delta BREADTH_{t-1}$ (U.S.) is the change in BREADTH calculated for U.S. investors from quarter *t*-1 to *t* times 100. $\Delta BREADTH_{t-1}$ (Non-U.S.) is the change in BREADTH calculated for non-U.S. investors from quarter *t*-1 to *t* times 100. $SIZE_{t-1}$ is the natural logarithm of market capitalization at the end of quarter *t*-1. BM_t is the natural logarithm of the most recent available book to market ratio at the end of quarter *t*-1. MOM_{t-1} is the cumulative return over quarter *t*-4 to *t*-1 times 100. $TURNOVER_{t-1}$ is the natural logarithm of the ratio of trading volume in quarter *t*-1 to number of shares outstanding. $NEWS\_FIRM_{t-1}$ equals the number of news articles mentioning the firms in quarter *t*-1 minus $NEWS\_GENOCIDE_{t-1}$ then divided by 100 in Model (1)-(3) and the number of news articles mentioning the firms in quarter *t*-1 minus $NEWS\_SUDAN\_DIVEST_{t-1}$ then divided by 100 in Model (4)-(6). All models include firm fixed effects. The standard errors are clustered at the stock level in each quarter and t-statistics are reported in parentheses. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively.

	NEWS_GENOCIDE			NEWS_SUDAN_DIVEST		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Controlling for $\Delta BREADTH_{t-1}$						
$NEWS\_CAMPAIGN_{t-1}$	14.227***	14.241***	13.672***	26.794***	26.313***	26.097***
	(8.835)	(6.258)	(9.465)	(5.836)	(5.529)	(5.986)
$\Delta BREADTH_{t-1}$ (All)	0.376			0.389		
	(0.385)			(0.431)		
$\Delta BREADTH_{t-1}$ (U.S.)		1.086*			1.050*	
		(1.745)			(1.659)	
$\Delta BREADTH_{t-1}$ (Non-U.S.)			-0.191			-0.151
			(-0.268)			(-0.219)
$SIZE_{t-1}$	-3.129	-2.810	-3.689	-3.888	-3.586	-4.396
	(-0.699)	(-0.744)	(-0.816)	(-0.916)	(-0.999)	(-1.015)
BM_{t-1}	12.778	13.247	11.796	12.952	13.290	12.063
	(1.144)	(1.288)	(1.090)	(1.132)	(1.263)	(1.081)
MOM_{t-1}	0.004	-0.003	0.004	0.003	-0.005	0.003
	(0.070)	(-0.058)	(0.067)	(0.045)	(-0.079)	(0.046)
$TURNOVER_{t-1}$	0.510	0.446	0.577	0.692	0.619	0.754
	(0.221)	(0.212)	(0.241)	(0.307)	(0.300)	(0.323)
$NEWS\_FIRM_{t-1}$	-0.090	-0.099	-0.084	-0.063	-0.071	-0.057
	(-1.121)	(-1.610)	(-1.000)	(-0.960)	(-1.461)	(-0.833)
Constant	46.183	43.655	51.046	52.772	50.343	57.201
	(1.222)	(1.354)	(1.317)	(1.457)	(1.619)	(1.526)
N	183	183	183	183	183	183
R^2	0.122	0.134	0.122	0.130	0.141	0.130

Table 3.5 (continued)

	NEWS_GENOCIDE			NEWS_SUDAN_DIVEST		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Controlling for IN_{t-1} and OUT_{t-1}						
$NEWS\_CAMPAIGN_{t-1}$	14.286***	14.76***	13.287***	27.050***	27.082***	25.701***
	(9.452)	(6.650)	(12.793)	(6.082)	(5.599)	(6.071)
IN_{t-1} (All)	-0.126			-0.130		
	(-0.097)			(-0.107)		
OUT_{t-1} (All)	-1.482			-1.536		
	(-1.377)			(-1.486)		
IN_{t-1} (U.S.)		0.665			0.613	
		(0.887)			(0.822)	
OUT_{t-1} (U.S.)		-1.812***			-1.801***	
		(-2.830)			(-2.729)	
IN_{t-1} (Non-U.S.)			-0.569			-0.533
			(-0.542)			(-0.530)
OUT_{t-1} (Non-U.S.)			-0.441			-0.494
			(-0.473)			(-0.542)
$SIZE_{t-1}$	-4.860	-3.662	-5.017	-5.688	-4.491	-5.736
	(-0.964)	(-0.904)	(-0.984)	(-1.176)	(-1.154)	(-1.171)
BM_{t-1}	11.007	12.616	10.020	11.143	12.605	10.306
	(0.970)	(1.189)	(0.918)	(0.960)	(1.161)	(0.919)
MOM_{t-1}	-0.001	-0.005	-0.000	-0.002	-0.006	-0.002
	(-0.008)	(-0.084)	(-0.006)	(-0.033)	(-0.107)	(-0.023)
$TURNOVER_{t-1}$	1.014	0.772	0.902	1.219	0.957	1.090
	(0.421)	(0.364)	(0.364)	(0.518)	(0.461)	(0.450)
$NEWS\_FIRM_{t-1}$	-0.083	-0.093	-0.079	-0.055	-0.064	-0.053
	(-0.924)	(-1.479)	(-0.860)	(-0.751)	(-1.324)	(-0.694)
Constant	65.348	53.612	65.219	72.697*	60.825*	71.557
	(1.457)	(1.558)	(1.405)	(1.670)	(1.812)	(1.591)
N	183	183	183	183	183	183
R^2	0.126	0.136	0.125	0.135	0.144	0.133

3.6. Robustness

3.6.1. Non-Campaign Related News about Sudan

To test that the effects on breadth of ownership and expected returns are due to the divestment campaign, we also examine the impact of non-campaign related news articles about Sudan on these two dependent variables. We count the number of news articles mentioning the firms and the word "Sudan" each quarter and then subtract the number of campaign related news articles. As we have two different measures of campaign related news count (NEWS_GENOCIDE and NEWS_SUDAN_DIVEST), we also created two measures of non-campaign related news count. We repeat our tests and present the results obtained using total number of news articles mentioning the firms and Sudan minus NEWS_SUDAN_DIVEST in Table 3.6. The results obtained using the other measure are qualitatively similar.

As reported in Table 3.6, the estimated coefficients on lagged number of non-campaign related news articles are insignificant at standard levels in all six models. Therefore, we do not find evidence that news about the firms' operations in Sudan but not the divestment campaign affects breadth of ownership and stock returns. This evidence suggests that the hypothesized effects of the divestment campaign are a plausible phenomenon.

Table 3.6 Robustness Test – Non-Campaign Related News Coverage

The table provides regression results where the dependent variables equal $\Delta BREADTH_t$ in Panel A and stock returns in quarter t expressed in percentage form in Panel B. $\Delta BREADTH_t$ is the change in BREADTH from quarter t-1 to t times 100. $NEWS\_SUDAN_{t-1}$ equals the number of news articles mentioning the firms and the word "Sudan" in quarter t-1 minus $NEWS\_SUDAN\_DIVEST_{t-1}$ then divided by 100. $NEWS\_SUDAN\_DIVEST_{t-1}$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter t-1. $SIZE_{t-1}$ is the natural logarithm of market capitalization at the end of quarter t-1. BM_t is the natural logarithm of the most recent available book to market ratio at the end of quarter t-1. MOM_{t-1} is the cumulative return over quarter t-4 to t-1 times 100. $TURNOVER_{t-1}$ is the natural logarithm of the ratio of trading volume in quarter t-1 to number of shares outstanding. $NEWS\_FIRM_{t-1}$ equals the number of news articles mentioning the firms in quarter t-1 divided by 100 then minus $NEWS\_SUDAN_{t-1}$. All models include firm fixed effects. The standard errors are clustered at the stock level in each quarter and t-statistics are reported in parentheses. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively.

	All Holders	U.S. Holders	Non-U.S. Holders
Panel A: Non-campaign related news coverage and $\Delta BREADTH_t$			
$NEWS\_SUDAN_{t-1}$	-0.002	-0.022	0.050
	(-0.076)	(-0.282)	(1.157)
$SIZE_{t-1}$	-0.555***	-0.462**	-0.685**
	(-2.751)	(-2.572)	(-2.399)
BM_{t-1}	-0.782	-0.325	-1.040
	(-1.160)	(-0.385)	(-1.597)
MOM_{t-1}	0.002	0.002	0.003
	(1.096)	(0.875)	(1.330)
$TURNOVER_{t-1}$	0.061	0.130	0.057
	(0.327)	(0.593)	(0.245)
$NEWS\_FIRM_{t-1}$	-0.003	0.001	-0.002
	(-0.422)	(0.346)	(-0.195)
Constant	5.282***	4.672**	6.270**
	(3.495)	(2.558)	(2.459)
N	184	184	184
R^2	0.116	0.036	0.101

Table 3.6 (continued)

	All Holders	U.S. Holders	Non-U.S. Holders
Panel B: Non-campaign related news coverage and stock returns			
$NEWS\_SUDAN_{t-1}$	1.920	1.866	2.098
	(0.949)	(0.944)	(1.072)
$\Delta BREADTH_{t-1}$	0.032	1.039	-0.545
	(0.032)	(1.610)	(-0.795)
$SIZE_{t-1}$	-4.941	-4.293	-5.732
	(-0.991)	(-0.995)	(-1.174)
BM_{t-1}	7.622	8.543	6.677
	(0.714)	(0.855)	(0.644)
MOM_{t-1}	-0.004	-0.012	-0.005
	(-0.069)	(-0.223)	(-0.088)
$TURNOVER_{t-1}$	-0.030	-0.133	0.090
	(-0.012)	(-0.057)	(0.034)
$NEWS\_FIRM_{t-1}$	-0.088	-0.099**	-0.080
	(-1.277)	(-2.063)	(-1.174)
Constant	57.665	52.298	64.595
	(1.387)	(1.451)	(1.557)
N	183	183	183
R^2	0.114	0.125	0.116

3.6.2. Institutional Ownership as the Dependent Variable

In this section, we adopt another measure of institutional ownership, $\Delta HOLD_t$, and repeat our tests. $\Delta HOLD_t$ is defined as the change in aggregated shareholding of foreign institutions divided by the total number of shares outstanding from quarter *t*-1 to *t*. The results are presented in Table 3.7.

Again, we find that increased campaign intensity leads to decreased institutional shareholding. The results are highly significant and hold for all holders, U.S. holders, and non-U.S. holders. However, as the estimated coefficients are much larger for U.S. holders than non-U.S. holders, the impact is larger for U.S. holders. Higher campaign intensity also induces higher stock returns while controlling for aggregated institutional holdings and other relevant firm characteristics.

Table 3.7 Robustness Test – Change in Aggregate Institutional Shareholding

The table provides regression results where the dependent variables equal $\Delta HOLD_t$ in Panel A and stock returns in quarter t expressed in percentage form in Panel B. $\Delta HOLD_t$ is the change in the ratio of aggregate institutional shareholding to total share outstanding from quarter t-1 to t times 100. NEWS_CAMPAIGN$_{t-1}$ equals NEWS_GENOCIDE$_{t-1}$ in model (1) and NEWS_SUDAN_DIVEST$_{t-1}$ in model (2). NEWS_GENOCIDE$_{t-1}$ is the number of news articles mentioning the firms and the word "genocide" in quarter t-1 divided by 100. NEWS_SUDAN_DIVEST$_{t-1}$ is the number of news articles mentioning the firms and the words "Sudan" and "divestment" in quarter t-1 divided by 100. SIZE$_{t-1}$ is the natural logarithm of market capitalization at the end of quarter t-1. BM$_t$ is the natural logarithm of the most recent available book to market ratio at the end of quarter t-1. MOM$_{t-1}$ is the cumulative return over quarter t-4 to t-1 times 100. TURNOVER$_{t-1}$ is the natural logarithm of the ratio of trading volume in quarter t-1 to number of shares outstanding. NEWS_FIRM$_{t-1}$ equals the number of news articles mentioning the firms in quarter t-1 minus NEWS_GENOCIDE$_{t-1}$ then divided by 100 in model (1) and the number of news articles mentioning the firms in quarter t-1 minus NEWS_SUDAN_DIVEST$_{t-1}$ then divided by 100 in model (2). All models include firm fixed effects. The standard errors are clustered at the stock level in each quarter and t-statistics are reported in parentheses. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively.

	All Holders		U.S. Holders		Non-U.S. Holders	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Divestment campaign and change in institutional ownership						
NEWS_CAMPAIGN$_{t-1}$	-3.526***	-5.347***	-2.763***	-4.991***	-0.988***	-0.649***
	(-2.895)	(-3.548)	(-3.190)	(-3.358)	(-3.558)	(-3.360)
SIZE$_{t-1}$	-1.697***	-1.549***	-2.092	-1.949	0.226	0.238
	(-5.094)	(-5.618)	(-1.557)	(-1.527)	(0.231)	(0.242)
BM$_{t-1}$	-5.733**	-5.569**	-5.415	-5.406	-0.653	-0.479
	(-1.984)	(-2.047)	(-1.545)	(-1.532)	(-1.334)	(-0.689)
MOM$_{t-1}$	0.000	0.001	-0.010	-0.010	0.010	0.010
	(0.010)	(0.177)	(-1.124)	(-1.048)	(1.365)	(1.349)
TURNOVER$_{t-1}$	-1.392	-1.400	-0.934	-0.963	-0.471	-0.449
	(-1.286)	(-1.314)	(-1.302)	(-1.336)	(-1.308)	(-1.308)
NEWS_FIRM$_{t-1}$	0.058***	0.052***	0.055	0.050	0.007	0.007
	(3.165)	(4.328)	(1.525)	(1.613)	(0.353)	(0.322)
Constant	7.748***	6.580**	12.947	11.726	-3.922	-3.926
	(3.248)	(2.422)	(1.560)	(1.503)	(-0.431)	(-0.435)
N	184	184	184	184	184	184
R^2	0.083	0.083	0.076	0.082	0.079	0.074

Table 3.7 (continued)

	All Holders		U.S. Holders		Non-U.S. Holders	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel B: Divestment campaign and stock returns						
NEWS_CAMPAIGN$_{t-1}$	13.741***	25.967***	13.904***	26.556***	13.896***	26.299***
	(5.250)	(4.939)	(5.812)	(5.589)	(5.667)	(5.772)
ΔHOLD$_{t-1}$	-0.143	-0.106	0.001	0.053	-0.469	-0.461
	(-0.275)	(-0.199)	(0.003)	(0.139)	(-0.367)	(-0.354)
SIZE$_{t-1}$	-3.522	-4.257	-3.477	-4.232	-3.593	-4.347
	(-0.842)	(-1.069)	(-0.850)	(-1.094)	(-0.880)	(-1.114)
BM$_{t-1}$	11.758	12.013	12.158	12.465	11.750	11.931
	(1.081)	(1.080)	(1.122)	(1.119)	(1.079)	(1.075)
MOM$_{t-1}$	0.006	0.004	0.005	0.004	0.009	0.008
	(0.089)	(0.062)	(0.075)	(0.054)	(0.141)	(0.114)
TURNOVER$_{t-1}$	0.423	0.632	0.546	0.764	0.409	0.595
	(0.174)	(0.265)	(0.229)	(0.326)	(0.170)	(0.253)
NEWS_FIRM$_{t-1}$	-0.085	-0.058	-0.086	-0.058	-0.078	-0.051
	(-1.045)	(-0.865)	(-1.084)	(-0.905)	(-1.109)	(-0.877)
Constant	49.017	55.540	49.164	55.866*	49.375	55.955
	(1.372)	(1.610)	(1.429)	(1.694)	(1.393)	(1.626)
N	183	183	183	183	183	183
R^2	0.123	0.130	0.121	0.130	0.124	0.132

3.7. Summary and Conclusions

Although divestment campaign activists have long claimed that institutional investors heed their stock boycott call and that this is followed by diminished stock prices, empirical evidence, consistent with or contradictory to these claims, is scant. We examine this phenomenon by analyzing changes in the breadth of a large sample of institutional holders in four foreign stocks that have been targeted by the long running Sudan divestment campaign. We devise measures of the campaign's intensity as reflected in media attention to the boycott following the politics and sociology literatures. We find a negative relationship between campaign intensity and the breadth of ownership. The boycott induces lower new inflow of shareholders in both the U.S. and the rest of the world, and more exits of existing shareholders in the U.S.

The boycott also influences expected stock returns. We find that campaign intensity is associated with depressed prices and thus higher future returns. This is consistent with the theoretically motivated hypothesis that the campaign leads to neglect of the targeted stocks by an important enough segment of investors which in turn results in compensating higher future returns. Taken together, the boycott seems to be effective in that it lowers the breadth of ownership in the targeted stocks and induces price pressure on these stocks. Our clinical study of one divestment campaign opens up opportunities for theorists to develop models to complement existing propositions for the effects of stock boycotts on equity markets. This study has also suggested a number of avenues for future empirical research. First, with the passage of time a larger sample of campaigns should become available for researchers to more comprehensively explore the validity of our findings and competing hypotheses. A potentially fruitful line of inquiry would be theories of causes and effects of variability in investor trading. Second, it should be possible to investigate whether institutions that trade against boycott compliant funds earn significant returns for providing liquidity. An examination of the predictability of divestment campaign driven transactions would help address the fiduciary concerns of some shareholders.

Appendix 3.1. Details of Institutional Holders

Table A3.1 Number of Institutions in Sample by Country of Domicile and Type

Panel A: Number of institutions by country of domicile

Country	No. of Institutions	% of Institutions
Australia	62	1.36
Austria	35	0.77
Belgium	28	0.61
Canada	155	3.40
Chile	11	0.24
China	175	3.84
Denmark	18	0.40
Finland	14	0.31
France	98	2.15
Germany	126	2.77
Greece	19	0.42
India	13	0.29
Ireland	15	0.33
Italy	57	1.25
Japan	79	1.73
Korea	33	0.72
Liechtenstein	16	0.35
Luxembourg	68	1.49
Malaysia	29	0.64
Mauritius	16	0.35
Netherlands	26	0.57
Norway	23	0.50
Portugal	11	0.24
Scotland	26	0.57
Singapore	127	2.79
South Africa	18	0.40
Spain	83	1.82
Sweden	36	0.79
Switzerland	159	3.49
Taiwan	47	1.03
United Arab Emirates	11	0.24
United Kingdom	304	6.67
United States	2,524	55.41
Other countries	93	2.04
Total	4,555	

Panel B: Number of institutions by type

Type	No. of Institutions	% of Institutions
Bank and Trust	275	6.04
Endowment Fund	8	0.18
Foundation	5	0.11
Hedge Fund	708	15.54
Independent Research Firm	3	0.07
Insurance Company	35	0.77
Investment Advisor	2,404	52.78
Investment Advisor/Hedge Fund	818	17.96
Pension Fund	61	1.34
Private Equity	75	1.65
Research Firm	106	2.33
Sovereign Wealth Fund	10	0.22
Venture Capital	47	1.03
Total	4,555	

Chapter 4

Performance Attribution between Firms and Individuals: Evidence from the Mutual Fund Industry

4.1. Introduction

Much attention in the mutual fund literature and the popular press has been placed on the individuals who manage funds. The profiles, investment philosophies, and job changes of successful fund managers often appear as top stories in the financial press. For some, having a "star manager" means a sense of security that their money is in the right hands. However, the extent to which fund managers determine a fund's results is not as obvious as it may seem. At the heart of this question is whether fund managers or fund companies are more important in determining a fund's successes and failures. Surprisingly, little is known about this question from the mutual fund literature.[26] In this study, we provide the first empirical examination on the attribution of fund performance between a fund and its manager. Specifically, we compare the relative importance of manager skills and fund skills (e.g., the personnel and resources of the fund company supporting the fund) in determining a fund's results.

Previous studies seem to implicitly acknowledge that both fund managers and fund companies are relevant to fund performance. On the one hand, studies focusing on fund managers suggest a strong relationship between fund performance and manager characteristics such as age, education and tenure (e.g., Golec, 1996; Chevalier and Ellison, 1999; Gottesman and Morey, 2006). Managerial turnover is also shown to have an impact on subsequent fund performance (e.g., Khorana, 2001; Ma, 2012). On the other hand, numerous studies find that fund performance can be explained by fund characteristics such as fund size, flow, expense ratio, and turnover ratio (e.g., Gruber, 1996; Zheng, 1999;

[26] The only exception is Baks (2001), who develops a model to examine the performance attribution between funds and managers.

Carhart 1997; Chen, Hong, Huang and Kubik, 2004; Ferreira, Keswani, Miguel and Ramos, 2012). Some recent studies also find that fund family size and family strategies have a significant impact on fund performance (e.g., Massa, 2003; Chen, Hong, Huang and Kubik, 2004; Nanda, Wang and Zheng, 2004; Gaspar, Massa and Matos, 2006; Bhattacharya, Lee and Pool, 2013). However, to the best of our knowledge, there is no unifying study to reconcile all these findings and answer the question "to whom should fund performance be attributed?" Even a meta-analysis of the existing literature cannot resolve the problem of deciding which party matters for performance because the disparate studies on manager or fund/family attributes often contain contradictory results. For instance, Chen, Hong, Huang and Kubik (2004) find that fund performance is negatively and significantly correlated with lagged fund size, while Elton, Gruber and Blake (2012) find no evidence of a significant relation between the two.[27]

The U.S. Securities and Exchange Commission (SEC) regulation of how performance track records are treated in the mutual fund industry implicitly attributes fund performance to individual fund managers. This has been the case since 1996 when the SEC permitted Elizabeth Bramwell, the former manager of the Gabelli Growth Fund, to include her performance information at Gabelli & Co. in the prospectus for a new fund at her own fund company.[28] This decision stirred much controversy in the investment management industry. The U.S. National Association of Securities Dealers (NASD), another important regulator that governs mutual fund advertising (as opposed to official prospectuses),

[27] The relevant literature is discussed in more detail in Section 4.2.

[28] See Bramwell Growth Fund, SEC No-Action Letter (August 7, 1996).

expressed concerns in its survey about this issue (National Association Of Securities Dealers, 1997):[29]

> Many mutual fund management companies employ or retain research analysts who recommend investment actions to the portfolio manager; traders who attempt to obtain best price and execution, which may be partially based on the volume of the fund's transactions; and other staff who assist the portfolio manager's investment selection and who help make the mutual fund's operations more efficient, thereby reducing the fund's expense ratio and enhancing its performance. … Would the presentation of manager performance necessarily mislead investors into believing that this performance was attributable solely to the efforts of the portfolio manager, even when it was largely attributable to the personnel and resources of the fund's investment adviser? (p. 383)

After obtaining suggestions from its member fund companies, the NASD decided to prohibit advertising of performance information by fund managers once they leave the fund company. The popular press also held mixed opinions towards the Bramwell decision. Some had similar concerns to the NASD (e.g., Laderman, 1997), while others considered it as a win-win strategy that benefits investors and successful fund managers who start their own businesses at the same time (e.g. Barnhart, 1997; Creswell, 1998). This debate has not been resolved to date. Fund companies frequently insist that their well-developed investment strategies are key to fund success, rather than the flair of any individual fund managers. In response to the Bramwell decision, for example, the Investment Company Institute petitioned the NASD Regulation (NASDR) as follows (Investment Company Institute, 1997):

> NASDR should not permit in sales material the presentation of performance of another mutual fund previously managed by the Advertised Fund's portfolio manager while he or she was with an unaffiliated investment advisory firm (the fact pattern in the Bramwell no-action letter). Such performance information would be confusing to investors, would create situations where different funds

[29] The NASD and the member regulation operations of the New York Stock Exchange were consolidated into the Financial Industry Regulatory Authority (FINRA) in 2007.

> would be advertising the same track record, and would allow outdated performance of the previous fund to be advertised. … It is extremely rare that there are situations where no factor other than the portfolio manager's own investment decisions is responsible for a mutual fund's performance.

In a recent study, Massa, Reuter, and Zitzewitz (2010) document a significant increase in the percentage of funds that choose either team management or anonymous management since the 1990s, which could be a fund company strategy to prevent fund managers from claiming credit for their track records.

To attribute performance between funds and managers, we trace the manager history of 2,834 actively managed U.S. equity mutual funds over the period 1987-2012, using information on manager names and tenure provided by Morningstar Direct. We start by examining the extent to which fund managers matter for fund performance. Using a fixed effects regression analysis, we find that, after controlling for time-varying fund and manager characteristics that may affect fund performance, a larger part of the unexplained variation in fund performance can be attributed to manager fixed effects than to fund fixed effects. Our results are robust when we remove all control variables, or replace fund fixed effects by firm or advisor fixed effects. The evidence is consistent with fund managers playing a more important role than fund companies in determining fund performance.

In the next step, we employ the commonly used skill measure, performance persistence, to cast further light on this comparison. A large number of previous studies examine the existence of skill by testing for persistence in fund performance (e.g., Grinblatt and Titman, 1992; Carhart, 1997). If success and failure were primarily due to skill rather than luck, one would expect that past winners continue to outperform and past losers continue to produce low returns. Conceptually, fund performance could be viewed as the sum of two components, one due to manager skills and the other due to fund skills. However, it is empirically impossible to separate persistence in performance due to these two components. As a result, we adopt an indirect approach by comparing the performance persistence of sole-managed and team-managed funds. Managers of sole-managed funds face fewer coordination issues (Dass, Nanda and Wang, 2013) and fewer investment restrictions (Almazan, Brown, Carlson and Chapman, 2004), and thus are able to fully exert their expertise and skills. Yet, the implementation of fund strategies in sole-managed funds may be subject to a discount due to the idiosyncratic discretion of individual managers. On the other hand, fund strategies could be better implemented in a team environment, as team management reduces the tendency towards eccentric distortion of individuals (Han, Noe and Rebello, 2008) and creates peer monitoring that helps to mitigate moral hazard problems (Arnott and Stiglitz, 1991). Yet, the expertise and skills of individual managers who work in a team environment may have to be compromised due to coordination efforts. Hence, if manager skills are more important, the performance of sole-managed funds should be more persistent than that of team-managed funds, while the opposite should hold if fund skills dominate. In support of the former prediction, we observe a higher degree of persistence in performance of sole-managed funds. The results hold with or without controlling for fund and manager characteristics that may affect performance. Further, among funds exhibiting the best performance in terms of Carhart (1997) four-factor alphas in a given year, sole-managed funds continue to produce alphas that are significantly positive in the following year, while team-managed and anonymously-managed funds generate subsequent alphas that are not significantly different from zero. Our results using performance persistence as the skill measure are consistent with manager skills being more important than fund skills in driving fund performance.

There could be alternative explanations for the difference in performance persistence between sole-managed and team-managed funds. For instance, one possibility is that sole-managed funds exhibit stronger performance persistence simply because their managers are more skilled. As Han, Noe, and Rebello (2008) show, skilled managers may self-select into sole-managed funds since it is easier for them to reveal their personal ability. This possibility cannot be ruled out using the previous setting. As a result, we conduct another test using a setting under which manager skills and fund skills can be separated to a certain extent. In this test, we focus on managerial turnover events of sole-managed funds. If manager skills are more important, it is expected that a fund's performance after replacing its manager can be forecast by the new manager's past performance at other funds. If fund skills are more important, it is expected that a fund's post-turnover performance can be forecast by the fund's pre-turnover performance with another manager. Controlling for fund characteristics that may influence performance, we find evidence consistent with the former prediction. Fund post-turnover performance is positively correlated with the past performance of the new manager, rather than the past performance of the fund. One may worry that the new manager chosen by a fund is more likely to be a skilled one, and thus exhibits more persistent performance. We address this concern by dividing new managers into those with better than average past performance and those with lower than average past performance. We find results consistent with the notion that manager past performance forecasts fund post-turnover performance in both groups. Our results using the managerial turnover setting are also consistent with manager skills dominating fund skills in determining fund performance.

In the final step, we ask whether manager skills have a real effect on the investment decisions of investors. If manager skills are rewarded by fund flows, one would expect that flows are more sensitive to performance for sole-managed funds than for team-managed funds, as manager skills are the main performance driver of sole-managed funds. Further, when a fund manager takes over a new fund, the manager's past performance should be able to forecast the fund's flows after the managerial turnover, especially when the manager manages the new fund alone. We find modest evidence that flows are more sensitive to performance in sole-managed funds. However, we do not find significant evidence for the latter prediction.

Our study contributes to the mutual fund literature by reconciling previous studies that look at the relation between fund performance and manager or fund/family attributes. Our results show that, even though fund performance could be affected by fund/family characteristics and family strategies, the main performance driver seems to stem from the skills of the individuals who manage funds.

The paper closest in spirit to this research is Baks (2001), who develops a Bayesian model to investigate the attribution of fund performance between funds and managers. However, Baks (2001) estimates that approximately 70% of performance can be attributed to funds, compared with only 30% to managers, which differs substantially from our empirical findings. The difference may result from the fact that Baks (2001)'s results rely heavily on the definition and assumptions of the model. Further, due to the conditions required by the model to produce valid estimates, only a small number of funds and managers are retained in the final sample.

Our study sheds light on the debate over who should own a fund's performance record. We find evidence consistent with personal skills of fund managers dominating fund performance, especially in sole-managed funds. Our results provide some justification for the SEC Bramwell decision to allow a fund manager's previous performance to be reported for a new fund, and cast doubt on the current NASD policy, which prohibits fund managers from citing their performance records obtained at a different fund company in fund sales material under all circumstances. The disclosure of manager past performance may provide useful and relevant information to investors. Given the positive relationship between fund performance and future flows (e.g., Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998), it may also benefit successful fund managers who leave a fund organization and start their own funds by attracting more flows into the new funds.

We also contribute to the finance literature on individual specific effects by emphasizing the importance of fund managers in driving fund performance. Several recent studies document that individual specific impacts are important for financial outcomes. For example, Bertrand and Schoar (2003) find that manager fixed effects are important for a wide range of corporate decisions, including investment, leverage, cash holdings and return on assets. Graham, Li and Qiu (2011) show that manager fixed effects explain a significant portion of the variation in executive compensation. Fracassi, Petry and Tate (2014) document that analyst fixed effects accounts for a large part of the variation in credit ratings, which further influence the financing activities of the rated firms. Consistent with these studies, we find that individuals play an important role in the mutual fund industry. The personal skills of fund managers have a significant impact on the performance outcomes of a fund.

More generally, we contribute to the literature on performance attribution between firms and individuals in knowledge intensive industries. So far, there is no clear consensus about this issue. Some studies support the importance of firm-specific skills and capabilities in determining performance by showing evidence that individual performance is not portable across organizations. For example, Groysberg, Lee and Nanda (2008) document an immediate decline in the performance of star security analysts who switch firms, especially those who switch to less capable firms. Huckman and Pisano (2006) show that the performance of cardiac surgeons at a hospital improves with the procedure volume at that hospital, but has little relationship with the procedure volume at other hospitals.

However, some other studies find evidence that individuals seem to matter more for financial outcomes. For example, Mollik (2012) demonstrates that individual differences best explain the performance variation in the game industry. Chemmanur, Ertugrul and Krishnan (2013) document evidence that investment bankers are the main value drivers of investment banks. In support of the latter stream of studies, our evidence from the mutual fund industry is consistent with individual skills being more important than firm skills for the performance outcomes of a fund.

The rest of this chapter proceeds as follows. Section 4.2 reviews the literature. Section 4.3 describes the data and variables, and reports the summary statistics of the full sample. Section 4.4 explores the extent to which fund managers matter using a fixed effects regression analysis. Section 4.5 employs the commonly used skill measure, performance persistence, to further compare the relative importance of manager skills and fund skills in driving fund performance, and also examines the portability of manager skills across funds. Section 4.6 explores the real effects of manager skills on the investment decisions of investors. Finally Section 4.7 concludes.

4.2. Literature Review

This section briefly reviews the literature on the determinants of mutual fund performance. Previous studies suggest that both fund managers and fund organizations play a role in driving fund performance. In the following two sub-sections, we review studies that focus on fund managers and studies that focus on funds/fund families, respectively.

4.2.1. Fund Managers and Fund Performance

Several studies find that fund performance can be explained by manager characteristics. For instance, Golec (1996) shows that funds with younger managers, managers who possess MBA degrees, and managers who have longer tenure exhibit higher risk-adjusted performance. Chevalier and Ellison (1999) document a strong relation between fund performance and the average SAT scores of the undergraduate institutions that fund managers attend. The authors also find that younger managers tend to perform better. Gottesman and Morey (2006), who focus on the relation between manager education and fund performance, find that the quality of the MBA program that fund managers attend has a positive and significant impact on fund performance.

Studies that look at the dynamic relation between fund performance and managerial turnover also provide indirect evidence that fund managers contribute to performance. For example, Khorana (1996) finds that funds with poor performance are more likely to replace their managers, indicating that fund managers could be crucial for performance. Khorana (2001) further examines the impact of mutual fund managerial turnover on subsequent fund performance, and documents significant performance improvements after the underperforming funds replace their managers. Ma (2012) studies the hiring decisions made by mutual funds, and finds that funds that hire managers with longer industry experience and higher education levels exhibit superior subsequent performance.

4.2.2. Funds/Fund Families and Fund Performance

The relation between fund performance and fund characteristics has been extensively studied. However, the findings are somewhat mixed, even among papers that study the same fund characteristics. For example, on fund size, Grinblatt and Titman (1989, 1994) find mixed evidence on the relation between fund performance and fund size, depending on how they measure fund performance. Chen, Hong, Huang and Kubik (2004) find a negative relation between fund returns and lagged fund size, while Elton, Gruber and Blake (2012) are unable to detect significant evidence on the relation between the two. More recently, Ferreira, Keswani, Miguel and Ramos (2012) study the performance of active equity mutual funds in 27 countries. The authors find that fund size has a negative and significant impact on fund performance for U.S. funds, but a positive and significant impact on fund performance for non-U.S. funds. On fund flows, Gruber (1996) and Zheng (1999) document a positive relationship between fund flows and future fund performance. However, Sapp and Tiwari (2004) show that the relationship becomes insignificant after the momentum effect is taken into consideration. Ferreira, Keswani, Miguel and Ramos (2012) find no evidence of a significant relation between fund flows and subsequent performance for U.S. funds, but a positive and significant relationship for non-U.S. funds. On fund fees, Carhart (1997) and Gil-Bazo and Ruiz-Verdu (2009), among others, find that fund expenses have a negative impact on fund performance, while Chen, Hong, Huang and Kubik (2004) find insignificant evidence on the relation between fees and performance. Ferreira, Keswani, Miguel and Ramos (2012) find that the impact of fund expenses on fund performance is insignificant for U.S. funds, but is negative and significant for non-U.S. funds in some model specifications. On fund turnover, Carhart (1997) demonstrates that turnover negatively impacts fund performance, while Chen, Hong, Huang, and Kubik (2004) find no evidence of a significant relationship between turnover and performance.

Fund organizations are also found to play a role in determining fund performance. First, Chen, Hong, Huang and Kubik (2004) find that fund performance increases with fund family size, which could be interpreted as economies of scale at the family level that are associated with trading commissions and lending fees. Second, some recent studies show that fund family strategies also affect fund performance. For example, Massa (2003) argues that fund families offering more diversified products rely less on performance to differentiate themselves from others, and thus may target a lower level of performance. Consistent with this argument, Massa detects a negative relation between fund family product differentiation and fund performance. Nanda, Wang and Zheng (2004) show that fund families may pursue a star-creating strategy, as star funds attract inflows not only to the funds themselves but also to other funds within the same family. Gaspar, Massa and Matos (2006) show that fund families favor some funds over others. Favored funds benefit from better IPO allocations and opposite trades with other member funds, which partly contribute to their superior performance. Bhattacharya, Lee and Pool (2013) focus on fund families that offer affiliated funds of mutual funds (AFoMFs), which are mutual funds that can only invest in other member funds within the family. The authors find evidence that AFoMFs provide liquidity to other member funds in the family, so that the performance of the member funds will not be significantly affected by fire sales.

As noted in the introduction, to the best of our knowledge, there is no unifying study that brings together these literatures.

4.3. Data, Variable Constructions and Summary Statistics

4.3.1. Data

We obtain data from the Morningstar Direct U.S. Mutual Fund Database. This survivorship-bias-free database provides comprehensive information on fund inception dates, management companies, advisory companies, returns, total net assets, expense ratios, turnover ratios and investment objectives. Importantly for this study, it provides a manager history variable containing the names and tenure of all managers who have managed a given fund. We base our empirical analyses on Morningstar rather than the more widely used mutual fund database, Center for Research and Security Prices (CRSP) Survivorship-Bias Free Mutual Fund Database, as information on fund managers in Morningstar is more accurate. Massa, Reuter and Zitzewitz (2010) show that Morningstar does a significantly better job of capturing the manager information disclosed in fund prospectuses and SEC filings than CRSP. Further, during the period 1993-2004, for most funds managed by more than three managers, CRSP simply reports "Team Managed", while Morningstar reports the names of all managers.

The initial sample includes all U.S. equity funds that have existed anytime in Morningstar from 1987 to 2012.[30] Restricting our analyses to a single asset class allows us to focus our interpretation of results on a comparable skill set. From the initial sample we exclude index funds according to the Morningstar index fund indicator, so that we concentrate on funds whose performance relies on the active investment of managers. For funds with multiple share classes, we use returns data of the share class with the longest history as fund returns.[31] We calculate fund assets as the sum of total net assets of all share classes. For expense and turnover ratio, we compute an asset-weighted average across different share classes. In each period, we exclude funds whose assets are less than US$15 million or that have existed for less than three years to eliminate potential selection biases.[32]

[30] These common equity funds have Morningstar categories: large growth, large value, large blend, mid-cap growth, mid-cap value, mid-cap blend, small growth, small value, and small blend.

[31] Our results are essentially the same if we calculate fund returns as the value-weighted average across different share classes.

[32] Our results are essentially the same if we include funds whose assets are less than US$15 million or that have existed for less than three years.

The final sample includes 2,834 actively managed U.S. equity funds managed by 5,885 fund managers.

4.3.2. Variable Constructions

A. Mutual Fund Performance

We measure mutual fund performance using the Carhart (1997) four-factor alpha estimated from the model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,1}MKTRF_t + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}UMD_t + \epsilon_{i,t} \quad (4.1),$$

where $R_{i,t}$ is the return on fund i, $R_{f,t}$ is the risk-free return, α_i is the performance measure, $MKTRF_t$ is the market return in excess of risk-free return, SMB_t is the return difference between small and big stocks, HML_t is the return difference between value and growth stocks, UMD_t is the return difference between stocks with high and low past returns, $\beta_{i,1}$ - $\beta_{i,4}$ are the factor loadings, and $\epsilon_{i,t}$ is an error term.[33] Following Elton, Gruber, and Blake (2012), we estimate alpha every year using weekly returns, requiring a minimum of 30 observations.

B. Fund Flows

Following Sirri and Tufano (1998), we define fund flows as the growth rate of total net assets (TNA) after adjusting for asset appreciation, assuming all dividends are reinvested. Specifically, it is calculated as:

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[33] We thank Professor Kenneth French for providing data on his website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on December 16, 2013).

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \quad (4.2),$$

where $TNA_{i,t}$ and $TNA_{i,t-1}$ are the total net assets of fund i at the end of year t and $t - 1$, respectively, and $R_{i,t}$ is the return of fund i over year t. This definition assumes that all flows occur at the end of the year. Our results are qualitatively similar if we recalculate this measure assuming that all flows occur at the beginning or in the middle of the year.

C. Other Variables

We follow standard convention and define the following fund and manager level controls. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Manager Tenure is the number of months that the manager has been working for the fund.

4.3.3. Summary Statistics

Table 4.1 reports summary statistics for the variables used in the analysis. The sample includes 2,834 distinct mutual funds. The funds, on average, earn a weekly abnormal return of -0.013%. The average fund size is about US$1.4 billion, while the average family size is about US$73 billion. A typical fund has existed for more than 15 years since its inception date. Its asset size grows at a rate of 10.59% each year after adjusting for asset appreciation. The average expense ratio is 1.19% and turnover ratio is 82.44%. The funds in the sample have been managed by 5,885 fund managers. The average tenure of a typical fund manager at a fund is about 5 years.

Table 4.1 Summary Statistics for the Full Sample

This table presents summary statistics for all the sample funds over the period 1987-2012. Alpha is Carhart (1997) four-factor alpha calculated each year using at least 30 weekly fund returns within that year. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date. Flow is the growth rate of fund TNA after adjusting for asset appreciation. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Manager Tenure is the number of months that the manager has been working for the fund.

	Mean	Median	Standard Deviation
No. of distinct funds	2,834		
No. of distinct managers	5,885		
Alpha (%)	-0.013	-0.016	0.142
Fund TNA ($M)	1,398	286	5,058
Family TNA ($M)	72,965	15,492	178,673
Fund Age (Months)	183	131	160
Flow (%)	10.59	-3.97	61.16
Expense Ratio (%)	1.19	1.15	0.41
Turnover Ratio (%)	82.44	63.80	79.89
Manager Tenure (Month)	67	54	54

4.4. Do Fund Managers Matter for Fund Performance?

4.4.1. Comparison between Manager and Fund Fixed Effects

We start by asking to what extent fund managers matter for fund performance. To answer this question, we explore how much of the unexplained variation in fund performance can be attributed to manager fixed effects, after accounting for relevant time-varying fund and manager characteristics, and how this extent compares with that of fund fixed effects. There are two basic approaches that can be used to separate manager and fund fixed effects. The first approach is introduced by Bertrand and Schoar (2003), who study the impact of individual managers on various corporate decisions. This approach separates manager fixed effects from firm fixed effects by focusing on managers who have switched firms. Specifically, the authors first identify managers who have worked for at least two firms, and then create a panel dataset that is composed of firm-year observations in which the firms are managed by these managers. This approach suffers from two major drawbacks. First, it may reduce the sample size significantly as managers that have switched jobs may only be a small proportion of all managers. Second, it may introduce a selection bias due to the potential differences between managers who have switched jobs and those who have not.

The second approach is introduced by Graham, Li and Qiu (2011), who study the influence of unobservable firm and manager characteristics on executive compensation. Similar to the first approach, this approach also requires the identification of managers who have switched firms. However, it creates a panel dataset consisting of all firm-year observations of the firms for which these switchers have ever worked, including those in which the firms are managed by non-switchers. This approach reduces the drawbacks of the first approach by adding some managers who have never switched firms into the sample. Thus, the sample size is increased, and the manager fixed effects are estimated not only for switchers but also for some non-switchers. Due to these advantages, we follow the second approach to separate manager and fund fixed effects in our study.

However, the manager-fund setting differs from the manager-firm setting in two aspects. First, in the manager-firm setting, a firm typically has only one manager at a specific position such as CEO or CFO, while a fund can be managed by a sole manager or a team of managers. As it is not clear how tasks are allocated within a team, we focus on only sole-managed funds in this section. Second, a firm manager only works for one firm at a specific time point, while a fund manager can manage multiple funds at the same time. Thus, we identify sole managers who have worked for at least two funds, including those who have switched funds and those who manage multiple funds simultaneously. We then create a list of funds that have been managed by these managers, and include all fund-year observations of the listed funds in which the funds are sole-managed to create a panel dataset. This sample includes 933 distinct funds managed by 904 fund managers. Among the sample managers, 485 (54%) have managed more than one fund.

Table 4.2 presents the summary statistics for the sample funds. The statistics are comparable with those presented in Table 4.1 for the full sample, except that the funds in this sample are somewhat larger and older, managed by relatively bigger fund families, and have slightly higher turnover ratios.

Table 4.2 Summary Statistics for the Fixed Effects Sample

This table presents summary statistics for the sample funds used to compare manager and fund fixed effects. Alpha is Carhart (1997) four-factor alpha calculated each year using at least 30 weekly fund returns within that year. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date. Flow is the growth rate of fund TNA after adjusting for asset appreciation. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Manager Tenure is the number of months that the manager has been working for the fund.

	Mean	Median	Standard Deviation
No. of distinct funds	933		
No. of distinct managers	904		
No. of managers that have managed multiple funds	485		
Alpha (%)	-0.012	-0.014	0.149
Fund TNA ($M)	1,761	395	5,250
Family TNA ($M)	118,304	21,072	239,473
Fund Age (Months)	201	139	174
Flow (%)	13.63	-2.32	60.45
Expense Ratio (%)	1.17	1.13	0.42
Turnover Ratio (%)	92.03	67.00	88.14
Manager Tenure (Month)	80	66	58

Using this dataset, we estimate the following regression:

$$\alpha_{i,t} = \beta X_{i,t-1} + \gamma_t + \delta_s + \lambda_i + \lambda_m + \epsilon_{i,t} \quad (4.3),$$

where $\alpha_{i,t}$ is fund i's performance in year t in terms of Carhart (1997) four-factor alpha estimated using weekly returns within that year, $X_{i,t-1}$ represents a vector of time-varying fund and manager characteristics, including fund TNA, family TNA, fund age, flow, expense ratio, turnover ratio, alpha rank, and manager tenure, γ_t are year fixed effects, δ_s are style fixed effects, λ_i are fund fixed effects, λ_m are manager fixed effects, and $\epsilon_{i,t}$ is an error term.

We present the regression results in Panel A of Table 4.3. Regression (1) serves as a benchmark specification that includes only time-varying control variables, year fixed effects, and style fixed effects. The adjusted R^2 for this regression is 16.8%. In regression (2), we further include fund fixed effects, while in regression (3), we further include manager fixed effects. Adding manager fixed effects increases the adjusted R^2 to 24.7%, while adding fund fixed effects only increases the adjusted R^2 to 20.3%. The absolute increase caused by adding manager fixed effects is more than twice that caused by adding fund fixed effects. In regression (4), we add both fund and manager fixed effects into the benchmark specification. Comparing the adjusted R^2 of this regression with those of regression (2) and (3), we find that adding manager fixed effects on top of fund fixed effects further increases the adjusted R^2 by 4.7%, while adding fund fixed effects on top of manager fixed effects only slightly increases the adjusted R^2 by 0.3%. According to the F-tests in regression (2)-(4), we are able to reject the null hypothesis that all fund/manager fixed effects are zero. Our results suggest that a larger part of the unexplained variation in fund performance can be attributed to manager fixed effects than to fund fixed effects. The evidence is consistent with manager fixed effects playing a more important role than fund fixed effects in explaining fund performance.

The fund fixed effects identified above may underestimate the real effects exerted by the fund company, as some of the effects have been absorbed by time-varying fund-level controls. For example, even though the fund size of a large fund changes over time, it may be consistently larger than the size of a small fund. To address this concern, we repeat our analysis without control variables. The results are presented in Panel B of Table 4.3. Adding manager fixed effects into the benchmark specification increases the adjusted R^2 by 8.6%, compared with only 2.7% after adding fund fixed effects. Further, adding manager fixed effects on top of fund fixed effects further increases the adjusted R^2 by 4.5%, while adding fund fixed effects on top of manager fixed effects does not increase the adjusted R^2. In fact, it reduces the adjusted R^2 by 1.4%. The results are consistent with our previous findings.

Table 4.3 Comparison between Manager and Fund Fixed Effects in Explaining the Variation in Fund Performance

This table presents the regression results for the comparison between manager fixed effects and fund fixed effects in explaining the variation in fund performance. Regressions in Panel A include time-varying fund and manager characteristics as control variables, while regressions in Panel B do not include these characteristics. The dependent variable is the current year Carhart (1997) four-factor alpha expressed in basis points that is calculated using at least 30 weekly fund returns within that year. All the independent variables are measured in the previous year. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date to the end of each year. Flow is the growth rate of fund TNA after adjusting for asset appreciation over a year. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Alpha Rank is the rank of Carhart (1997) four-factor alpha calculated using weekly fund returns within a year, ranging from 0 to 1. Manager Tenure is the number of months that the manager has been working for the fund. All regressions include year and style fixed effects. Regression (2), (4), (6), and (8) include fund fixed effects. Regression (3), (4), (7), and (8) include manager fixed effects. The standard errors are clustered at the fund level and the t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for fund and manager characteristics				
	(1)	(2)	(3)	(4)
Fund TNA (log)	-0.409***	-3.709***	-1.391***	-4.351***
	(-2.963)	(-9.790)	(-6.805)	(-7.040)
Family TNA (log)	0.118	0.816	-0.117	-0.347
	(1.145)	(1.128)	(-0.551)	(-0.304)
Fund Age (log)	-0.387	-1.892	0.581	-0.792
	(-1.466)	(-1.266)	(1.469)	(-0.311)
Flow	-0.701*	-0.702	-0.985**	-0.459
	(-1.826)	(-1.406)	(-2.296)	(-0.812)
Expense Ratio (%)	-1.498***	-2.886	-3.287***	-4.860
	(-2.886)	(-1.222)	(-2.668)	(-1.307)
Turnover Ratio (%)	-0.007**	-0.005	0.005	0.003
	(-2.447)	(-0.992)	(0.924)	(0.472)
Alpha Rank	5.543***	0.994	0.317	-2.130***
	(8.714)	(1.415)	(0.477)	(-2.878)
Manager Tenure (log)	0.018	-0.473	-0.376	-1.441
	(0.070)	(-1.176)	(-0.948)	(-1.520)
Year fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Fund fixed effects		Yes		Yes
Manager fixed effects			Yes	Yes
Clustering by fund	Yes	Yes	Yes	Yes
Observations	6,334	6,334	6,334	6,334
Adjusted R-squared	0.168	0.203	0.247	0.250
p-value for F-test on fund fixed effects		.000***		.000***
p-value for F-test on manager fixed effects			.000***	.000***

Table 4.3 (continued)

Panel B: Not controlling for fund and manager characteristics				
	(5)	(6)	(7)	(8)
Year fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Fund fixed effects		Yes		Yes
Manager fixed effects			Yes	Yes
Clustering by fund	Yes	Yes	Yes	Yes
Observations	6,334	6,334	6,334	6,334
Adjusted R-squared	0.150	0.177	0.236	0.222
p-value for F-test on fund fixed effects		.000***		.000***
p-value for F-test on manager fixed effects			.000***	.000***

4.4.2 Comparison between Manager and Firm/Advisor Fixed Effects

So far, we have documented that manager fixed effects play a more important role than fund fixed effects in explaining the variation in fund performance. However, as fund managers may manage multiple funds within the same fund company, or stay with the same fund company when switching funds, it is possible that manager fixed effects only capture the fixed effects of fund companies. Further, fund companies often outsource the management of their funds to advisory companies (Chen, Hong, Jiang and Kubik, 2013), in which case there may be advisor fixed effects in the performance of funds sharing the same advisory company. To address these concerns, we also compare manager fixed effects with firm and advisor fixed effects. If manager fixed effects simply proxy for firm/advisor fixed effects, one would expect that adding manager fixed effects into the benchmark specification would increase the adjusted $R^2$by the same level as adding firm/advisor fixed effects. Further, adding manager fixed effects on top of firm/advisor fixed effects would not increase the adjusted R^2significantly.

To conduct the robustness tests, we need new datasets that allow us to separate manager fixed effects and firm/advisor fixed effects. The approach we use to construct the datasets is similar to the one used in the comparison between manager and fund fixed effects. For example, to compare manager fixed effects and firm fixed effects, we identify fund managers who have served multiple fund companies and create a list of all fund companies they have worked at. We then identify all funds managed by these fund companies and create the panel dataset by including all fund-year observations of these funds.

The results of the comparisons between manager and firm fixed effects, and manager and advisor fixed effects are presented in Panel A and B of Table 4.4, respectively. As shown in Panel A, adding manager fixed effects increases the adjusted R^2 from 17.5% to 25%. The absolute increase is about five times of that caused by adding firm fixed effects. In addition, adding manager fixed effects on top of firm fixed effects further increases the adjusted R^2 by 5.8%, while adding firm fixed effects on top of manager fixed effects reduces the adjusted R^2 slightly by 0.2%. The results are similar when we compare manager fixed effects and advisor fixed effects.

Overall, our results from the fixed effects regression analysis suggest that fund performance is affected by manager heterogeneity. In addition, manager fixed effects appear to be more important than fund, firm or advisor fixed effects in determining fund performance.

Table 4.4 Comparison between Manager and Firm/Advisor Fixed Effects in Explaining the Variation in Fund Performance

Panel A and B of the table present the regression results for the comparisons between manager fixed effects and firm fixed effects, and manager fixed effects and advisor fixed effects in explaining the variation in fund performance, respectively. The dependent variable is the current year Carhart (1997) four-factor alpha expressed in basis points that is calculated using at least 30 weekly fund returns within that year. All the independent variables are measured in the previous year. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date to the end of each year. Flow is the growth rate of fund TNA after adjusting for asset appreciation over a year. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Alpha Rank is the rank of Carhart (1997) four-factor alpha calculated using weekly fund returns within a year, ranging from 0 to 1. Manager Tenure is the number of months that the manager has been working for the fund. All regressions include year and style fixed effects. Regression (2) and (4) include firm fixed effects. Regression (6) and (8) include advisor fixed effects. Regression (3), (4), (7), and (8) include manager fixed effects. The standard errors are clustered at the fund level and the t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Comparing manager and firm fixed effects				
	(1)	(2)	(3)	(4)
Fund TNA (log)	-0.418***	-0.649***	-1.532***	-1.598***
	(-3.475)	(-4.774)	(-7.587)	(-6.952)
Family TNA (log)	0.304***	-1.547***	-0.103	-1.987***
	(3.239)	(-3.847)	(-0.563)	(-2.902)
Fund Age (log)	-0.048	0.131	0.930**	1.060**
	(-0.200)	(0.514)	(2.519)	(2.331)
Flow	-0.800***	-0.890***	-1.427***	-1.428***
	(-2.742)	(-3.005)	(-4.362)	(-4.135)
Expense Ratio (%)	-1.553***	-1.798***	-1.373*	-1.221
	(-3.477)	(-3.051)	(-1.949)	(-1.383)
Turnover Ratio (%)	-0.012***	-0.008***	0.007	0.007
	(-4.684)	(-3.135)	(1.386)	(1.302)
Alpha Rank	4.442***	3.497***	-1.021	-1.306*
	(7.774)	(5.989)	(-1.532)	(-1.901)
Manager Tenure (log)	-0.097	-0.140	-0.302	-0.471
	(-0.416)	(-0.559)	(-0.747)	(-1.015)
Year fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects		Yes		Yes
Manager fixed effects			Yes	Yes
Clustering by fund	Yes	Yes	Yes	Yes
Observations	6,959	6,959	6,959	6,959
Adjusted R-squared	0.175	0.190	0.250	0.248
p-value for F-test on firm fixed effects		.000***		.000***
p-value for F-test on manager fixed effects			.000***	.000***

Table 4.4 (continued)

Panel B: Comparing manager and advisor fixed effects				
	(5)	(6)	(7)	(8)
Fund TNA (log)	-0.427***	-0.762***	-1.546***	-1.561***
	(-3.527)	(-5.209)	(-7.656)	(-6.747)
Family TNA (log)	0.279***	-0.403	-0.150	-1.283**
	(2.931)	(-1.147)	(-0.830)	(-2.566)
Fund Age (log)	-0.056	0.264	1.021***	1.157***
	(-0.229)	(0.991)	(2.790)	(2.648)
Flow	-0.817***	-0.994***	-1.538***	-1.658***
	(-2.757)	(-3.215)	(-4.768)	(-4.809)
Expense Ratio (%)	-1.596***	-1.406**	-1.565**	-1.348
	(-3.519)	(-2.222)	(-2.207)	(-1.569)
Turnover Ratio (%)	-0.010***	-0.007***	0.008	0.008
	(-3.880)	(-2.633)	(1.630)	(1.582)
Alpha Rank	4.394***	3.367***	-1.094*	-1.492**
	(7.658)	(5.770)	(-1.658)	(-2.193)
Manager Tenure (log)	-0.014	-0.247	-0.111	-0.533
	(-0.059)	(-0.977)	(-0.276)	(-1.205)
Year fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Advisor fixed effects		Yes		Yes
Manager fixed effects			Yes	Yes
Clustering by fund	Yes	Yes	Yes	Yes
Observations	6,823	6,823	6,823	6,823
Adjusted R-squared	0.176	0.192	0.256	0.259
p-value for F-test on advisor fixed effects		.000***		.000***
p-value for F-test on manager fixed effects			.000***	.000***

4.5. Comparison between Manager and Fund Skills in Driving Performance

4.5.1. Performance Persistence as the Skill Measure

The results from the fixed effects analysis suggest that manager skills dominate fund skills in determining fund performance. In this section, we shed further light on this comparison using the commonly employed skill measure, performance persistence.

In the mutual fund literature, the traditional way to test for skill is to examine the persistence in fund performance. If performance is driven by skill rather than luck, one would expect that funds would produce persistent performance over time. In particular, past winners would continue to produce higher returns, while past losers would continue to underperform. Conceptually, fund performance can be viewed as a combination of two components, one due to manager skills and the other due to fund skills. However, it is empirically impossible to separate these two components, and to observe the persistence in performance due to each of them separately. Therefore, we adopt an indirect approach by comparing the persistence in performance of sole-managed and team-managed funds. Compared with team managers, sole managers face fewer conflict issues (Dass, Nanda and Wang, 2013) and fewer investment constraints (Almazan, Brown, Carlson and Chapman, 2004), and thus are allowed to fully exert their expertise and skills in the decision making process. However, in sole-managed funds, the implementation of fund strategies may be subject to a discount, as individual managers may have idiosyncratic discretions when exercising a given strategy. On the other hand, fund strategies may be better implemented in team-managed funds, as team management may reduce eccentric distortion of individual managers (Han, Noe and Rebello, 2008) and create peer monitoring that helps to reduce moral hazard problems (Arnott and Stiglitz, 1991). However, the expertise and skills of individual managers who work in a team environment may have to be compromised in the decision making process due to coordination efforts. Hence, if manager skills dominate fund performance, one would expect that sole-managed funds exhibit a higher degree of performance persistence, while if fund skills dominate, one would expect to observe a higher degree of persistence in performance of team-managed funds.

To examine which of the predictions might be applicable, we track the performance of sole-managed and team-managed funds that share similar past performance. Specifically, every year, we divide all funds into ten deciles according to their performance in that year. We then calculate the average performance of sole-managed and team-managed funds sharing the same decile in the following year. We present the average performance of the top and bottom deciles, as well as the difference between these two in Table 4.5.

Panel A of Table 4.5 reports the results for the ranking year. The average weekly abnormal return for sole-managed funds that are among the top 10% of all funds in the ranking year is 0.237%, compared with 0.201% for top-decile team-managed funds. The average weekly abnormal return for sole-managed funds that are among the bottom 10% of all funds in the ranking year is -0.247%, compared with -0.234% for bottom-decile team-managed funds. Since we sort on performance, it is not surprising that the average performance of the top decile is significantly higher than that of the bottom decile.

In Panel B of Table 4.5, we present the results for the post-ranking year. For sole-managed funds, the difference in average performance between the top and bottom deciles is significantly larger than zero. Further, the average weekly abnormal return for the top decile is 0.033%, which is significantly positive and equivalent to 1.731% over a year.[34] For team-managed funds, even though the performance difference between the top and bottom deciles is also significantly positive, it is mainly driven by the persistent underperformance of the bottom decile. For the top decile, the average weekly abnormal return is negative and not significantly different from zero. Dividing team-managed funds further into those managed by small teams (2-3 managers) and those managed by big teams (4+ managers), we find that neither of these groups have the ability to maintain good performance in the post-ranking year. We separate funds that are anonymously managed from sole-managed and team-managed funds, and create a separate column in Table 4.5. For anonymously-managed funds, the difference between the top and bottom deciles in the post-ranking year is negative and insignificant. Thus, we find no evidence of performance persistence in these funds. Overall, our results suggest that only sole-managed funds have the ability to maintain good performance, which is consistent with manager skills dominating a fund's performance.

[34] We calculate the annual abnormal return using $(1 + \text{weekly abnormal return})^{52} - 1$.

Table 4.5 Performance Persistence of Sole-Managed and Team-Managed Funds: Portfolio Approach

This table compares performance persistence between sole-managed and team-managed funds using the portfolio approach. Each year, we divide all funds into deciles according to their Carhart (1997) four-factor alphas in that year. We further divide funds in the top and bottom deciles into groups according to their management structures. Panel A reports the average alphas for different fund groups in the ranking year. Panel B reports the average alphas for different fund groups in the post-ranking year. We calculate the averages both across funds and across time. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

		1 Manager	Team	2-3 Managers	4+ Managers	Anonymous
Panel A: Ranking year alpha (%)						
Low (Decile 1)	N	1,063	1,179	883	296	45
	Avg. alpha	-0.247***	-0.234***	-0.236***	-0.223***	-0.245***
	t-statistic	(-64.042)	(-63.800)	(-51.758)	(-37.014)	(-14.162)
High (Decile 10)	N	1,134	1,318	966	352	18
	Avg. alpha	0.237***	0.201***	0.205***	0.193***	0.178***
	t-statistic	(41.248)	(50.738)	(43.425)	(25.901)	(4.665)
High-Low	Avg. alpha	0.484***	0.435***	0.441***	0.417***	0.423***
	t-statistic	(69.057)	(80.122)	(66.975)	(42.341)	(11.626)
Panel B: Post-ranking year alpha (%)						
Low (Decile 1)	N	1,063	1,179	883	296	45
	Avg. alpha	-0.056***	-0.035***	-0.033***	-0.042***	-0.035
	t-statistic	(-10.089)	(-7.461)	(-5.794)	(-4.631)	(-1.567)
High (Decile 10)	N	1,134	1,318	966	352	18
	Avg. alpha	0.033***	-0.003	0.002	-0.015*	-0.040
	t-statistic	(5.267)	(-0.608)	(0.414)	(-1.784)	(-1.157)
High-Low	Avg. alpha	0.089***	0.033***	0.035***	0.027**	-0.005
	t-statistic	(10.563)	(4.895)	(4.416)	(2.197)	(-0.131)

In the above test, we do not consider determinant variables of fund performance other than past performance. For robustness, we re-examine the difference in performance persistence between sole-managed and team-managed funds after accounting for a set of fund and manager characteristics that may affect performance. Specifically, we estimate the following regression:

$$\alpha_{i,t} = \beta_0 + \beta_1 Team_{i,t-1} + \beta_2 \alpha_{i,t-1} + \beta_3 \alpha_{i,t-1} \times Team_{i,t-1} + \lambda Controls_{i,t-1} + \epsilon_{i,t} \quad (4.4),$$

where $\alpha_{i,t}$ is the performance of fund i in year t measured by Carhart (1997) four-factor alpha, $Team_{i,t-1}$ is a dummy variable that equals 1 when the fund is managed by a team, and 0 when the fund is managed by a sole manager, $\alpha_{i,t-1}$ is the performance rank of fund i in year $t-1$ that ranges from 0 to 1, and $Controls_{i,t-1}$ are a group of fund and manager characteristics (including fund TNA, family TNA, fund age, flow, expense ratio, turnover ratio and manager tenure), and $\epsilon_{i,t}$ is an error term.

We report the regression results in the first column of Table 4.6. The coefficient on fund past performance is positive and significant, indicating that when a fund is sole-managed, past fund performance positively predicts fund performance in the next year. The coefficient on the interaction term between fund past performance and team dummy is negative and significant, which suggests that when a fund is team-managed, the prediction power of past fund performance on future fund performance is significantly reduced. The evidence is consistent with sole-managed funds having more persistent performance than team-managed funds.

In the second regression of Table 4.6, we further divide team-managed funds into those managed by small teams (2-3 managers) and those managed by big teams (4+

managers), and replace the team dummy by two dummies representing the two sub-groups respectively. We find that the coefficient on the interaction term between past fund performance and either of these two is significantly negative. Thus, as long as the fund is managed by more than one manager, the prediction power of past performance on future performance will be reduced. The results are also consistent with sole-managed funds being more capable of maintaining performance, which provides supports to the robustness of our previous results.

Overall, our findings are consistent with manager skills dominating fund performance. As there are fewer conflict issues and fewer investment constrictions in sole-managed funds, the expertise and skills of fund managers is the main driver of fund performance. For team-managed funds, due to the lack of fund skill and various obstacles that interrupt the translation of manager skills into actual investment decisions, fund performance is mainly driven by luck and thus good performance is not persistent.

Table 4.6 Performance Persistence of Sole-Managed and Team-Managed Funds: Regression Approach

This table compares performance persistence between sole-managed and team-managed funds using the regression approach. The dependent variable is the current year Carhart (1997) four-factor alpha expressed in basis points that is calculated using at least 30 weekly fund returns within that year. All the independent variables are measured in the previous year. Team is a dummy variable that equals 1 if the fund is managed by a team and 0 if the fund is managed by a sole manager. 2-3 Managers and 4+ Managers are dummy variables that equal 1 if a fund is managed by 2 to 3 managers and more than 4 managers, respectively. Alpha Rank is the rank of Carhart (1997) four-factor alpha calculated using weekly fund returns within a year, ranging from 0 to 1. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date to the end of each year. Flow is the growth rate of fund TNA after adjusting for asset appreciation over a year. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Manager Tenure is the number of months that the manager has been working for the fund. All regressions include year and style fixed effects. The standard errors are clustered at the fund level and the t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Team	1.767***	
	(4.983)	
2-3 Managers		1.641***
		(4.300)
4+ Managers		2.082***
		(4.228)
Alpha Rank	5.767***	5.767***
	(11.464)	(11.463)
Alpha Rank × Team	-3.940***	
	(-6.435)	
Alpha Rank × 2-3 Managers		-3.527***
		(-5.392)
Alpha Rank × 4+ Managers		-5.012***
		(-5.869)
Fund TNA (log)	-0.442***	-0.437***
	(-6.017)	(-5.919)
Family TNA (log)	0.241***	0.240***
	(5.010)	(4.991)
Fund Age (log)	0.152	0.146
	(1.050)	(1.004)
Flow	-0.185	-0.195
	(-1.117)	(-1.174)
Expense Ratio (%)	-1.370***	-1.380***
	(-4.844)	(-4.887)
Turnover Ratio (%)	-0.010***	-0.010***
	(-5.826)	(-5.813)
Manager tenure (log)	-0.012	-0.013
	(-0.117)	(-0.127)
Constant	0.266	0.289
	(0.264)	(0.286)
Year fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Clustering by fund	Yes	Yes
Observations	20,950	20,950
R-squared	0.149	0.149

4.5.2. Portability of Manager Skills

So far, we have shown that sole-managed funds exhibit more persistent performance than team-managed funds, which is consistent with manager skills dominating fund performance. However, according to Han, Noe and Rebello (2008), skilled managers may self-select into sole-managed funds, as it is easier for them to reveal their personal ability. Thus, an alternative explanation for our previous results is that sole-managed funds have more persistent performance simply because their managers are more skilled. This concern cannot be addressed using our previous setting, as manager skills cannot be observed separately from fund skills. As a result, in this section we focus on managerial turnover events of sole-managed funds, which serve as a cleaner setting that allows the separation between manager skills and fund skills to a certain extent.

In a managerial turnover event, a fund replaces its previous manager by a new manager. If fund skills dominate fund performance, one would expect that the fund's performance after replacing its manager can be forecast by the fund's past performance with the previous manager. If manager skills dominate fund performance, one would expect that the fund's performance after replacing its manager can be forecast by the new manager's past performance at other funds. To examine which of the predictions might be applicable, we estimate the following regression:

$$\alpha_{i,t+1\ to\ t+12} = \beta_0 + \beta_1 \alpha^{fund}_{i,t-12\ to\ t-1} + \beta_2 \alpha^{mgr}_{i,t-12\ to\ t-1} + \lambda Controls_{i,t-1} + \epsilon_{i,t}, \qquad (4.5)$$

where t is the month in which fund i replaces its manager, $\alpha_{i,t+1\ to\ t+12}$ is the fund's post-turnover performance measured by Carhart (1997) four-factor alpha over the twelve-month period after the turnover, $\alpha^{fund}_{i,t-12\ to\ t-1}$ is the fund's pre-turnover performance measured by alpha rank over the twelve-month period before the turnover, $\alpha^{mgr}_{i,t-12\ to\ t-1}$ is the new manager's pre-turnover performance measured by the average alpha rank of other funds managed by the manager over the twelve-month period before the turnover, $Controls_{i,t-1}$ are a group of fund characteristics (including fund TNA, family TNA, fund age, flows, expense ratio and turnover ratio), and $\epsilon_{i,t}$ is an error term.

Panel A of Table 4.7 reports the sample selection process. Initially we identify 1,879 managerial turnover events of sole-managed funds during the sample period. However, as the fund must have pre-turnover and post-turnover performance, and the new manager must solely manage other funds over the twelve-month period before taking over the fund, the sample size reduces to 230 events. After retaining funds that have fund-level controls at the end of the twelve-month period prior to the event month, there are 194 managerial turnovers that are associated with 166 funds and 152 fund managers.

Panel B of Table 4.7 presents the summary statistics for the managerial turnover sample. Prior to the managerial turnover, the average alpha rank of the sample funds is slightly lower than an average fund, while the average alpha rank of the sample managers is slightly higher than an average manager. The average pre-turnover fund TNA, family TNA, fund age, and turnover ratio appear to be larger than the averages of the full sample, while the other variables are comparable with the full sample.

Table 4.7 Sample Construction Process and Summary Statistics for the Turnover Sample

Panel A of the table presents the number of managerial turnover events after each step of the sample construction process. Panel B presents the summary statistics for the turnover sample. We identify the month in which a sole-managed fund replaces its manager as the event month t. Fund Post-Turnover Alpha is Carhart (1997) four-factor alpha calculated using at least 30 weekly fund returns over month t+1 to t+12. Fund Pre-Turnover Alpha Rank is the rank of the fund's Carhart (1997) four-factor alpha calculated using at least 30 weekly fund returns over month t-12 to t-1, ranging from 0 to 1. Manager Pre-Turnover Alpha Rank (EW) and Manager Pre-Turnover Alpha Rank (VW) are the equally- and asset-weighted averages of the alpha ranks of the funds managed by the new manager over month t-12 to t-1, respectively, ranging from 0 to 1. Fund Pre-Turnover TNA is the market value of the fund's assets at the end of month t-1. Family Pre-Turnover TNA is the market value of the assets held by the fund's family at the end of month t-1. Fund Pre-Turnover Age is the number of months since the fund's inception date at the end of month t-1. Flow is the growth rate of fund TNA over month t-12 to t-1 after adjusting for asset appreciation. Pre-Turnover Expense Ratio is the ratio of operating expenses to total investment at the end of month t-1. Pre-Turnover Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets.

Panel A: Sample selection process for the turnover sample	
Initial no. of managerial turnovers by sole-managed funds	1,879
No. of managerial turnovers with available fund post-turnover performance	1,046
No. of managerial turnovers with available fund pre-turnover performance	908
No. of managerial turnovers with available manager pre-turnover performance	230
No. of managerial turnovers with available fund-level controls	194

Panel B: Summary statistics for the turnover sample			
	Mean	Median	Standard Deviation
No. of distinct funds	166		
No. of distinct managers	152		
Fund Post-Turnover Alpha (%)	-0.017	-0.020	0.147
Fund Pre-Turnover Alpha Rank	0.43	0.44	0.32
Manager Pre-Turnover Alpha Rank (EW)	0.53	0.56	0.31
Manager Pre-Turnover Alpha Rank (VW)	0.51	0.51	0.28
Fund Pre-Turnover TNA ($M)	2,291	344	5,652
Family Pre-Turnover TNA ($M)	156,556	35,331	275,037
Fund Pre-Turnover Age (Months)	220	156	187
Pre-Turnover Flow (%)	9.67	-8.87	79.14
Pre-Turnover Expense Ratio (%)	1.20	1.14	0.43
Pre-Turnover Turnover Ratio (%)	104.17	84.50	72.72

The regression results are presented in Table 4.8. In regression (1), (3), and (5), we calculate manager pre-turnover performance using equally-weighted averages of fund alpha ranks, while in regression (2), (4), and (6), we calculate manager pre-turnover performance using asset-weighted averages of fund alpha ranks. In regression (1)-(4), we find that the coefficient on manager pre-turnover performance is positive and statistically significant, which suggests that fund post-turnover performance can be forecast by manager pre-turnover performance. The result holds with or without the presence of fund-level controls. On the other hand, the coefficient on fund pre-turnover performance is negative, and is not significant or significant at 10% level depending on different model specifications, which indicates that the post-turnover performance of a fund cannot be forecast by the fund's own performance before the managerial turnover.

The results may be driven by the selection bias that managers chosen by funds tend to be more skilled, and thus exhibit more persistent performance. The concern could be reasonable as the mean and median of manager pre-turnover alpha ranks are both slightly higher than 0.5. To address this issue, we divide the sample managers into two sub-groups: those with above average past performance and those with below average past performance. In regression (5) and (6), we replace manager pre-turnover alpha rank using the interactions between manager pre-turnover alpha rank and either of these two sub-groups. We find that the coefficients on both terms are positive and statistically significant, which provides supports to the robustness of our previous findings.

In summary, our results from the managerial turnover setting suggest that fund managers are able to maintain performance across funds, while funds do not have persistent performance with different fund managers. The findings are again consistent with manager skills dominating fund performance.

Table 4.8 Forecasting Fund Post-Turnover Performance Using Fund and Manager Pre-Turnover Performance

This table presents the regression results for fund and manager pre-turnover performance as predictors of fund post-turnover performance. We identify the month in which a sole-managed fund replaces its manager as the event month t. The dependent variable is Fund Post-Turnover Alpha, which is measured by Carhart (1997) four-factor alpha calculated using at least 30 weekly fund returns over month t+1 to t+12, expressed in basis points. Fund Pre-Turnover Alpha Rank is the rank of the fund's Carhart (1997) four-factor alpha calculated using at least 30 weekly fund returns over month t-12 to t-1, ranging from 0 to 1. In regression (1), (3), and (5), Manager Pre-Turnover Alpha Rank is the equally-weighted average of the alpha ranks of the funds managed by the new manager over month t-12 to t-1, ranging from 0 to 1. In regression (2), (4), and (6), Manager Pre-Turnover Alpha Rank is the asset-weighted average of the alpha ranks of the funds managed by the new manager over month t-12 to t-1, ranging from 0 to 1. Fund Pre-Turnover TNA is the market value of the fund's assets at the end of month t-1. Family Pre-Turnover TNA is the market value of the assets held by the fund's family at the end of month t-1. Fund Pre-Turnover Age is the number of months since the fund's inception date at the end of month t-1. Flow is the growth rate of fund TNA over month t-12 to t-1 after adjusting for asset appreciation. Pre-Turnover Expense Ratio is the ratio of operating expenses to total investment at the end of month t-1. Pre-Turnover Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. The standard errors are clustered at the fund level and the t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	EW	VW	EW	VW	EW	VW
Fund Pre-Turnover Alpha Rank	-4.235	-4.108	-7.660*	-7.582*	-6.441	-6.741
	(-1.198)	(-1.157)	(-1.916)	(-1.884)	(-1.173)	(-1.195)
Mgr. Pre-Turnover Alpha Rank	8.401**	7.838**	11.377***	10.800***		
	(2.345)	(2.200)	(3.041)	(2.909)		
Mgr. Pre-Turnover Alpha Rank ×					10.445**	10.149**
Above Average					(2.260)	(2.159)
Mgr. Pre-Turnover Alpha Rank ×					11.990***	11.202***
Below Average					(2.723)	(2.615)
Fund Pre-Turnover TNA (log)			-0.866	-0.851	-0.877	-0.859
			(-1.117)	(-1.099)	(-1.125)	(-1.105)
Family Pre-Turnover TNA (log)			1.125*	1.134*	1.120*	1.132*
			(1.701)	(1.729)	(1.668)	(1.708)
Fund Pre-Turnover Age (log)			0.782	0.765	0.799	0.776
			(0.549)	(0.540)	(0.561)	(0.547)
Pre-Turnover Flow			1.548	1.529	1.547	1.526
			(1.309)	(1.291)	(1.297)	(1.279)
Pre-Turnover Expense Ratio (%)			2.750	2.816	2.758	2.817
			(0.912)	(0.933)	(0.915)	(0.931)
Pre-Turnover Turnover Ratio (%)			-0.016	-0.017	-0.016	-0.017
			(-1.069)	(-1.128)	(-1.062)	(-1.125)
Constant	-3.935**	-3.744*	-16.635	-16.517	-17.060	-16.790
	(-1.994)	(-1.864)	(-1.534)	(-1.522)	(-1.614)	(-1.583)
Clustering by fund	Yes	Yes	Yes	Yes	Yes	Yes
Observations	230	230	194	194	194	194
R-squared	0.030	0.027	0.078	0.074	0.079	0.074

4.6. Manager Skills and Fund Flows

We have shown that manager skills not only matter but also appear to dominate fund performance. In this section, we ask whether manager skill is appreciated by the market and whether it affects the investment decisions of investors. If manager skills are rewarded by fund flows, one would expect that flows are more sensitive to performance for sole-managed funds than for team-managed funds. This is because manager skills are the main performance driver of sole-managed funds, and thus good performance of sole-managed funds tends to be more persistent. Further, if manager skills are appreciated by investors, fund flows would chase fund managers rather than funds. Therefore, one would expect that when a manager takes over a new fund, the fund's flows can be forecast by the manager's past performance at other funds. We test the two predictions in the following two sub-sections, respectively.

4.6.1. Comparison of the Flow-Performance Relationship between Sole-Managed and Team-Managed Funds

To compare the sensitivity of fund flows to performance between sole-managed and team-managed funds, we estimate the following regression:

$$flow_{i,t} = \beta_0 + \beta_1 Team_{i,t-1} + \beta_2 \alpha_{i,t-1} + \beta_3 \alpha_{i,t-1} \times Team_{i,t-1} + \lambda Controls_{i,t-1} + \epsilon_{i,t} \quad (4.6),$$

where $flow_{i,t}$ is the flow of fund i in year t, $Team_{i,t-1}$ is a dummy variable that equals 1 when the fund is managed by a team, and 0 when the fund is managed by a sole manager, $\alpha_{i,t-1}$ is the alpha rank of fund i in year $t-1$ that ranges from 0 to 1, and $Controls_{i,t-1}$ are a group of fund and manager characteristics (including fund TNA, family TNA, fund age, flows, expense ratio, turnover ratio and manager tenure), and $\epsilon_{i,t}$ is an error term.

The regression results are presented in Table 4.9. In regression (1), the estimated coefficient on the interaction term between fund past performance and the team dummy is negative but not statistically significant. Further dividing team-managed funds into those managed by small teams (2-3 managers) and those managed by big teams (4+ managers) in regression (2), we find that the decrease in the sensitivity of flows to performance is not significant for funds managed by small teams, but is significant at the 5% level for funds with more than three managers. Overall, we find modest evidence that the flow-performance relationship is more sensitive for sole-managed funds.

Table 4.9 Flow-Performance Relationship of Sole-Managed and Team-Managed Funds

This table provides regression results for the comparison in the flow-performance relationship between sole- and team-managed funds. The dependent variable is the current year flow. All the independent variables are measured in the previous year. Team is a dummy variable that equals 1 if the fund is managed by a team and 0 if the fund is managed by a sole manager. 2-3 Managers and 4+ Managers are dummy variables that equal 1 if a fund is managed by 2 to 3 managers and more than 4 managers, respectively. Alpha Rank is the rank of Carhart (1997) four-factor alpha calculated using weekly fund returns within a year, ranging from 0 to 1. Fund TNA is the market value of the fund's assets at the end of each year. Family TNA is the market value of the assets held by the fund's family at the end of each year. Fund Age is the number of months since the fund's inception date to the end of each year. Flow is the growth rate of fund TNA after adjusting for asset appreciation over a year. Expense Ratio is the ratio of operating expenses to total investment. Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. Manager Tenure is the number of months that the manager has been working for the fund. All regressions include year and style fixed effects. The standard errors are clustered at the fund level and the t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Team	0.010	
	(0.890)	
2-3 Managers		0.011
		(0.884)
4+ Managers		0.042**
		(2.506)
Alpha Rank	0.309***	0.311***
	(16.563)	(16.896)
Alpha Rank × Team	-0.022	
	(-0.923)	
Alpha Rank × 2-3 Managers		-0.004
		(-0.172)
Alpha Rank × 4+ Managers		-0.082**
		(-2.517)
Fund TNA (log)	-0.051***	-0.051***
	(-13.764)	(-13.681)
Family TNA (log)	0.023***	0.023***
	(10.161)	(10.190)
Fund Age (log)	-0.016***	-0.016***
	(-3.200)	(-3.192)
Flow	0.256***	0.256***
	(22.601)	(22.569)
Expense Ratio	2.410**	2.400**
	(2.478)	(2.472)
Turnover Ratio	0.003	0.003
	(0.497)	(0.523)
Manager Tenure (log)	0.020***	0.020***
	(5.468)	(5.498)
Constant	-0.072*	-0.080**
	(-1.897)	(-2.101)
Year fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Clustering by fund	Yes	Yes
Observations	21,430	21,430
R-squared	0.181	0.181

4.6.2. Comparison between Fund and Manager Pre-Turnover Performance as Determinants of Post-Turnover Flows

In this sub-section, we focus on managerial turnover events and examine the relationship between fund/manager pre-turnover performance and post-turnover flows. Specifically, we estimate the following regression:

$$flow\_obj_{i,t+1\ to\ t+12} = \beta_0 + \beta_1 \alpha^{fund}_{i,t-12\ to\ t-1} + \beta_2 \alpha^{mgr}_{i,t-12\ to\ t-1} + \lambda Controls_{i,t-1} + \epsilon_{i,t}, \tag{4.7}$$

where t is the month in which fund i replaces its manager, $flow\_obj_{i,t+1\ to\ t+12}$ is the fund's post-turnover objective adjusted flow, $\alpha^{fund}_{i,t-12\ to\ t-1}$ is the fund's pre-turnover performance measured by the alpha rank over the twelve-month period before the turnover, $\alpha^{mgr}_{i,t-12\ to\ t-1}$ is the new manager's pre-turnover performance measured by the average alpha rank of other funds managed by the manager over the twelve-month period before the turnover, $Controls_{i,t-1}$ are a group of fund characteristics (including fund TNA, family TNA, fund age, flows, expense ratio and turnover ratio), and $\epsilon_{i,t}$ is an error term.

We present the results in Table 4.10. In regression (1), the estimated coefficient on fund pre-turnover performance is positive and significant, while that on manager pre-turnover performance is positive but not significant. The results suggest that the flows can be forecast by fund past performance rather than manager past performance. However, the result could be driven by the turnover events of team-managed funds. This is because when team-managed funds replace managers, it is more likely that only a part of the management team is replaced. To address this concern, we further divide fund managers into those who move to sole-managed funds and those who move to team-managed funds.

The results are presented in regression (2) of Table 4.10. The estimated coefficients on the two interaction terms are positive but again insignificant. Thus, we do not find significant evidence that flows chase the performance of fund managers.

Table 4.10 Forecasting Post-Turnover Flows Using Fund and Manager Pre-Turnover Performance

This table presents the regression results for fund and manager pre-turnover performance as predictors of post-turnover flows. We identify the month in which a sole-managed fund replaces its manager as the event month t. The dependent variable is objective adjusted fund flow over month $t+1$ to $t+12$. Fund Pre-Turnover Alpha Rank is the rank of the fund's Carhart (1997) four-factor alpha calculated using at least 30 weekly fund returns over month t-12 to t-1, ranging from 0 to 1. Manager Pre-Turnover Alpha Rank is the asset-weighted average of the alpha ranks of the funds managed by the new manager over month t-12 to t-1, ranging from 0 to 1. Sole is a dummy variable that equals 1 if the fund is managed by a sole manager after the managerial turnover and 0 otherwise. Team is a dummy variable that equals 1 if the fund is managed by a team after the managerial turnover and 0 otherwise. Fund Pre-Turnover TNA is the market value of the fund's assets at the end of month t-1. Family Pre-Turnover TNA is the market value of the assets held by the fund's family at the end of month t-1. Fund Pre-Turnover Age is the number of months since the fund's inception date at the end of month t-1. Pre-Turnover Flow is the growth rate of fund TNA over month t-12 to t-1 after adjusting for asset appreciation. Pre-Turnover Expense Ratio is the ratio of operating expenses to total investment at the end of month t-1. Pre-Turnover Turnover Ratio is equal to the minimum of aggregated purchases or sales of securities by the fund divided by the fund's assets. The standard errors are clustered at the fund level and the t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Fund Pre-Turnover Alpha Rank	0.206***	0.206***
	(3.683)	(3.703)
Manager Pre-Turnover Alpha Rank	0.038	
	(0.720)	
Manager Pre-Turnover Alpha Rank × Sole		0.040
		(0.601)
Manager Pre-Turnover Alpha Rank × Team		0.038
		(0.673)
Fund Pre-Turnover TNA (log)	-0.061***	-0.061***
	(-3.964)	(-3.906)
Family Pre-Turnover TNA (log)	0.027***	0.027***
	(2.723)	(2.670)
Fund Pre-Turnover Age (log)	-0.022	-0.022
	(-0.939)	(-0.923)
Pre-Turnover Flow	0.283***	0.283***
	(5.447)	(5.445)
Pre-Turnover Expense Ratio (%)	0.168	0.163
	(0.044)	(0.042)
Pre-Turnover Turnover Ratio (%)	-0.033	-0.033
	(-1.342)	(-1.343)
Constant	-0.002	-0.002
	(-0.012)	(-0.009)
Clustering by fund	Yes	Yes
Observations	3,017	3,017
R-squared	0.138	0.138

4.7. Conclusion

In this study, we present the first empirical examination on performance attribution between funds and managers. Using a sample of actively managed U.S. equity funds, we find evidence consistent with manager skills being more important than fund skills in determining fund performance. Our empirical analysis starts with a fixed effects regression analysis, in which we find that a larger part of the unexplained variation of fund performance can be attributed to manager fixed effects than to fund fixed effects. We shed further light on this comparison by looking at performance persistence of sole-managed and team-managed funds. We find that the performance of sole-managed funds is more persistent than that of team-managed funds. Among funds exhibiting the best performance in a given year, only sole-managed funds continue to outperform in the following year. Moreover, when a fund replaces its manager, its performance with the new manager can be forecast by the new manager's past performance at other funds, rather than the fund's own past performance with another manager. In the final step, we examine whether fund managers have a real effect on the investment decisions of investors. We only find modest evidence that fund flows are affected by manager skills.

Taken together, the results shed light on the source of skill in the mutual fund industry, which is at the heart of the debate over whether fund managers or fund companies should claim credit for a fund's track record. Our findings support the notion that manager skills are crucial for fund performance, and thus provide some justification for performance portability and advertising by fund managers. Our study contributes to the finance literature by reconciling previous mutual fund studies that examine the determinants of fund performance, and emphasizing the importance of individuals in determining financial outcomes. We also provide new evidence to the literature on performance attribution between firms and individuals in knowledge intensive industries.

Chapter 5

Conclusion

This thesis explores three issues regarding the performance and trades of institutional investors. Chapter 2 examines information sharing among delegated portfolio managers that are connected by investment mandates between plan sponsors and their sub-advisors. The results are consistent with mandate networks providing new channels for information sharing. Specifically, mutual funds managed by investment companies that share mandate networks are more closely correlated in terms of returns, holdings and trades than those not connected by investment mandates. Further, after two investment companies first join the same mandate network, the returns, holdings and trades of the mutual funds managed by these investment companies become more similar. There is also preliminary evidence that information about both individual firms and general investment styles is shared within mandate networks.

Chapter 3 investigates to what extent institutional investors are engaged in socially responsible investing by analysing changes in the ownership breadth of a large sample of institutional investors in stocks that have been targeted by the long running Sudan divestment campaign. The empirical results suggest a negative relationship between campaign intensity and the breadth of institutional ownership. Higher campaign intensity prevents institutional investors from entering the targeted stocks in both the U.S. and the rest of the world, and encourages existing holders to exit only in the U.S. The intensity of the divestment campaign also influences stock returns. Higher campaign intensity is associated with depressed prices and thus higher future returns, which is consistent with the theoretically motivated hypothesis that the campaign leads to neglect of the targeted stocks by an important enough segment of investors, and thus in turn results in compensating higher future returns. Taken together, the divestment campaign seems to be effective in that it lowers the breadth of ownership in the targeted stocks and induces price pressure on these stocks. The evidence is consistent with institutional investors engaging in socially responsible investing.

Chapter 4 presents evidence of performance attribution between firms and individual in the mutual fund industry. Previous studies suggest that both fund organizations and individual fund managers play a role in determining fund performance. However, little is known about which party matters more for performance. Based on a sample of actively managed U.S. equity funds, the empirical results provide evidence consistent with fund managers being more important than fund organizations in driving fund performance. First, the results from a fixed effects analysis show that a larger part of the unexplained variation in fund performance can be attributed to manager fixed effects than to fund fixed effects. Second, the performance of sole-managed funds is more persistent than that of team-managed funds, which is consistent with manager skills dominating fund skills in driving fund performance. Third, manager skills are portable across different funds. When a fund replaces its manager, its performance with the new manger can be forecast by the new manager's past performance at other funds, rather than the fund's own past performance with another manager. However, the results provide only modest evidence that manager skills affect the investment decisions of investors.

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