THREE ESSAYS ON THE ROLE OF INFORMATION NETWORKS IN FINANCIAL MARKETS

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THREE ESSAYS ON THE ROLE OF INFORMATION NETWORKS IN FINANCIAL MARKETS

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To Madhup, my best friend and husband,
my sister, and my parents

- my very own bad weather deflectors

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SUMMARY

In the first essay, I examine informal information channels among fund managers (*fund-fund networks*) and between the holding companies and the fund managers (*fund-company networks*). The empirical methodology measures the likelihood of a network existing between an information source and recipient as a function of geographical proximity. The main findings indicate that (1) fund-fund (fund-company) information networks help in generating positive risk-adjusted returns from holdings in absence of fund-company (fund-fund) networks; (2) fund-company networks create information advantage only when the networks are relatively exclusive, but hurt when a large number of funds have access to similar information networks. The stock selections of superior networks in a portfolio quarter seem to predict positive future stock performance beyond the quarter, alluding to potential asset pricing implications of the existence of investor networks.

In the second essay, I examine the performance implications of mutual fund managers' tendency to deviate from the strategies of their peers. In the presence of incentives to herd, mutual fund managers may choose to deviate from their peers' strategies either due to private information, overconfidence or conflict of interest with shareholders. The performance impacts of the different motivations to deviate are distinctly different. Using both fund total returns and holdings' based risk-adjusted returns, the results indicate a significantly negative relationship between the managers' deviating tendency relative to peers and their ability to generate superior performance. The evidence does not support the notion of deviations being motivated by valuable private information. For within-portfolio analyses for a fund manager, evidence points to fund managers overweighting (underweighting) stocks that underperform

(outperform) in the future, again supporting the notion that the average fund manager is more likely to make erroneous decisions when they deviate from their peers.

The third essay investigates the determinants of target choices in corporate investment in acquisitions, specifically focusing on the geographical proximity preference in these investments. During 1990-2003, firms are found to exhibit a home bias that is strikingly similar to the well documented behavior of portfolio investors but more compelling in magnitude. The study reveals that there are various factors, independent of information asymmetries, which may drive this behavior. Logistic regressions show that an acquirer's propensity to acquire in-state targets (i) increases with economic opportunities in the acquirer's home state, (ii) decreases with the severity of anti-takeover regimes in the acquirer's home state, (iii) increases with the propensity of other managers domiciled in the acquirer' city and industry to choose in-state targets, suggesting a herding behavior arising out of local interactions, and (iv) decreases with the acquirer' size and book-to-market ratio. Regression results are similar when we use the distance-based local bias, instead of the dichotomous choice of in-state vs. out-of-state targets.

CHAPTER 1

INTRODUCTION TO THESIS

The complexities of understanding the impact of information heterogeneities and frictions in financial markets are being increasingly acknowledged by researchers. While the existence of various factors like social influences on information generation and informal networks are acknowledged for participants in financial markets, the magnitude, nature and spectrum of their impacts still remains understudied. In my first two dissertation essays, I study information processes that impact the investment outcomes of mutual fund managers, and in my third essay I focus on corporate investment decisions, specifically in domestic mergers and acquisitions (M&A). The motivation to delve deeper into the implications of information frictions in financial markets is rooted in the evidence that there are information heterogeneities in capital markets.

The second chapter aims to provide important insights on the informal information processes that play a role in the portfolio investment decisions of money managers. The existing literature has not distinguished between managerial skills in picking stocks and the ability of managers to acquire differential information via networking. We focus our attention on two forms of information networks: (1) *fund-fund information networks*, which transfer information between fund managers about potential investment opportunities; and (2) *fund-company information networks*, which facilitate a manager's acquisition of differential information about a company via networks with the companies. This essay proposes a simple framework of disentangling the marginal impacts of different information networks on stock selection ability, and investigating the interplay between them. The study contributes to the literature on informed traders by identifying information environments that can drive the performance of investments. Academic papers have separately acknowledged, explicitly or implicitly, the existence of each of the information channels considered here. However, to the best of my knowledge, this paper is the first to investigate the relative and conditional efficiency of these information processes and draw attention to situations which give rise to informational advantage.

The third chapter investigates the performance consequences of mutual fund managers' deviation tendencies relative to their peers. Previous literature has suggested that there exist substantial incentives, like reputational concerns, for mutual fund managers to herd with other fund managers in their portfolio strategies. In the presence of incentives to herd, mutual fund managers may choose to deviate from their peers' strategies because of private information, overconfidence, conflicts of interest with shareholders, among other factors. However, the performance impacts of the different motivations to deviate are different. Using the portfolio allocations of actively managed funds in the U.S. for ten quarters in the period July 2003-December 2005, this paper conducts an empirical investigation into the potential causes and consequences of fund managers' deviating tendencies relative to their peers. The deviating tendency of a fund manager in a portfolio quarter is measured as the absolute deviation of the allocated portfolio weight in a stock (as percentage of total net assets (TNA)) from the mean weight allocated to the stock by other fund managers in the same peer group, averaged across all stocks in her portfolio. The determinants of deviating tendencies are examined followed by a study of the relationship between deviating tendencies and performance of mutual fund portfolios. This paper broadly contributes to the literature on informed trading and herding in capital markets.

The fourth chapter studies the factors that impact investment choices made by acquiring firm managers during corporate investment in domestic M&A. M&A are an important form of corporate investments and have major implications for the industry, shareholders as well as policy makers. In particular, the focus of the study is on the role of proximity preference in these investment decisions. There has been a recent renaissance of literature that relates geographical location to various factors that impact business interactions and outcomes, like information asymmetry, familiarity, networks and economic spillovers. This paper explores various drivers including those related to information asymmetries that may impact the proximity preference in corporate investments in M&A, like proximate economic opportunities, antitakeover legal regimes, herding behavior, acquiring and target firm characteristics. This paper provides new insights into corporate decision-making processes. By focusing attention on the geography of investment choices, we have been able to distinguish some factors that directly or indirectly play a substantial role in the outcomes of the decision processes.

In the three essays, this dissertation attempts to reduce the vast gap between the awareness that there may be many informal information flows that critically impact decision-making processes of players in financial markets, and a coherent understanding of the nature and depth of the influences. The empirical evidence suggests important implications for various participants in financial markets, including individual investors, money managers, corporate executives, as well as policy makers.

CHAPTER 2

INFORMAL INFORMATION NETWORKS: THE IMPACT ON PERFORMANCE OF MUTUAL FUND PORTFOLIOS

2.1. Introduction

The skilled and informed portfolio manager is the holy grail of mutual fund investors. Often thought of in conjunction, *skill* has traditionally referred to the managerial ability to process information, while an *informed* manager may have the ability to acquire differential information relative to the other players in the market by capitalizing on information frictions. This idea is rooted in the evidence that there are information heterogeneities in capital markets, creating potential opportunities for gathering differential information. The underlying notion in this paper is that being informed about an asset refers to the acquisition of information that may provide a strategic advantage to the fund manager.

Hong, Kubik and Stein (2005) posit that there is word-of-mouth communication between fund managers located in the same city, manifested in correlated trading in the same stocks. Their study suggests an information process via which a fund manager acquires information about assets that is not simultaneously available to the universe of investors. Additionally, Coval and Moskowitz (1999, 2001) show that mutual fund managers disproportionately weight their portfolios in local companies and earn positive abnormal returns on these holdings.[1] This literature indicates that there may be some processes by which information diffuses from companies to certain fund managers, creating informational advantages. We refer to the channels by which there is information dissemination as *information networks*. The Oxford dictionary defines networking as "interacting with others to exchange information and develop contacts". To the extent that information networks exist in financial markets, an investor can use networking skills to lower search costs associated with acquiring and processing information.

Considerable research in sociology and economics points to the propensity of information exchanges to occur predominantly within limited geographical and social spaces. Limitations in the spatial circumference of information networks arise out of the higher likelihood of random interactions between agents located in proximate social and business circles (see for example, Sorensen and Stuart (2001), Hong, Kubik and Stein (2004), Ivković and Weisbenner (2007)). Since real information networks are not observable, we rely on this literature while determining likely information networks. The likelihood of an information network existing between an information source and a recipient is measured as a function of their geographical proximity (or inverse of geographical distance).

We focus our attention on two forms of information networks: (1) *fund-fund information networks*, which transfer information between fund managers about potential investment opportunities; and (2) *fund-company information networks*, which facilitate a manager's acquisition of differential information about a company via networks with the

[1] Ivković and Weisbenner (2005) find similar evidence for individual investors. In contrast, Zhu (2002) does not find evidence of information advantage in the local investments of individual investors.

companies. This paper proposes a simple framework of disentangling the marginal impacts of different information networks on stock selection ability, and investigating the interplay between them.[2]

Risk-adjusted returns on holdings, considered a reflection of stock selection ability, are computed based on Daniel et al's (1997) characteristic-based benchmark portfolios. We develop measures of the strength of different networks associated with each fund-holding pair, along the following two dimensions: fund-fund networks (constructed at the fund level), and fund-company networks (constructed at the holding level). First, the likelihood of existence of a fund-fund information network between any two managers is calculated as the inverse of geographical distance between the managers.[3] A measure of fund-fund networks for each manager in our sample is computed as the summation of the likelihoods of the fund manager having an information network with another manager, across all other managers in the sample (excluding those in the same family).[4] For example, in our metric Boston-based Putnam's fund managers are likely to have more

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[2] Note that this framework does not assume that the information transfers are direct, and allow for transfers occurring through information intermediaries. For example, the implications of our framework of fund-company networks do not change if fund managers acquire differential information about local companies by following local media (that does not have a widespread audience), instead of acquiring information by direct communication with the company's management or employees. Similarly, in case of fund-fund networks, information can transmit from one fund manager to another via other intermediaries.

[3] Following Hong, Kubik and Stein (2005), Coval and Moskowitz (1999, 2001), the location of a manager is identified using the city where the fund is headquartered. The underlying assumption is that while a manager may use research conducted in other locations etc., the primary information hub and decision-making is at the headquarter location.

[4] The possibility of intra-family information transfers are considered separately in the paper.

frequent information transfers with other fund managers compared to a manager for Principal Management Corp., which is based in Des Moines, Iowa. The funds comprising the highest (lowest) quintile of the fund-fund network metric are identified as having strong (weak) fund-fund networks. Second, the likelihood of existence of a fund-company information network between the fund manager and a company held in the manager's portfolio is calculated as the inverse of geographical distance between the fund's and company's headquarters. Within each fund portfolio, the companies comprising the highest (lowest) deciles of the fund-company network metric are identified as having strong (weak) fund-company networks.

Using domestic equity holdings data for 2,463 U.S. actively managed mutual funds for ten quarters during July 2003-December 2005, we show that information networks have a substantial impact on holdings' performance. Evidence indicates that managers associated with weak fund-fund networks generate higher risk-adjusted returns from portfolio holdings where they have strong fund-company information networks, compared to stocks where fund-company networks are absent (with the difference in annualized returns being roughly 5.2%). In striking contrast, the managers associated with strong fund-fund information transfers generate significantly negative risk-adjusted returns when investing in stocks associated with strong fund-company networks, but positive returns in holdings where fund-company networks are absent (with the difference in annualized returns of roughly -6.6%). Additionally, the managers with strong fund-fund networks outperform managers with weak fund-fund networks when fund-company networks are absent (by about 2.9%), but underperform in holdings where fund-company networks exist (by about -8.9%). Taken together, our main results indicate that (1) fund-fund (fund-company) information networks help in generating positive risk-adjusted returns in absence of fund-company (fund-fund) networks, (2) fund-company networks create information advantage when relatively few funds have comparable networks with the holdings company, but hurt when a large number of funds have access to similar information networks with the company (diluting potential information advantages). The results strongly suggest that the marginal impacts of an informal information network are conditional on the nature of other information flows present.

Overall results hold across fund size, family size, fund age and portfolios of large cap stocks having high information availability. To the extent that fund size (Berk and Green (2004)) and family size proxies for managerial skills, the empirical results are consistent with the marginal impact of information networks being higher for more skilled managers.[5] External networks complement private information arising out of skill, in-house research resources and possible intra-family networks. While information networks matter both for young and old funds, the marginal impact of fund-company (fund-fund) networks is higher (insignificant) for older funds. It is possible that older funds develop networks with other fund managers over time, irrespective of geographical location. Less reputed funds, like young and small family funds, located in strong fund-fund network areas fail to reap benefits from either fund-fund or fund-company networks. Results also

[5] Additionally, managers of larger funds may be the originators of the information that is being transmitted via fund-fund networks. In this case, these managers are more likely to have taken long positions in stocks before the information diffuses to other managers and results in increases in stock price. This would reflect as higher returns and consequently higher marginal impacts of fund-fund networks for these managers. However, this process cannot clearly explain the relationship between marginal impacts of fund-company networks and fund size, since managers of smaller funds can also develop direct networks with companies.

indicate that the value of information networks is independent of public information availability about a stock.

In general, the subportfolios that outperform other portfolios are (1) strong fund-company information portfolios for funds with weak fund-fund networks, and (2) weak fund-company information portfolios for funds with strong fund-fund networks. Based on these results, this paper conducts a preliminary examination of possible information that can be inferred about future asset prices after identifying superior information networks of investors and observing their investment choices. Using fund holdings reported at the end of a quarter (which is stale information for all subsequent quarters), a hypothetical portfolio of stocks associated with the two information networks that generate superior risk-adjusted returns in mutual fund investments is constructed, called the *Best Information Portfolio* (or BIP). This portfolio strategy replicates the holdings of the information portfolios with superior performance from reports at the end of a quarter, and holds it in subsequent quarters starting at the beginning of the month following the reported quarter. For a wide range of holding periods, average monthly raw returns for the BIP are significantly positive (about 1.7%), with the risk-adjusted monthly returns also significantly outperforming their benchmarks by 72 basis points annually. These results suggest that the stock selections of superior information networks predict the future performance of those stocks, even beyond the quarter in which the investment is observed.

This study contributes to the literature on informed traders by identifying information environments that can drive the performance of investments. The existing literature has not distinguished between managerial skills in picking stocks and the ability of managers to acquire differential information via networking. While the latter ability to form information networks may also be considered a managerial skill, the implications are distinct from the traditional notion of skilled portfolio managers. A novel implication of this study is that a fund manager can compensate for a lack of skill in processing information by having a superior ability to form external information networks. Academic papers have separately acknowledged, explicitly or implicitly, the existence of each of the information channels considered here. However, to the best of our knowledge, this paper is the first to investigate the relative and conditional efficiency of these information processes and draw attention to situations which give rise to informational advantage. The findings strongly indicate that a portfolio manager should be able to improve performance by being aware of the relative efficiencies of different information flows, and being proactive in establishing valuable information networks.

The paper is organized as follows. Section 2.2. briefly reviews existing literature on informal networks. Section 2.3. describes the data. Section 2.4. discusses the empirical methodology. Results are presented in section 2.5. Section 2.6. concludes the essay.

2.2. A Note on Informal Information Networks

Networks refer to any channel by which communication can occur. Networks can exist between people in a society, firms operating in a market, countries engaged in diplomatic relationships, and even electronic devices. Formal information networks are relatively easy to observe and access. For instance, analyst recommendations being aired on national television can be accessed by the wide spectrum of investors in the market.

On the other hand, informal networks are much harder to observe and quantify but play a substantial role in the functioning of a wide range of economic systems.

Sociologists have long posited that informal interactions in a society impact individual behavior and decision-making. Information exchanges occur in social relationships. These relationships may arise out of neighborhood interactions, going to the same church, having overlapping social circles etc. Academic research in economics has only recently begun to theorize the relationship between informal interactions and economic behavior. Different strands of literature in economics have focused on the role of networks and informal interactions on a diverse range of economic and social outcomes. Some examples of papers interested in individual behavior include studies on crime (Glaeser et al. (1996), Bayer et. al. (2004)); peer effects in education (Hoxby (2000), Sacerdote (2001), Zimmerman (2003), Zax and Rees (2002)); employment choices and wages (Bayer, Ross and Topa (2005)); and welfare program participation (Bertrand et al. (2000)). Other studies have focused on firm-level outcomes like technological innovation and adaptation (Conley and Udry (2003), Bandiera and Rasul (2006), Burke et al. (2004)); knowledge spillovers and economic agglomeration (Krugman (1991), Glaeser et al. (1992), Jaffe et al. (1993), Audretsch and Feldman (2001)).

Empirical evidence on the existence and impact of informal information exchanges in financial markets is limited.[6] In their study on credit markets, Garmaise and Moskowitz

[6] Theoretical work on informal communication in financial markets is also limited. Some recent theoretical research has begun to draw attention to the impact of social networks and communication on asset prices (Ozsoylev (2005), Colla and Mele (2005)). Stein (2006), on the other hand, formulates a theory of incentives and conditions under which information exchanges occur between managers who are competitors.

(2003) document the role of informal networks in connecting the borrowers with service intermediaries, who in turn have links with lenders. Shiller (2000) in his well known book *Irrational Exuberance* discusses the role of informal communications among stock market investors in causing bubbles and crashes in stock markets. He posits that frequent communication of opinions and interests among peers influences the behavior of individuals in a peer group, causing the group to have similar thinking. Hong, Kubik and Stein (2004) empirically document the relationship between social interaction and stock market participation of U.S. investors. After controlling for various factors, they show that households that are engaged in more social interactions (presumably having more informal information networks) are more likely to participate in stock market investment. Ivković and Weisbenner (2007) find word-of-mouth communications among individual investors as reflected in trades of neighbors, while Ng and Wu (2006) find similar evidence for investors in the same trading room. Duflo and Saez (2002, 2003) uncover word-of-mouth effects in retirement planning among employees in the same department.

In summary, while the existence of informal information networks has been acknowledged to some extent, an understanding of the magnitude of their impact on the spectrum of economic activities is still elusive. This study focuses on the role of informal information networks in the rapidly growing investment management industry.

2.3. Data

The primary data source used in this study is the CRSP Survivor-bias Free US Mutual Fund Database (MFDB) which provides data on fund characteristics and returns. In

January 2005, CRSP added a mutual fund holdings database that includes stocks, bonds, mortgage-backed securities, other mutual funds, futures and options, among others. CRSP holdings data includes information on the market value of the holdings, number of shares held and names of securities, from reports dating September 2003 to December 2005. Fund holdings in some cases are reported for quarters before September 2003, but we exclude these because of largely missing data on a majority of the funds. For our analyses, quarterly data for the ten quarters between September 2003 and December 2005 is obtained. Portfolio holdings are usually reported at the end of each quarter, where the portfolio information is effective in the previous three months.

Given that the CRSP holdings database is relatively new, we verify the accuracy of the information by spot matching with the CDA/Spectrum database that has been widely used for accessing mutual fund holdings information. The identification and amount invested information for holdings are nearly identical between the two databases with negligible difference.

We first construct the sample of funds by choosing US equity funds primarily investing in domestic equity (excluding index, sector and bond funds) having aggressive growth, growth, growth and income or balanced as stated objective categories from CRSP MFDB. Our final sample consists of 2,463 unique funds in the sample period. The main fund identifier in CRSP MFDB is the ICDI code. However, CRSP assigns multiple ICDI codes to different share classes of the same fund. We prevent erroneous counting of funds by merging information of multiple ICDI codes representing the same fund into one unique fund. We only include stock holdings of publicly traded companies headquartered in the U.S. and have stock returns data available from CRSP, and exclude other assets held in the portfolios.

The holdings database uses a unique portfolio identifier that is matched to ICDI codes in a separate CRSP mapping file. Each portfolio code represents a unique portfolio, and multiple ICDI can be mapped to the same portfolio code if the underlying portfolios are identical. For example, multiple ICDI codes representing different share classes of the same fund have the same underlying portfolio, and are mapped to a common portfolio code. After matching the portfolio codes to ICDI codes, we match data on mutual fund characteristics like monthly total net assets, management company etc. with the CRSP MFDB. Finally, we get stock price and returns data for the holding companies from CRSP monthly stock files.

Fund location information (i.e., city and state) is obtained from *Nelson's Directory of Investment Managers*. Disclosure database provides information on the headquarter location of all publicly traded companies in our sample. The city and state information of the funds and companies are matched to latitude and longitude coordinates from US Census Bureau's freely available Gazetteer geographical data source. We use the latitude and longitude information to calculate geographical distances between two cities.

2.4. A Framework of Information Networks and Performance

In this section, we describe the empirical methodology used in this study. We first outline a method by which we measure informal information channels and then outline the framework used to observe the performance implications of these information channels.

2.4.1. Network Measures

Ideally, data on real information networks via which each fund manager receives information about investment opportunities should be employed to study the impact of these networks on investment performance. However, data on fund managers' real informal information sources is not available. While not a perfect measure, we employ a methodology using *likelihoods* of informal interactions as proxies for real information networks.

A. Fund-Fund Information Networks

In this study, the first type of informal information transfers considered are those via which a fund manager can acquire information from other managers investing in similar asset classes (in this case, domestic stocks). In the spirit of Hong, Kubik and Stein (2005), proximately located mutual fund managers are considered as more likely to engage in informal information transfers. Additionally, the focus is on information networks between a fund manager and other funds external to the family which the fund belongs to. Intra-family information exchanges are considered separately in this paper.

Based on this premise, the likelihood of a fund-fund (*FF*) information network link existing between fund manager j and fund manager i is

$$L^{FF}(Network)_{j,i} = \frac{1}{(1+Distance_{j,i})} \tag{1}$$

Here, $Distance_{j,i}$ is the geographical distance between the city where fund j is located and the city in which fund i is located. The likelihoods of FF networks between a fund manager and all other fund managers not belong to the same fund family are then aggregated for each fund in the sample. This provides an estimate of the size of informal information networks a fund manager j has with other fund managers and is expressed as

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i} = \sum_{i=1}^{N} \frac{1}{(1+Distance_{j,i})} \tag{2}$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund j.

Finally, each quarter, all funds in the sample are sorted according to the measures of FF information networks ($(Network)_j^{FF}$) and ranked into quintiles. The funds in the lowest quintile in a quarter are considered the funds with weak FF information networks ($Q^{FF,weak}$). The funds in the highest quintile are considered the funds with strong FF information networks ($Q^{FF,strong}$).

A caveat is in order regarding the measure of fund-fund information networks used in this study. This measure includes only the funds in our sample, which is restricted based on various criteria like active management, predominantly domestic equity investments etc. It does not account for all information flows involving managers of the universe of mutual funds. For example, while a sector fund manager is excluded from our sample, she may be an information source for a manager in our sample. However, we conjecture that our measure of fund networks is highly correlated with a similar measure based on the universe of money managers, since the geographical cluster patterns are unlikely to change significantly. In this case, the relative ranking of networks is also unlikely to change substantially if we had based our measure on the universe of money managers.

B. Fund-Company Information Networks

The second type of informal information networks considered in this paper are networks between fund managers and companies in which they invest. These fund-company (*FC*) information networks are estimated at the stock holding-level for each fund, and are measured for each stock in a fund's portfolio in a given quarter. The likelihood of a *FC* information network existing between fund manager *j* and the company issuing stock *n* that is held in *j*'s portfolio is

$$L^{FC}(Network)_{j,n} \;=\; \frac{1}{(1+Distance_{j,n})} \tag{3}$$

Here, $Distance_{j,n}$ is the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered.

Next, the stocks in each fund portfolio in each quarter are sorted by measures of *FC* information network likelihoods ($L^{FC}(Network)_{j,n}$) and ranked into deciles. Within each portfolio, the lowest decile is considered the sub-portfolio of stocks associated with weak *FC* networks ($D_j^{FC,weak}$). On the other hand, the holdings in the highest decile are considered to be the sub-portfolio of stocks with strong *FC* information networks ($D_j^{FC,strong}$). For each fund *j*, difference $D_j^{FC,strong} - D_j^{FC,weak}$ gives the marginal effect of *FC* information networks.

Alternatively, for robustness checks, we consider metrics used in Coval and Moskowitz (1999, 2001) of local (a portfolio company located within 100 km radius from a fund) versus non-local (all portfolio companies further than 100 km) to define the high and low likelihoods of existence of fund-company networks, respectively.

2.4.2. Methodology

Based on the empirical metrics of information networks discussed previously, a framework of studying marginal impacts of informal information networks is developed. The goal is to empirically disentangle the impacts of informal information transfers on investment performance.

Fig. 2.1. presents the outline of our information metric that can impact the investments decisions associated with a particular investment. Four groups of investments are considered and allocated into portfolios *P1, P2, P3* and *P4*. For each fund in the subsample having strong (weak) fund-fund networks, i.e. compose groups $Q^{FF,strong}$ ($Q^{FF,weak}$), the holdings with strong (weak) fund-company networks, i.e. form deciles $D_j^{FC,strong}$ ($D_j^{FC,weak}$) in the fund-quarter portfolio, are chosen.

Developing these categories of investment portfolios lays the foundation for disentangling the performance impacts of different informal information networks using empirical data. The manner of construction enforces that each fund in the smallest and largest network deciles should have at least one stock holding that can be classified into the each of the strongest and weakest fund-company information network portfolio. For example, in Fig. 2.1. the holdings in portfolio *P1* are located geographically close to the

FF Network / *FC Networks*	*Weak Fund-Fund Networks* ($Q^{FF,weak}$)	*Strong Fund-Fund Networks* ($Q^{FF,strong}$)	*Marginal Impacts* (*FF* Networks)
Strong Fund-Company Networks ($D_j^{FC,strong}$)	Portfolio P1 ($Q^{FF,weak}, D_j^{FC,strong}$) Type of Information: *Fund-Company* *Manager skills*	Portfolio P3 ($Q^{FF,strong}, D_j^{FC,strong}$) Type of Information: *Fund-Fund* *Fund-Company* *Manager skills*	Difference: R^{adj} (*P3*)- R^{adj} (*P1*)
Weak Fund-Company Networks ($D_j^{FC,weak}$)	Portfolio P2 ($Q^{FF,weak}, D_j^{FC,weak}$) Type of Information: *Manager skills*	Portfolio P4 ($Q^{FF,strong}, D_j^{FC,weak}$) Type of Information: *Fund-Fund* *Manager skills*	Difference: R^{adj} (*P4*)- R^{adj} (*P2*)
Marginal Impacts (*FC* Networks)	Difference: R^{adj} (*P1*)- R^{adj} (*P2*)	Difference: R^{adj} (*P3*)- R^{adj} (*P4*)	

Figure 2.1. Marginal Impacts of Informal Information Networks

This figure reports a metric for forming portfolios of stocks held by mutual funds according to information flows associated with the stock. The likelihood of a *FC* information network existing between fund manager *j* and the company issuing stock *n* that is held in *j*'s portfolio is $L^{FC}(Network)_{j,n} = 1/(1+Distance_{j,n})$ where, $Distance_{j,n}$ is the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered. For each fund j, each quarter the holdings are sorted by $L^{FC}(Network)_{j,n}$ and ranked into deciles, with $D_j^{FC,strong}$ ($D_j^{FC,weak}$) being the highest (lowest) likelihood deciles and form the portfolios *Strong Fund-Company Networks* (*Weak Fund-Company Networks*) in each portfolio quarter. The likelihood of an information network existing between fund manager *j* and fund manager *i* is $L^{FF}(Network)_{j,i} = 1/(1+Distance_{j,i})$ where, $Distance_{j,i}$ is the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The size of informal information networks a fund manager *j* has with other fund managers is computed as

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Each quarter the funds are sorted by $(Network)_j^{FF}$ and ranked into quintiles, with $Q^{FF,strong}$ ($Q^{FF,weak}$) being the highest (lowest) quintile and form the categories *Strong Fund-Company Networks* (*Weak Fund-Company Networks*). R^{adj} is the risk-adjusted return generated from a portfolio of holdings.

fund, and presumably have higher likelihood of fund-company information transfers, compared to stocks in portfolio *P2,* which are geographically distant and likely to have weaker information transfers. So, the information processes related to portfolio *P1* is different from *P2* by the additional fund-company information flows associated with *P1,* but not with *P2*. Note that the method of disentangling fund-company information networks makes it possible to avoid confounding effects arising out of heterogeneities in other fund-, manager-, family- and time-specific factors. Similarly, when other across-fund differences are ignored, portfolio *P1* is different from *P3* in that *P3* is associated with fund-fund networks generating an additional information process, while *P1* is not. To observe the marginal impact of fund-fund information networks, across-fund comparisons are necessary. However, this gives rise to the possibility of significant differences in other fund-specific factors that can impact performance, like managerial ability. In further empirical analyses, we compare funds which have similar attributes along dimensions other than information networks. It is also interesting to note that in this framework, portfolio *P2* can be viewed as a control group where only the private information that arises out of managerial skills is the main driver of investment decisions, since other obvious external information processes are negligible.

Risk-adjusted returns computed following DGTW (1997) for each fund holding is the measure of investment performance used in this paper. For each fund in quintile $Q^{FF,weak}$ ($Q^{FF,strong}$), raw returns for sub-portfolios *P1* and *P2* (*P3* and *P4*) are computed in each quarter as

$$\mathrm{R}^{\mathrm{raw}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} R_{i,t} \tag{4}$$

Here, $w_{i,t}$ is the portfolio weight of stock i in month t, and S is the number of stocks in the sub-portfolio. The weights in each sub-portfolio sum to one. Similarly, risk-adjusted sub-portfolio returns for each fund are computed in each quarter as

$$R^{adj} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}) \qquad (5)$$

Here, R_i^{bench} is the value-weighted monthly return of stock i's DGTW quintile benchmark portfolio (following Daniel et al. (1997)). Along the framework of disentangling marginal impacts of informal information portfolios discussed before, the differences in the sub-portfolio returns form the basis of studying the marginal performance impacts of these information networks. For the baseline empirical analyses, the difference in risk-adjusted returns R^{adj} (*P3*)- R^{adj} (*P1*) between the portfolios *P3* and *P1* reflects the marginal impact of *FF* information networks, when strong *FC* networks are present. For holdings associated with weak *FC* networks, difference R^{adj} (*P4*)- R^{adj} (*P2*) between the portfolios *P4* and *P2* gives the marginal impact of *FF* information networks. For the funds with weak *FF* networks, difference R^{adj} (*P1*)- R^{adj} (*P2*) measures the marginal performance impact of *FC* information networks. Similarly, R^{adj} (*P3*)- R^{adj} (*P4*) measures the marginal impact of *FC* information networks for the strong *FF* network funds. Note that the marginal impact of a type of information network is examined conditional on the extent of other type of information networks that may impact the same set of investments. This method allows the marginal impact of one type of information network to differ depending on what other information exchanges are affecting the investment decisions for the same holding. For instance, a fund manager having larger networks with other funds may rely more on information acquired via inter-fund networks when she does not have strong networks with the holding company.

In summary, the empirical methodology operationalizes an examination of the marginal impacts of informal information networks along the framework of the simple theoretical model stated in earlier sections. In the following section, we present the empirical results on the relationship between information networks and investment performance of mutual funds.

2.5. Results

2.5.1. Summary statistics: Mutual fund and portfolio characteristics

Table 2.1. presents summary statistics on the sample of funds and overall characteristics of the stocks held in fund portfolios. The sample consists of 2,463 actively managed U.S. funds focused on domestic equity in the period 2003-2005, spanning across 569 investment management family complexes. During this period, these funds invested in stocks of 4,796 unique public companies headquartered in the U.S. Recall that the sample excludes all other holdings like cash, bonds etc. Due to high levels of skewness in the data, we usually report median values of most data fields.

The median fund size (i.e. total net assets) in the sample is $69.5 million, and the median fund age (based on first offer date) is six years. Since the metrics of informal information networks developed in this paper are based on geography, Table 2.1. also reports a summary geographical distribution of the mutual fund holdings and managers.

Table 2.1.
Summary Statistics on U.S. Mutual Funds

Summary statistics are for all U.S. mutual funds that invest primarily in U.S. equity as reported in CRSP Mutual Fund Database, excluding index and sector funds during September 2003-December 2005. Fund age in the holding quarter is computed as the difference between the year of the first month in the quarter and the year of the fund's first offer date. Proximity distribution of a fund's holdings is reported as the percentage of total amount invested in domestic equity in a quarter, in stocks of companies that are 0-100 kilometer (km), 100-500 km, 500-1000 km and more than 1000km from the location of the fund. Proximity distribution of mutual funds is computed for each fund as the percentage of funds located 0-100km, 100-500km, 500-1000km and more than 1000km from the fund, and reported as an average across all funds. Median number of companies in a fund's portfolio is the average across all quarters. Daniel et al (DGTW) (1997) is followed to compute the size, book-to-market and momentum quintiles for the stocks held. Company age is the difference between the year of the first month of the quarter and the year in which a company was established, reported in years.

Total number of funds in sample	2,463
Total number of mutual fund families in sample	569
Total number of different stocks held in sample period	4,796
Median total net assets ($ million)	69.5
Median fund age (in years)	6.0
Proximity distribution of fund investments:	
Avg. % invested in stocks: 0-100 km	6.88
Avg. % invested in stocks: 100-500 km	14.66
Avg. % invested in stocks: 500-1000 km	13.22
Avg. % invested in stocks: >1000 km	65.24
Proximity distribution of fund managers:	
Avg. % of funds located 0-100 km	8.35
Avg. % of funds located 100-500 km	19.06
Avg. % of funds located 500-1000 km	13.74
Avg. % of funds located >1000 km	58.85
Portfolio characteristics:	
Median number of companies in portfolio	86
Median value-weighted DGTW Size quintile	4.46
Median value-weighted DGTW B/M quintile	2.54
Median value-weighted DGTW MOM quintile	3.08
Median company age (in years)	35.0

In the median fund portfolio, 6.88% of the total amount invested in domestic equity holdings is concentrated in stocks of companies less than 100 km away (or 'local') from the fund location. More than half (65.2%) of the total amount invested is in stocks of companies more than 1000 km from the fund. The geographical distribution of mutual funds across the country is also presented. For the median fund in the sample, 8.35% of funds are located within 100 km distance, while 58.85% are located more than 1000 km away.[7] While the mutual fund industry may be concentrated in a few cities, there is substantial dispersion in the data to allow an examination of cross-sectional differences.

Table 2.1. also reports summary statistics on the stocks held in mutual fund portfolio in the sample period. The median fund portfolio is invested in 86 stocks, with median company age of 35 years. The characteristics of the stocks reported are the three dimensions in DGTW (1997), namely, size, book-to-market ratio and momentum. The median stock holding is in a value-weighted DGTW size quintile of about 4.5, indicating that mutual funds on average concentrate their investments in stocks of larger companies. The median value-weighted DGTW book-to-market (B/M) quintile of stocks held is about 2.5, suggesting that mutual funds in the sample have relatively dispersed investments across growth (low B/M) and value stocks (high B/M). The median fund shows a preference for stocks having higher past year returns, or momentum, by investing in stocks slightly above the third DGTW momentum quintile.

Table 2.2. presents summary statistics for the stock holdings that form the sub-portfolios associated with different information networks discussed in section 2.4. It is possible that the characteristics of investments vary substantially across the different network portfolios.

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[7] Note that the geographical distribution of mutual funds is reported in terms of frequency, and not as aggregated dollar amounts managed by the universe of funds. This is because in order to operationalize the metrics of information networks among fund managers, each fund manager is considered a potential network link and can transfer information, irrespective of the size of the funds they manage.

Table 2.2.
Summary Statistics on Portfolio Characteristics (by Information Networks)

Summary statistics are for all U.S. mutual funds that invest primarily in U.S. equity as reported in CRSP Mutual Fund Database, excluding index and sector funds during September 2003-December 2005. The likelihood of a fund-company (FC) information network existing between each fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is $L^{FC}(Network)_{j,n} = 1/(1+ Distance_{j,n})$. Here, $Distance_{j,n}$ is the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (*FF*) network measures for each fund *j* is computed as:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

where, $i = 1,\ldots N$ are all funds not in the same family as fund *j*, $L^{FF}(Network)_{j,i} = 1/(1+ Distance_{j,i})$, and $Distance_{j,i}$= distance in km. between city of fund *i* and fund *j*. Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. Daniel et al (DGTW) (1997) is followed to compute the size, book-to-market and momentum quintiles for the stocks held. Company age is the difference between the year of the first month of the quarter and the year in which a company was established, reported in years. t-tests for differences are done using means comparisons for within- and across-fund value-weighted portfolios.

Variables	*Weak Fund-Fund (F-F) Network funds*		*Strong Fund-Fund (F-F) Network funds*		*Difference: Strong-Weak F-F Networks*	
Strong Fund-Company (F-C) Network Stocks:						
Median value-wt. [equally-wt.] DGTW Size quintile	4.36	[4.00]	4.64	[4.00]	0.28***	[0.00]
Median value-wt. [equally-wt.] DGTW B/M quintile	2.43	[2.00]	2.64	[3.00]	0.21***	[1.00]
Median value-wt. [equally-wt.] DGTW MOM quintile	3.25	[3.00]	3.09	[3.00]	-0.16***	[0.00]
Median value-wt. [equally-wt.] company age	39.83	[28.00]	57.17	[34.00]	17.34***	[6.00]
No. of fund-quarter observations	3,094		3,424			
Weak Fund-Company (F-C) Network Stocks:						
Median value-wt. [equally-wt.] DGTW Size quintile	4.44	[4.00]	4.63	[4.00]	0.19**	[0.00]
Median value-wt. [equally-wt.] DGTW B/M quintile	2.56	[2.00]	2.10	[2.00]	-0.46***	[0.00]
Median value-wt. [equally-wt.] DGTW MOM quintile	3.19	[3.00]	3.37	[4.00]	0.18***	[1.00]
Median value-wt. [equally-wt.] company age	45.40	[26.00]	36.00	[22.00]	-9.40***	[-4.00]
No. of fund-quarter observations	3,097		3,425			
Difference: Strong-Weak F-C Network						
Value-weighted [equally-wt.] DGTW Size quintile	-0.08***	[0.00]	0.01***	[0.00]		
Value-weighted [equally-wt.] DGTW B/M quintile	-0.13***	[0.00]	0.54***	[1.00]		
Value-weighted [equally-wt.] DGTW MOM quintile	0.06***	[0.00]	-0.28***	[-1.00]		
Value-weighted [equally-wt.] company age	-5.57**	[2.00]	21.17***	[12.00]		

*, **, *** represent significance at 10%, 5% and 1% level respectively

Funds having weak fund-fund (*FF*) networks invest in somewhat smaller and younger companies with lower B/M ratios when fund-company (*FC*) networks are strong compared to holdings associated with weak *FC* networks. The difference in value-weighted DGTW quintiles between the strong and weak *FC* networks for size and book-to-market dimensions are -0.08 and -0.13, with both differences being statistically significant at 1% level. Perhaps somewhat surprisingly, the funds are relatively bigger momentum chasers for the stocks having strong *FC* networks, compared to when they invest in stocks with weak *FC* networks. It may be the case that the differential information fund managers have about the future value of the strong *FC* network stocks reinforces a preference for higher momentum stocks. Interestingly, the statistics for funds having strong *FF* networks are qualitatively dissimilar compared to the funds with weak *FF* networks. These funds invest in significantly larger, older and higher B/M stocks associated with strong *FC* networks, as compared to stocks associated with weak *FC* networks. On the other hand, the strong *FC* network stocks have lower momentum than weak *FC* network stocks. The DGTW quintile differences for size, book-to-market and momentum between strong and weak FC stocks are 0.01, 0.54 and -0.28 respectively, with all values being significant at the 1% level.

Table 2.2. also reports across-fund comparisons between strong and weak *FF* network funds, conditional on *FC* networks. In the presence of strong *FC* networks, funds with strong *FF* networks invest in stocks assigned in higher size, higher book-to-market and lower momentum quintiles compared to funds having small *FF* networks. Additionally, strong *FF* network funds invest in companies about 17.3 years older than companies held by weak *FF* network stocks, for the subsample of strong *FC* network

holdings. When the subsample of weak *FC* network holdings is considered, strong *FF* network funds invest in higher size, lower book-to-market and higher momentum DGTW quintiles compared to weak *FF* network funds. Strong *FF* network funds also invest in younger companies compared to weak *FF* network funds, when weak FC network holdings are considered. It is hard to conclude any unambiguous differences between the riskiness of the stocks held by strong and weak *FF* network funds.

2.5.2. Information networks and portfolio performance

Table 2.3. reports the baseline empirical results on the relationship between informal information networks and investment performance of stock holdings. Average returns on quarterly holdings are presented along with standard deviation of returns as a measure of total risk of the portfolios.[8] Value-weighted returns and standard deviation of the value-weighted returns across quarters are computed for each fund sub-portfolio in the sample. The average values reported in the table are weighted by fund total net assets (TNA).

First, Panel A presents raw returns on the sub-portfolios and standard deviation of raw returns. Among the four sub-portfolios, the portfolio of stocks associated with strong networks between the fund manager, who has weak networks with other funds, and the holdings company has the highest raw returns of 20.74% during the sample period. The second highest raw returns (16.26%) are on the portfolio of stocks held by fund manager associated with strong fund-fund networks investing in companies with which they are

[8] See Sirri and Tufano (1998) who measure funds' relative riskiness in terms of their total risk (measured as standard deviation of returns), rather than by measures like beta, which capture the systematic portion of portfolio risk.

Table 2.3.
Performance of Mutual Funds and Information Networks (Percentage Annualized Returns)

Every quarter during Sept 2003-Dec 2005, the likelihood of a fund-company (FC) information network existing between each fund manager j and each company issuing stock n that is held in j's portfolio is computed as $L^{FC}(Network)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the geographical distance between the city where fund j is located and the city in which company n is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (FF) network measures for each fund j is computed as:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

where, $i = 1,\ldots N$ are all funds not in the same family as fund j, $L^{FF}(Network)_{j,i}$ = 1/(1+ $Distance_{j,i}$), and $Distance_{j,i}$= distance in km. between city of fund i and fund j. Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. For each fund, portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{raw}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} R_{i,t} \, ,$$

where $w_{i,t}$ is the portfolio weight of stock i in month t, and S is the number of stocks in the portfolio. Risk-adjusted portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}) \, ,$$

where R_i^{bench} is the value-weighted monthly return of stock i's DGTW quintile benchmark portfolio (following Daniel et al. (1997)). Reported returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) and averaged across quarters. Standard deviation of portfolio returns (in percentage) is calculated for each fund and is reported as a value-weighted average by fund TNA. *, **, *** represent significance at 10%, 5% and 1% level respectively.

Panel A: Raw Returns			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Raw Returns (Std. Dev. (in %))	Raw Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	20.74	12.19	-8.55**
	(32.15)	(24.50)	[-1.99]
Weak Fund-Company (FC) Network	14.77	16.26	1.49**
	(31.38)	(32.37)	[2.50]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	5.97***	-4.07***	
	[4.66]	[-3.79]	
No. of Fund-Quarter Obs.:	3,084	3,407	

Panel B: Risk-adjusted Returns			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	5.52	-3.38	-8.90***
	(23.39)	(16.12)	[-5.87]
Weak Fund-Company (FC) Network	0.30	3.19	2.89**
	(23.00)	(24.65)	[1.81]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	5.22***	-6.57***	
	[5.08]	[-6.86]	
No. of Fund-Quarter Obs.:	3,084	3,407	

not likely to have frequent informal interactions. However, higher raw returns may simply be a compensation for higher levels of risk borne by the manager in these portfolios.

In Panel B, risk-adjusted returns are reported for the four sub-portfolios and are the more appropriate measures of performance. A comparison of Panel A and Panel B shows that risk-adjusted returns are qualitatively similar to the pattern of raw returns across the four sub-portfolios. Marginal impacts of fund-company (*FC*) networks are reported conditional on fund-fund (*FF*) networks. *FC* networks have a significantly positive impact when funds having weak fund-fund (*FF*) networks are considered. The results are consistent with Coval and Moskowitz (2001) who find that fund managers in remote locations (who are likely to form the subsample of weak *FF* network managers in this paper) can earn higher abnormal returns on proximate holdings. The findings are also consistent with the implications of the theoretical model, based on which it is expected that the marginal impact of *FC* networks is higher when fewer fund managers have access to similar *FC* networks with the companies. Further, empirical results show that funds in areas where there are strong *FF* networks are unable to translate fund-company information channels into better performance on the corresponding holdings, earning a negative risk-adjusted annualized return of -3.38% on these holdings. This may be a reflection of the fact that for companies located in areas where there are larger concentrations of mutual funds, the potential to generate information advantages about the company is low. Too many fund managers may form information networks with the same companies leading to a dilution of information advantage for any one manager. Weak *FF* network funds generate positive risk-adjusted returns on holdings with strong

FC networks that exceed returns on holdings with weak *FC* networks by 5.22% annually, with significance at the 1% level. Contrastingly, the strong *FF* network funds underperform on their holdings associated with strong *FC* networks relative to holdings with weak *FC* networks. For these strong *FF* network funds, the marginal impact of *FC* networks on risk-adjusted returns is negative, having a value of -6.57%, and significant at 1% level. In summary, consistent with theoretical predictions, the marginal impacts of fund-company networks are bigger for funds in weak *FF* network areas compared to funds in strong *FF* network areas.

Table 2.3. also presents the marginal impact of *FF* networks, conditional on the level of *FC* networks. Recall that, unlike the analyses of marginal impacts of *FC* networks where within-fund portfolio decompositions are used; studying marginal impact of *FF* networks necessitates across-fund comparisons. This gives to the possibility that other heterogeneities between the funds drive performance differences, and are considered in later robustness checks. In the baseline empirical results, a means comparison between sub-portfolio returns for each quarter is used to determine marginal impact of *FF* networks, conditional on *FC* networks. Funds with strong *FF* networks underperform the funds with weak *FF* networks by 8.90% (significant at 1% level), for holdings linked with strong *FC* networks. On the other hand, for holdings associated with weak *FC* networks, the strong *FF* network funds outperform the weak *FF* network funds by 2.89% annually (at 5% level significance). In summary, *FF* networks help in the absence of strong *FC* networks, but not when the funds can form strong information channels with the holding companies.

2.5.3. Do intra-family networks substitute for external networks?

The baseline results presented thus far support the implications of the theory in this paper. However, there remains a concern that other factors, which may impact performance in general, are the underlying differences between the funds and not the information networks. For example, funds with stronger *FF* networks may be part of bigger family complexes, while the weaker *FF* network funds belong to small families. In this case, the unaccounted differences in family characteristics can be driving the differences in performance, instead of variations in the extent of *FF* networks that the fund can avail. Moreover, family size is also likely to be a proxy for the level of intra-family information channels that is available to a fund manager.[9] It may be the case that external networks with other fund managers are only important for managers who do not have substantial information sources within the complex.

In Table 2.4., the issue of family size is addressed. To make sure that comparisons are made between funds in similar families, each quarter the sample of funds is sorted by the number of funds in the family. The funds are then sorted into terciles comprising small, medium and large family funds. The fund managers from small families (with average funds in family being approximately 10) are least likely to gain from the intra-family informal interactions that facilitate information transfers. The fund managers from large fund families (average number of funds in family being approximately 188) are likely to have more intra-family information channels, in addition to the availability of resources

[9] To the extent that family size reflects organizational differences, Stein (2002) also posits that hierarchical versus decentralized structures that may characterize big versus small complexes respectively, hinder or encourage the collection and use of "soft information" (like the information gathered via informal communications) by managers.

Table 2.4.
Performance of Mutual Funds and Information Networks (by family size)

Every quarter during Sept 2003-Dec 2005, the likelihood of a fund-company (FC) information network existing between each fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is computed as $L^{FC}(Network)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (FF) network measures for each fund *j* is computed as:

$$(Network)_j^{FF} \; = \; \sum_{i=1}^{N} L^{FF}\,(Network)_{\,j,i}$$

where, $i = 1, \ldots N$ are all funds not in the same family as fund *j*, $L^{FF}(Network)_{j,i}$ = 1/(1+ $Distance_{j,i}$), and $Distance_{j,i}$= distance in km. between city of fund *i* and fund *j*. Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. Risk-adjusted portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \; \sum_{t=1}^{3} w_{i,t}\,(R_{i,t} - R_i^{\,bench})\,,$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) and averaged across quarters. Standard deviation of portfolio returns (in percentage) is calculated for each fund and is reported as a value-weighted average by fund TNA. *, **, *** represent significance at 10%, 5% and 1% level respectively

Panel A: Small Intra-family Network funds (Mean #funds/family=10.6)			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	8.05	-2.62	-10.67***
	(22.65)	(19.48)	[-3.15]
Weak Fund-Company (FC) Network	0.99	-1.76	-2.75
	(23.17)	(32.71)	[0.74]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	7.06***	-0.86***	
	[4.04]	[-2.75]	
No. of Fund-Quarter Obs.:	1,464	1,291	

Panel B: Large Intra-family Network funds (Mean #funds/family= 188.3)			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	9.94	-1.83	-11.77***
	(26.65)	(15.92)	[-4.36]
Weak Fund-Company (FC) Network	-2.89	4.52	7.41**
	(22.92)	(23.60)	[2.21]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	12.83***	-6.35***	
	[5.69]	[-5.07]	
No. of Fund-Quarter Obs.:	672	992	

(like research units etc.) that a large family can provide to gather information. On the other hand, fund managers from larger families may also be more reputed among peers, facilitating the formation of networks with other managers. So, while fund managers from larger families may have the least need for information from informal external channels, they are the most likely to have informal information networks available to them.

Panel A reports results for the subsample of funds forming the smallest family size tercile and were also ranked in either the weakest or strongest *FF* network quintiles. Consistent with the baseline results, the marginal impact of *FC* networks continues to be positive and significant for funds with weak *FF* networks. The risk-adjusted returns on holdings in companies where strong *FC* networks exist exceed holdings associated with weak *FC* information channels by 7.06% annually, with significant at the 1% level. Again, the funds in strong *FF* network areas underperform in their strong *FC* network holdings compared to weak *FC* network holdings by 0.86% (at 1% level significance). The substantial difference in results compared to baseline results is for the marginal impact of *FF* information networks for these funds from small families. The empirical evidence suggests that, unlike for the universe of funds in the sample, fund managers from these small families are unable to take advantage of being in strong *FF* network areas. The marginal impact of *FF* networks is statistically insignificant, and the magnitude is negative.

In Panel B, the results for the funds belonging to the largest family complexes and also ranked in either the weakest or strongest *FF* network quintiles are presented. For weak *FF* network funds from large families, the marginal impact of strong *FC* networks on risk-adjusted portfolio returns is positive and significant (at 1%) with magnitude 12.83% annually. In contrast, the strong *FF* network funds from large families underperform on their strong *FC* network holdings compared to weak *FC* network holdings by 6.35%. These results are qualitatively similar to the baseline results, with the marginal impact of *FC* networks for large family funds with weak *FF* networks being more pronounced than for the baseline analyses. Additionally, the marginal impact of *FF* networks remains significant even for funds from large *FF* network families. Therefore, the evidence does not indicate that intra-family information networks replace external information networks. For holdings associated with strong *FC* networks, large family funds with weak *FF* networks outperform large family funds with strong *FF* networks by 11.77%, compared to the 8.90% for the baseline results. For these large family funds, the marginal impact of *FF* networks on returns from holdings where there are weak *FC* networks is 7.41%, compared to the marginal impact of 2.89% for the full sample.

Overall, the results suggest that marginal impacts of informal information networks is bigger for funds belonging to large families, and intra-family networks do not compensate for external networks. It may be concluded that funds from larger complexes leverage their reputation and visibility among their peers to form informal networks that produce more magnified informational advantages than fund managers from small families. Also, it is likely that larger fund families systematically hire managers with more ability than small fund families. The magnified marginal impacts of *FC* and *FF* information networks are consistent with the theoretical model, with managers likely to have more ability being able to generate bigger marginal impact of differential information on investment performance.

2.5.4. *Are bigger funds better at using information networks?*

Fund size has been shown to proxy for various unobservable fund- and manager-specific factors. Stein (2002) posits that the difference between decentralized and hierarchical organizational forms determines performance in capital allocation in information-intensive projects. For this reason, it is important to look at the impact of informal information processes (largely "soft information" that cannot be immediately verified) separately for both organizational forms in the mutual fund industry. Also, Berk and Green (2004) argue that larger funds have managers with more managerial skills. By comparing the marginal impacts of information networks separately for large and small funds, it may be possible to see whether there is a role played by managerial ability in determining the marginal impact of informal information networks. The theoretical model posits that the marginal impact of differential information on investment performance will be higher for managers with more skills, since they have more ability to process information into accurate strategies. Comparisons within fund size categories also act as robustness checks to uncover whether the baseline results hold across the spectrum of funds.

Table 2.5. presents the analyses of risk-adjusted performance on holdings across fund size terciles. Funds each quarter are ranked into size terciles based on total net assets (TNA). Due to space considerations, results for medium sized funds are excluded since they are qualitatively similar to those for small and large funds. Panel A reports the analyses for the subsample of funds forming the smallest fund size tercile (with mean TNA $16 million) that were also ranked in either the weakest or strongest *FF* network quintiles. The marginal impact of *FC* networks on performance continues to be bigger for

Table 2.5.
Performance of Mutual Funds and Information Networks (by fund size)

Every quarter during Sept 2003-Dec 2005, the likelihood of a fund-company (FC) information network existing between each fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is computed as $L^{FC}(Network)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (FF) network measures for each fund *j* is computed as:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

where, $i = 1, \ldots N$ are all funds not in the same family as fund *j*, $L^{FF}(Network)_{j,i}$ = 1/(1+ $Distance_{j,i}$), and $Distance_{j,i}$= distance in km. between city of fund *i* and fund *j*. Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. Risk-adjusted portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t}(R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) and averaged across quarters. Standard deviation of portfolio returns (in percentage) is calculated for each fund and is reported as a value-weighted average by fund TNA. *, **, *** represent significance at 10%, 5% and 1% level respectively

Panel A: Small Funds (Mean TNA= $16 mill)			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	2.23 (23.46)	-2.04 (17.36)	-4.27*** [-3.06]
Weak Fund-Company (FC) Network	-1.27 (21.79)	0.65 (27.50)	1.92** [1.60]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	3.50*** [2.84]	-2.69*** [-2.93]	
No. of Fund-Quarter Obs.:	1,221	1,155	

Panel B: Large Funds (Mean TNA= $1,563 mill)			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	6.38 (22.50)	-3.27 (15.80)	-9.65*** [-5.71]
Weak Fund-Company (FC) Network	0.98 (22.29)	3.54 (24.67)	2.56* [1.37]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	5.40*** [3.21]	-6.81*** [-4.43]	
No. of Fund-Quarter Obs.:	662	1,012	

weak *FF* network funds compared to strong *FF* network funds, supporting the prediction that information advantages are higher for more exclusive *FC* networks. The marginal impact is positive (3.50%) for the weak *FF* network funds and negative (-2.69%) for the strong *FF* network funds. Also, the marginal impact of *FF* networks remains significantly negative (-4.27%) for holdings with strong *FC* information channels, and significantly positive (1.92%) in the absence of *FC* networks. In Panel B, the subsample of funds forming the largest fund size tercile (with mean TNA $1,563 million) that were also independently ranked in either the weakest or strongest *FF* network quintiles are included. Again, consistent with evidence presented so far, the marginal impact of differential information acquired via strong *FC* networks is higher for weak *FF* network funds compared to funds with strong *FF* information networks. Weak *FF* network funds are able to generate an additional 5.40% risk-adjusted return on investments in companies with which they have strong *FC* networks, compared to the marginal impact of 3.50% for small funds in Panel A. For investments in companies associated with strong *FC* networks, strong *FF* network funds underperform weak *FF* network funds by 9.65% annually. On the other hand, the strong *FF* network funds outperform the weak *FF* network funds by 2.56% annually in investments lacking substantial *FC* networks, compared to a corresponding value of 1.92% for small funds (See Panel A).

To summarize, the evidence on the marginal impact of information networks holds across fund sizes. Moreover, to the extent that fund sizes reflect managerial ability, the empirical findings support the notion that managers with more skills are able to generate higher performance from differential information acquired via informal interactions.

2.5.5. Fund age, information networks and performance

One important aspect of informal information networks that has not been considered so far is the role of fund experience on the development of these information channels. While the primary measures of information networks employed in this paper depend on cross-sectional variations in the likelihood of a fund manager's informal interactions, fund experience may be an important determinant of the extent of networks developed over time. Consider the fundamental findings in sociology and economics on which the network measures are developed. The likelihood of existence of an information network is considered to be a function of the likelihood of a random interaction via social or business connections. Though most of this paper models the likelihood of a random interaction as a function of geographical distance (known to translate into social distance), the likelihood of a random interaction is also likely to be a function of the length of time the fund has been a participant in the market. In effect, funds that have been a part of the mutual fund industry for a long time may have the opportunity to develop informal information channels, irrespective of geographical factors.

In Table 2.6., the role of information networks in generating risk-adjusted returns is examined across experienced and inexperienced funds. Fund age is measured as the number of years between the first offer date and the portfolio quarter. The funds are ranked into terciles by fund age, with the lowest tercile being the young funds (median age 3 years) and highest tercile being the old funds (median age 14 years). The young and old funds that were also ranked in the weakest and strongest *FF* network quintiles are included in the two groups.

Table 2.6.
Performance of Mutual Funds and Information Networks (by fund age)

Every quarter during Sept 2003-Dec 2005, the likelihood of a fund-company (FC) information network existing between each fund manager j and each company issuing stock n that is held in j's portfolio is computed as $L^{FC}(Network)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the geographical distance between the city where fund j is located and the city in which company n is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (FF) network measures for each fund j is computed as:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

where, $i = 1,\ldots N$ are all funds not in the same family as fund j, $L^{FF}(Network)_{j,i}$ = 1/(1+ $Distance_{j,i}$), and $Distance_{j,i}$= distance in km. between city of fund i and fund j. Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. Risk-adjusted portfolio returns are computed in each quarter as:

$$R^{adj} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t}(R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock i's DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) and averaged across quarters. Standard deviation of portfolio returns (in percentage) is calculated for each fund and is reported as a value-weighted average by fund TNA. *, **, *** represent significance at 10%, 5% and 1% level respectively.

Panel A: Young Funds (Median Fund Age= 3 years)			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	2.76	-4.43	-7.19***
	(21.45)	(18.97)	[-4.80]
Weak Fund-Company (FC) Network	0.23	-0.62	-0.85***
	(21.12)	(20.10)	[3.66]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	2.53***	-3.81***	
	[3.42]	[-5.16]	
No. of Fund-Quarter Obs.:	1,337	1,158	

Panel B: Old Funds (Median Fund Age= 14 years)			
	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	8.80	-3.87	-12.67***
	(20.56)	(22.10)	[-7.03]
Weak Fund-Company (FC) Network	1.41	3.39	1.98
	(19.64)	(22.56)	[0.84]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	7.39***	-7.26***	
	[3.62]	[-4.41]	
No. of Fund-Quarter Obs.:	944	1,199	

As shown in Panel A, young funds are able to leverage strong *FC* information channels and outperform in their holdings with weak *FC* networks by 2.53%. Also, the marginal impact of *FC* networks remains bigger for weak *FF* network funds compared to strong *FF* network funds. Weak *FF* network funds outperform strong *FF* network funds in holdings associated with strong *FC* networks by 7.19% annually. However, the results for marginal impact of *FF* networks on performance of investments in weak *FC* network companies for these young funds differs from the evidence so far. Young funds in strong *FF* network areas fail to capitalize on *FF* networks, and underperform weak *FF* network young funds in both strong and weak *FC* network investments. The results suggest that young funds are neither able to gain information advantages via informal interactions with companies in areas where there are many funds present, nor are they able to generate superior performance using information acquired via networks with other fund managers.

Panel B reports the evidence for the subsample of old funds. Interestingly, while most results do not change, the marginal impact of *FF* networks in generating superior performance on holdings with weak *FC* networks loses significance. This is consistent with the notion that experienced funds, while located in weak *FF* network areas, can build informal information channels over time that are similar to funds in strong *FF* network areas. In other words, it is possible that spatial limitations to informal interactions are overcome by the opportunity to form informal information links over time. Moreover, while the marginal impacts of *FF* networks on investment performance decreases for older funds, the marginal impact of *FC* networks is more pronounced compared to younger funds. These results suggest that while informal networks among funds can be independent of spatial boundaries, information channels with companies can become stronger over time and increase the degree of differential information that a fund manager can acquire via fund-company networks.

2.5.6. Do information networks matter when information availability is high?

The potential to create differential information about an asset may be insubstantial when information availability about the future value of an asset is high. The information availability of a company depends on the size, since larger firms are more visible and get more attention from media, analysts etc. In general, the information in the public domain about large firms is much higher than for small firms. It may be possible that the role of informal information networks is insignificant for investments in the stocks of large companies, where most pertinent information is publicly available.

In Table 2.7., the baseline analyses are repeated for the subset of stock holdings in companies that were ranked in the fourth and fifth highest DGTW size quintiles. Results are qualitatively similar to the findings so far and suggest that informal information networks have significant marginal impact on performance even when information availability about the assets is high. The marginal impact of *FC* networks is higher when fewer funds have *FC* networks with the same companies. Conditional on the existence of weak *FF* networks, *FC* networks have a positive and significant marginal impact of 4.74% annually on risk-adjusted returns. Strong *FF* network funds underperform weak *FF* network funds in their strong *FC* network holdings by 9.58%. For weak *FC* network holdings, *FF* networks have a positive marginal impact of 2.32%, significant at the 5% level. The analyses were also conducted with the subsample of fund holdings in the fifth

Table 2.7.
Performance in Large Cap Stocks and Information Networks

Every quarter during Sept 2003-Dec 2005, the likelihood of a fund-company (FC) information network existing between each fund manager j and each company issuing stock n that is held in j's portfolio is computed as $L^{FC}(Network)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the geographical distance between the city where fund j is located and the city in which company n is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (FF) network measures for each fund j is computed as:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

where, $i = 1,\dots N$ are all funds not in the same family as fund j, $L^{FF}(Network)_{j,i}$ = 1/(1+ $Distance_{j,i}$), and $Distance_{j,i}$= distance in km. between city of fund i and fund j. Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. Risk-adjusted portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t}(R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock i's DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) and averaged across quarters. Standard deviation of portfolio returns (in percentage) is calculated for each fund and is reported as a value-weighted average by fund TNA. *, **, *** represent significance at 10%, 5% and 1% level respectively.

	Weak Fund-Fund (FF) Network (1)	*Strong Fund-Fund (FF) Network* (2)	Marginal Impact: *Strong-Weak FF Net.* [t-statistic]
	Risk-adjusted Returns (Std. Dev. (in %))	Risk-adjusted Returns (Std. Dev. (in %))	
Strong Fund-Company (FC) Network	6.78 (32.89)	-2.80 (17.89)	-9.58*** [-3.92]
Weak Fund-Company (FC) Network	2.04 (32.85)	4.36 (26.54)	2.32** [1.96]
Marginal Impact: *Strong-Weak FC Net.* [t-statistic]	4.74*** [4.39]	-7.16*** [-9.44]	
No. of Fund-Quarter Obs.:	2,430	2,763	

highest DGTW size quintile only, and results hold. To summarize, results on the marginal impact of informal information networks hold for mutual fund investments in stocks that have high information availability associated with them.

2.5.7. Copycat portfolios and future asset prices

Based on the empirical analyses in this paper, the portfolios that show superior performance are (1) strong fund-company network portfolios for funds with weak fund-fund networks, and (2) weak fund-company network portfolios for funds with strong fund-fund networks. The results suggest that the information used to drive investments in these holdings is superior to other information channels. It is possible that fund investments made based on the information acquired via these 'superior' networks are indicative of longer term future values of the stocks, beyond the horizon of three-month quarterly portfolios. If so, since fund holdings become publicly available information at the end of each portfolio quarter, then there are ways to infer future values of these assets based on observing these portfolio strategies.

In Table 2.8., a preliminary examination of identifying superior information networks of mutual fund managers and their relationship with future value of the stocks chosen is presented. Using fund holdings reported in the previous quarter (which is stale information for all subsequent quarters), a hypothetical or 'copycat' portfolio is constructed including the stocks of holdings which were chosen by the two information networks that generate superior risk-adjusted returns in mutual fund investments, called the *Best Information Portfolio* (or BIP). This portfolio strategy replicates the holdings of

Table 2.8.
Hypothetical Portfolio Strategies based on Information Networks

Every quarter during Sept 2003-Dec 2005, the likelihood of a fund-company (*FC*) information network existing between each fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is computed as $L^{FC}(Network)_{j,n} = 1/(1+ Distance_{j,n})$. Here, $Distance_{j,n}$ is the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered. Every quarter, each fund is split into a *Strong Fund-Company Network* portion (defined as any holding in the highest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter) and a *Weak Fund-Company Network* portion (defined as any holding in the lowest $L^{FC}(Network)_{j,n}$ decile among all the fund's holdings in the same quarter). Fund-fund (*FF*) network measures for each fund *j* is computed as:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

where, $i = 1,\ldots N$ are all funds not in the same family as fund *j*, $L^{FF}(Network)_{j,i} = 1/(1+ Distance_{j,i})$, and $Distance_{j,i}$= distance in km. between city of fund *i* and fund *j.* Network quintiles are computed by sorting all funds in the sample into quintile groups according to the network measure computed above. *Strong Fund-Fund (F-F) Network* funds are the funds in the highest network quintile and *Weak Fund-Fund (F-F) Network* funds are funds in the lowest network quintile. We generate a hypothetical portfolio called the *"Best Information Portfolio" (BIP)* comprising of stocks which are classified as (1) *Strong Fund-Company Network* stocks for *Weak Fund-Fund Network* funds and (2) *Weak Fund-Company Network* stocks for *Strong Fund-Fund Network* funds. *BIP* is formed at the beginning of month t, based on the publicly released information on mutual fund holdings for a quarter comprising months t-3, t-2, t-1. Panel A reports the average monthly returns of an equally-weighted portfolio of BIP stocks for 3-, 6-, …, 24-month holding periods. Panel B reports risk-adjusted returns for value-weighted portfolios based on the dollar value of the holding in a fund's quarterly report. Risk-adjustment is done using benchmark portfolio returns computed using the methodology of Daniel et al. (1997). t-statistics are reported in parentheses.

Panel A: Average Monthly Returns									
Hyp. Portfolio	No. of Obs.	3-mth return	6-mth return	9-mth return	12-mth return	15-mth return	18-mth return	21-mth return	24-mth return
BIP (All Qtr)	8,488	0.017	0.014	0.012	0.012	0.013	0.011	0.012	0.014
		(23.92)	(3.11)	(2.60)	(2.36)	(2.38)	(2.22)	(1.88)	(1.65)
BIP (Qtr 1)	987	0.049	0.033	0.022	0.014	0.021	0.015	0.015	0.016
		(22.05)	(22.35)	(18.37)	(13.55)	(23.70)	(17.26)	(18.85)	(20.98)
BIP (Qtr 2)	995	0.017	0.010	0.003	0.014	0.008	0.009	0.011	0.011
		(8.43)	(7.03)	(2.18)	(15.10)	(8.45)	(10.70)	(13.24)	(14.38)
BIP (Qtr 3)	877	0.004	-0.004	0.013	0.005	0.008	0.010	0.010	
		(1.83)	(-2.64)	(12.51)	(5.18)	(8.38)	(11.52)	(11.96)	
BIP (Qtr 4)	1,050	0.002	0.021	0.008	0.011	0.013	0.010		
		(0.87)	(17.47)	(7.39)	(11.54)	(14.84)	(12.41)		
BIP (Qtr 5)	889	0.047	0.015	0.015	0.017	0.016			
		(25.02)	(11.43)	(14.45)	(17.16)	(18.24)			
BIP (Qtr 6)	896	-0.018	-0.001	0.006	0.007				
		(-9.09)	(-0.44)	(5.45)	(7.06)				
BIP (Qtr 7)	970	0.026	0.019	0.016					
		(13.17)	(14.10)	(12.43)					
BIP (Qtr 8)	1,019	0.015	0.017						
		(7.29)	(11.70)						
BIP (Qtr 9)	943	0.010							
		(5.69)							

Panel B: Average Risk-adjusted Monthly Returns									
Hyp. Portfolio	No. of Obs.	3-mth return	6-mth return	9-mth return	12-mth return	15-mth return	18-mth return	21-mth return	24-mth return
BIP-Bench.	8,488	0.006	0.006	0.006	0.005	0.006	0.006	0.004	0.005
		(2.61)	(3.11)	(2.61)	(2.36)	(2.38)	(2.23)	(1.88)	(1.65)
HP (Qtr 1)	987	0.006	0.005	0.007	0.005	0.007	0.007	0.005	0.005
		(1.28)	(2.14)	(2.40)	(1.60)	(1.51)	(1.34)	(1.19)	(1.20)
HP (Qtr 2)	995	0.005	0.008	0.004	0.007	0.006	0.004	0.006	0.007
		(0.82)	(1.51)	(0.80)	(1.08)	(0.98)	(0.88)	(1.03)	(1.16)
HP (Qtr 3)	877	0.009	0.010	0.010	0.006	0.005	0.007	0.003	
		(1.71)	(1.28)	(1.16)	(0.93)	(0.93)	(1.20)	(1.60)	
HP (Qtr 4)	1,050	0.001	0.007	0.005	0.003	0.005	0.007		
		(-0.23)	(0.97)	(0.81)	(0.57)	(0.93)	(1.07)		
HP (Qtr 5)	889	0.013	0.009	0.003	0.006	0.007			
		(1.30)	(1.00)	(0.55)	(1.08)	(1.16)			
HP (Qtr 6)	896	0.006	0.000	0.006	0.006				
		(0.71)	(0.08)	(1.01)	(1.08)				
HP (Qtr 7)	970	0.002	0.005	0.007					
		(0.50)	(1.62)	(1.68)					
HP (Qtr 8)	1,019	0.008	0.007						
		(1.35)	(2.10)						
HP (Qtr 9)	943	0.004							
		(0.89)							

the two information portfolios with superior performance from reports at the end of a quarter, and holds it starting the first month of the next quarter for up to two years (the maximum time horizon allowed based on our data).

Panel A presents returns for three to twenty-four month holding strategies, with three month increments. Average monthly raw returns for the BIP are positive and significant for all eight holding periods, with somewhat decreasing statistical significance as the portfolio horizon increases. The returns on these portfolio strategies range between the maximum of 1.70% (with t-statistic of 23.92) for the first three months following the quarter for which the holdings are reported by mutual funds, and the minimum of 1.1% (with t-statistic of 2.22) for the 18-month holding strategy. The returns on the eight holdings strategies are also presented separately for the nine sets of quarterly reports that form the dataset used in this paper. This is done as a robustness check to detect if outliers in portfolio strategy returns drive the significance of the aggregated findings. Using the reported holdings of each of the nine quarters separately, the copycat portfolios are constructed for the eight holdings periods. The first three-month holding strategy generates significantly positive returns for seven of the nine quarters, with the maximum average monthly return of 4.90% for the first quarter. Similarly, the results for the seven other holding periods also hold and are not driven by outliers. However, these returns may be a compensation for the risk borne by these portfolios.

In Panel B, risk-adjusted returns are used instead of raw returns. Average risk-adjusted monthly returns of the BIP are also significantly positive for the eight holding periods, although they are of considerably smaller magnitude than raw returns. Overall, the average monthly risk-adjusted return on the eight holding strategies range between

0.6% and 0.4%. Results suggest that there may be potential asset pricing implications of identifying more efficient investor information networks, where certain information networks are more likely to predict superior future stock performance. A more comprehensive investigation of these asset pricing implications is beyond the scope of this study and left for future research.

2.6. Conclusions

This study provides new insights on the role of informal information channels on the ability of money managers to generate superior performance from holdings. The focus is on two forms of informal information networks that exist in the mutual fund industry: (1) *fund-fund information networks*, which transfer information between fund managers about potential investment opportunities; and (2) *fund-company information networks*, which facilitate a manager's acquisition of differential information about a company via networks with the companies. By studying marginal impacts of these information channels, empirical challenges associated with distinguishing the relationship between informal information networks and net fund performance are largely avoided.

It is shown that information networks have substantial marginal impacts on performance of holdings. In general, superior stock selection ability is shown by strong fund-fund (fund-company) networks in the absence of strong fund-company (fund-fund) networks. Results uncover poor performance in holdings when strong fund-company networks overlap for many fund managers, i.e. are less exclusive, possibly via dilution of informational advantages. Overall findings hold across fund size, family size, fund age and investments in large cap stocks having high information availability. Results are also consistent with the notion that higher managerial ability allows managers to better translate information acquired via informal interactions into positive performance. Copying the stock selections of superior information networks, in months subsequent to when the quarterly reports become public, generate significantly positive monthly risk-adjusted returns. The results allude to the possibility that certain superior information networks can identify misvaluations in asset prices that persist beyond the portfolio quarter. While this may be in violation of the semistrong form of market efficiency, if a sizeable group of investors begin to implement these copycat strategies, the gains may be short-lived or disappear.

While informal information networks have often been recognized in sociology and to some extent in economics, formal studies on their role in financial markets is a recent phenomenon. The findings in this paper suggest that managerial skills in networking with relevant, efficient and exclusive informal information sources can improve performance in professional investment management. Evidence on the superiority of certain information networks and the predictive value of their investments allude to asset pricing implications of investor networks, an intriguing avenue for future research. Another facet of the existence of informal communication and information sharing in financial markets that demands exploration, both empirically and theoretically, are the incentives and externalities that drive market participants to pool information.

CHAPTER 3

WHEN MUTUAL FUND MANAGERS DEVIATE FROM THEIR PEERS: THE IMPACT ON PORTFOLIO PERFORMANCE

3.1. Introduction

"Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."

- John Maynard Keynes

Previous literature has suggested that there exist substantial incentives, like reputational concerns, for mutual fund managers to herd with other fund managers in their portfolio strategies. Scharfstein and Stein (1990) were among the first to depict the tendency and incentives to herd among investment managers. Some other studies which study herding behavior are Banerjee (1992), Bikhchandani et al. (1992), Froot et al. (1992), Grinblatt and Keloharju (2000), among others. On the other hand, Grinblatt et al. (1995) find relatively weak empirical evidence of herding among mutual fund managers. Researchers have also been concerned about the potential increase in volatility of asset prices caused by herding. The recent stock market bubble in the late 1990s, driven by overpricing of U.S. technology stocks, is often cited as anecdotal evidence of the dark side of herding among investors in capital markets. A recent article in the *New York Times* says that "mutual funds are a destabilizing force in the stock market", further stating that there are profit opportunities for investors who follow contrarian strategies relative to the herd.[10] There is some evidence in the academic literature that implicitly indicates potential gains from strategies that deviate away from benchmarks. For example, Kacperczyk, Sialm and Zheng (2005) show that funds which have higher industry concentration in their portfolios outperform well-diversified industry portfolios. Baks, Busse and Green (2007) find that fund manages who take bigger bets in a few stocks outperform those who do not.

In general, herding may be reflected in the tendency of mutual fund managers to follow similar buying and selling decisions and portfolio allocations. However, given the incentives to follow their peers, the instances where fund managers deviate away from the strategies of others may contain information pertinent to mutual fund investors.

Mutual fund managers may deviate from the portfolio allocation strategies of their peers due to various reasons. They may deviate by overweighting or underweighting stocks, relative to their peers' allocations, based on private information. A fund manager's deviating tendency may also be because of a conflict of interest between the manager and the investors. Due to the well documented asymmetric relationship between flow and performance (see, Sirri and Tufano (1998)), investors substantially reward superior performance but do not proportionately penalize poor performance. In this case, a fund manager may deviate from peers and follow riskier strategies to increase chances of outperforming other managers.[11] In summary, there may be several different reasons including irrationality, information or agency problems which may lead fund managers to deviate from the choices made by their

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[10] *New York Times* (April 8th, 2007), Mark Hubert, *"How to Find Profit Away From the Herd"*

[11] See Brown, Harlow and Starks (1995).

peers. However, the different drivers of deviation strategies should have different implications for performance. If informed trading generates deviating tendencies among fund managers, then we should observe higher future performance as a consequence of deviations. On the other hand, if the deviations arise out of agency problems or irrational biases like managerial overconfidence, the performance impact is likely to be negative. Finally, if deviations are random and are not a systematic indication of information, then it is unlikely that there is a detectable relationship between performance and managers' deviating tendencies.

Using the portfolio allocations of actively managed funds in the U.S. for ten quarters in the period July 2003-December 2005, we conduct an empirical investigation into the potential causes and consequences of fund managers' deviating tendencies relative to their peers. We measure the deviating tendency of a fund manager in a portfolio quarter as the absolute deviation of the allocated portfolio weight in a stock (as percentage of total net assets (TNA)) from the mean weight allocated to the stock by other fund managers in the same peer group, averaged across all stocks held by the peer group. For instance, if a fund manager on average overweights or underweights stocks by 2% of the TNA relative to the mean portfolio weights allocated by other managers in her peer group to the same stocks, her deviating tendency would be computed as 2%. We consider three alternative definitions of 'peer group' for fund managers: all other funds in the sample, all other funds in the same objective, and all other funds in the same objective and of similar size. We also conduct various robustness checks for alternative definitions of peer groups and fund objective classifications.

Firstly, we examine the determinants of fund managers' deviating tendencies. The deviating tendency of a fund manager decreases with the fund size, family size, fund turnover, and strength of networks with other mutual fund managers. We measure networks between fund managers as function of geographical proximity, in which case our results suggest that managers located in areas with a higher concentration of fund managers are less likely to deviate from their peers. We also find a non-linear relationship between a manager's deviating tendency and past fund performance, indicating a U-shaped relationship between deviating tendency and past performance. Therefore, the best and worst performers deviate more than the intermediate performers in subsequent periods. Additionally, single manager funds and funds investing in larger (higher momentum) stocks have a higher (lower) deviating tendency. Moreover, we find striking persistence in deviating tendencies over time.

Secondly, we investigate the relationship between fund performance and deviating tendency using clustered multivariate OLS regressions. The empirical findings suggest a significantly negative relationship between deviating tendency and contemporaneous fund performance relative to their objectives, after controlling for various factors. Deviating tendencies also seem to partially predict future underperformance of the fund. The results are robust to the definition of peer group and hold across different fund size and past performance categories.

Lastly, we dig deeper into the consequences of a fund manager's decision to deviate from the portfolio allocation strategies of their peers by employing a portfolio decomposition approach. Each fund manager's portfolio holdings are ranked into deciles by the magnitude of deviation, with the highest (lowest) decile comprising the most overweighted (underweighted) stocks, relative to the weights allocated by other managers in the peer group. If the manager deviates based on information, the portfolio of overweighted stocks should in general outperform the portfolio of underweighted stocks in the future. However, the findings contradict this 'information hypothesis'. In fact, the average fund manager overweights stocks that subsequently underperform compared to the stocks that the manager underweights. The underperformance is significant and the magnitude is an annualized benchmark-adjusted return of about -4.6%.[12] These findings hold across peer group definitions, fund size categories and fund past performance categories.

This paper broadly contributes to the literature on informed trading and herding in capital markets. Most existing literature has focused attention on the incentives and consequences of herding by investors in stock markets. In spirit, our study focuses on the reverse dimension of herding, i.e the situations where fund managers deviate from their peers' strategies. There are several important implications of the findings that fund managers display persistent deviating tendencies and higher deviations are associated with underperformance both at the fund and the holdings' level. The results suggest that mutual fund investors who are unable to identify skilled portfolio managers may do better by avoiding funds which have higher disparity in portfolio allocations relative to comparable funds. Also, if managers' deviating tendencies have a detrimental impact on performance, the persistence in deviating tendencies seem to suggest agency problems in the investment management industry.

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[12] Benchmark-adjusted returns are computed following the methodology of Daniel et al. (1997)

The remaining paper is organized as follows. Section 3.2. discusses the data used for the empirical study. Section 3.3. discusses the empirical methodology employed in the study. Results are presented in section 3.4. Section 3.5. concludes.

3.2. Data

The primary data source used in this study is the CRSP Survivor-bias Free US Mutual Fund Database (MFDB) which provides data on fund characteristics and returns. In January 2005, CRSP added a mutual fund holdings database that includes stocks, bonds, mortgage-backed securities, other mutual funds, futures and options, among others. CRSP holdings data includes information on the market value of the holdings, number of shares held and names of securities, from reports dating September 2003 to December 2005. Fund holdings in some cases are reported for quarters before September 2003, but we exclude these because of largely missing data on a majority of the funds. For our analyses, quarterly data for the ten quarters between September 2003 and December 2005 is obtained. Portfolio holdings are usually reported at the end of each quarter, where the portfolio information is effective in the previous three months.

Given that the CRSP holdings database is relatively new, we verify the accuracy of the information by spot matching with the CDA/Spectrum database that has been widely used for accessing mutual fund holdings information. The identification and amount invested information for holdings are nearly identical between the two databases with negligible difference.

We first construct the sample of funds by choosing US equity funds primarily investing in domestic equity (excluding index, sector and bond funds) having aggressive growth, growth, growth and income or balanced as stated objective categories from CRSP MFDB. We finally follow Kacperzcyk et al. (2005) and select funds with ICDI objective codes: AG, GI, LG, IN. We also impose a minimum fund size criterion of $5 million in total net assets for the fund to be included in the sample.

Our final sample consists of 1,631 unique funds in the sample period. The main fund identifier in CRSP MFDB is the ICDI code. However, CRSP assigns multiple ICDI codes to different share classes of the same fund. We prevent erroneous counting of funds by merging information of multiple ICDI codes representing the same fund into one unique fund. We only include stock holdings of publicly traded companies headquartered in the U.S. and have stock returns data available from CRSP, and exclude other assets held in the portfolios.

The holdings database uses a unique portfolio identifier that is matched to ICDI codes in a separate CRSP mapping file. Each portfolio code represents a unique portfolio, and multiple ICDI can be mapped to the same portfolio code if the underlying portfolios are identical. For example, multiple ICDI codes representing different share classes of the same fund have the same underlying portfolio, and are mapped to a common portfolio code. After matching the portfolio codes to ICDI codes, we match data on mutual fund characteristics like monthly total net assets, management company etc. with the CRSP MFDB. Finally, we get stock price and returns data for the holding companies from CRSP monthly stock files.

Fund location information (i.e., city and state) is obtained from *Nelson's Directory of Investment Managers*. Disclosure database provides information on the headquarter location of all publicly traded companies in our sample. The city and state information of the funds and companies are matched to latitude and longitude coordinates from US Census Bureau's freely available Gazetteer geographical data source. We use the latitude and longitude information to calculate geographical distances between two cities.

Table 3.1. reports summary statistics on the sample of equity mutual funds used in this paper and some portfolio characteristics. The final sample of 1,631 unique mutual funds is managed by 381 unique investment companies for the ten quarters during July 2003 to December 2005. There were 4,897 publicly traded stocks of U.S. companies that were held by these mutual fund managers in this period. The median fund in the sample has eight years of experience and has total net assets (TNA) of about $109 million. The median fund turnover is 66% per year, and the median fund portfolio size is 89 stocks. On a value-weighted basis, funds invest in relatively larger market cap stock in the size quintile of 4.5, book-to-market ratio of around 2.5 and stock above the third DGTW momentum quintile.

3.3. Empirical Methodology

3.3.1. Performance measures

We construct two measures of excess performance in using returns data from the CRSP Mutual Fund Database. First, we compute a fund's objective-adjusted performance

Table 3.1.
Summary Statistics on U.S. Mutual Funds

This table reports summary statistics for the funds in our sample. It includes U.S. mutual funds that invest primarily in U.S. equity as reported in CRSP Mutual Fund Database, excluding index and sector funds during July 2003-December 2005. Fund age is the number of years since the organization of the fund, in the portfolio quarter. Single manager funds (in % of funds per quarter) are reported as the % of funds in a portfolio quarter that are managed by a single manager, averaged across all quarters in the sample. Expenses are stated as the total annual management fees and expenses as a percentage of the year-end TNA. Turnover ratio is the fund turnover expressed as the minimum of purchases and sales over average TNA for the calendar year. The portfolio weight allocated to a stock is the amount invested in the stock as a percentage of the fund TNA. A fund's objective-adjusted return is reported at the quarter level, and is winsorized below at the 1% level and above the 99% level. The number of companies in a fund's portfolio is reported as the average across all quarters. Daniel et al (DGTW) (1997) is followed to compute the size, book-to-market and momentum quintiles for the stocks held.

	Mean	Median	Std. Dev.
Total number of funds in sample	1,631		
Total number of mutual fund families in sample	381		
Total number of different stocks held in sample period	4,897		
Total net assets (TNA) (in $ million)	756.75	109.35	2856.10
Fund age (in years)	11.37	8.00	11.71
Single manager funds (in % of funds per quarter)	34.32		
Expenses (in %)	1.29	1.26	0.43
Turnover ratio	0.99	0.66	0.16
Portfolio Weight of a stock (as % of TNA)	1.52	1.20	0.86
Fund Objective-adjusted Returns in % (OAR) (quarterly)	0.05	0.02	2.17
Portfolio characteristics:			
Number of companies in portfolio	141	89	200
Value-weighted DGTW Size quintile	4.02	4.51	1.06
Value-weighted DGTW B/M quintile	2.57	2.54	0.47
Value-weighted DGTW MOM quintile	3.11	3.07	0.48

by subtracting the performance of the median fund in the matched investment objective from the return of the fund. The quarterly OAR of a fund *j* in quarter *t* is computed as

$$\boldsymbol{OAR}_{j,t} = (1+\boldsymbol{R}_1^j)*(1+\boldsymbol{R}_2^j)*(1+\boldsymbol{R}_3^j) - (1+\boldsymbol{R}_1^{obj})*(1+\boldsymbol{R}_2^{obj})*(1+\boldsymbol{R}_3^{obj}) \quad (1).$$

Here, $\boldsymbol{R}_1^j$, $\boldsymbol{R}_2^j$, $\boldsymbol{R}_3^j$ are the fund's total returns reported in CRSP in the three months in the quarter, and $\boldsymbol{R}_1^{obj}$, $\boldsymbol{R}_2^{obj}$, $\boldsymbol{R}_3^{obj}$ are the median returns of other funds in the same objective as fund *j* in the corresponding months.

The advantage of employing the simplistic objective-adjusted returns (OAR) is that the methodology does not require a long time-series of returns data to compute the fund's abnormal performance. The disadvantage of using OAR as a performance measure is that it ignores potentially large dispersions in risk exposures within the same objective. Therefore, the excess returns may just be capturing rewards for holding higher levels of risk rather than differences in performance. Hence, as a second measure, we also compute holdings' based benchmark-adjusted abnormal returns using the methodology of Daniel et al. (DGTW) (1997).

Raw returns for portfolios are computed in each portfolio quarter following DGTW (1997) for each fund holding as

$$\boldsymbol{R}^{raw} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} \boldsymbol{w}_{i,t} \boldsymbol{R}_{i,t} \tag{2}$$

Here, $w_{i,t}$ is the portfolio weight of stock *i* in month *t*, and *S* is the number of stocks in the sub-portfolio. The weights in each sub-portfolio sum to one. As the second measure of abnormal returns, we similarly construct risk-adjusted sub-portfolio returns for each fund computed in each quarter as

$$\boldsymbol{R}^{adj} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} \boldsymbol{w}_{i,t} (\boldsymbol{R}_{i,t} - \boldsymbol{R}_{i,t}^{bench}) \tag{3}$$

Here, R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintile benchmark portfolio (following Daniel et al. (1997)).

3.3.2. Measures of deviation from peer groups

Our measures of the degree to which a fund manager deviates from their peer group are based on the portfolio weight allocations to the stocks held in their portfolios and fall into two broad categories.

First, we examine the overall tendency of a fund manager to deviate in their portfolio allocations from others in their peer groups. Throughout the paper, we use three alternative definitions of peer groups: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as

$$\boldsymbol{Deviation_{i,t} = w_{i,t} - \overline{w}_{i,t}} \tag{4}$$

Here, $\boldsymbol{w_{i,t}}$ is the portfolio weight of stock *i* in portfolio quarter *t* expressed as percent of TNA of the fund, and $\boldsymbol{\overline{w}_{i,t}}$ is the mean portfolio weight of stock *i* held by all other funds in the peer group in the same portfolio quarter. All stocks in which a fund manager's peer group invested in the portfolio quarter comprises the universe of stocks considered for each manager. In effect, if $\boldsymbol{Deviation_{i,t}}$ is positive (negative), the fund manager is overweighting (underweighting) stock *i* relative to the portfolio weight assigned to the stock by the fund managers peers. Table 3.2. reports summary statistics on the measures of deviations used in this paper. There is substantial variation in the portfolio weights (as % of TNA) allocated in holdings and deviation measures.

A fund manager's overall deviation tendency is then computed as

$$\boldsymbol{Fund\_Deviation_{j,t} = \sum_{i=1}^{S} | Deviation_{i,t} |} \tag{5}$$

Table 3.2.
Summary Statistics on Deviations from Peer Groups

Summary statistics are for all U.S. mutual funds that invest primarily in U.S. equity as reported in CRSP Mutual Fund Database, excluding index and sector funds during July 2003-December 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. Daniel et al (DGTW) (1997) is followed to compute the size, book-to-market and momentum quintiles for the stocks held.

	Peer Groups		
	All Funds (1)	Objective (2)	Objective, Size (3)
Mean portfolio weight (as % TNA)	0.844	0.844	0.844
Min (Max) portfolio weight	0.00 (40.41)	0.00 (40.41)	0.000 (40.41)
Mean deviation	0.584	0.577	0.563
Min (Max) deviation	-44.23 (47.63)	-44.15 (47.24)	-44.56 (49.49)
Mean deviation:			
DGTW Size Quintiles: 1	0.369	0.350	0.315
2	0.459	0.444	0.431
3	0.517	0.505	0.497
4	0.572	0.563	0.555
5	0.726	0.722	0.715
DGTW B/M Quintiles: 1	0.600	0.588	0.577
2	0.580	0.571	0.558
3	0.588	0.580	0.569
4	0.564	0.556	0.544
5	0.572	0.565	0.552
DGTW Mom Quintiles: 1	0.594	0.586	0.573
2	0.597	0.589	0.578
3	0.595	0.586	0.573
4	0.576	0.567	0.556
5	0.566	0.554	0.544

Here, $|\boldsymbol{Deviation}_{i,t}|$ is the absolute value of the deviation in portfolio weight in stock *i*, as expressed in equation (4), and *S* is the set of stocks held by the peer group in quarter *t*.

Second, we use a measure of within-portfolio relative holdings' deviations for fund portfolios. We employ a portfolio decomposition methodology to identify the holdings in which a fund manager deviates the most, in terms of overweighting or underweighting, in a stock relative to their peers in the concurrent quarter. For this, we rank the holdings in a fund's portfolio into decile ranks based on $\boldsymbol{Deviation}_{i,t}$, with Decile 1 (Decile 10) representing the sub-portfolio of stocks where the fund manager has chosen to most underweight (overweight) the stock relative to the portfolio weight allocated to that stock by all other fund managers in the same peer group. If the tendency to deviate reflects private information of the manager, the holdings in which a manager overweights relative to the peer group should have superior future performance relative to holdings where they underweight relative to the peer group.

We use both overall fund managers' deviation tendency measures and within-portfolio deviation measures because (i) each produces a different measure of a fund's proclivity towards deviation in a particular holding, (ii) fund-level deviations are more likely to capture overall managerial behavior and may be correlated with other heterogeneities, while within-portfolio deviation comparisons control for heterogeneities like managerial skills etc., and (iii) both types of measures may reflect different motivations for deviation.

3.3.3. Other variables

Most of the other variables that we use in this study have been used in previous studies. For fund level characteristics, we consider variables that have been shown to matter in previous studies on fund performance. *Log (TNA)* is the natural logarithm of a fund's total net assets reported in millions of dollars. *Log (Age)* is the natural logarithm of the fund age in years, computed from the fund's first offer date. *Turnover* is the fund's turnover ratio. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past performance (6 mths)* is a measure of recent fund performance, and is calculated as the objective-adjusted average monthly return of the fund in the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* for each fund *j* is computed as the natural logarithm of the following:

$$(\boldsymbol{Network})_j^{FF} = \sum_{i=1}^{N} \boldsymbol{L}^{FF}(\boldsymbol{Network})_{j,i} \tag{6}$$

Here, $i = 1,\ldots N$ are all funds in the same objective category but not in the same family as fund j, $L^{FF}(Network)_{j,i}$ is the likelihood of a network existing between fund managers j and i, and is computed as: $L^{FF}(Network)_{j,i} = 1/(1+ log(Distance_{j,i}))$, where $Distance_{j,i}$= distance in km between the cities of fund *i*'s headquarters and fund *j*'s headquarters.[13]

Previous literature has indicated that there may be substantial variation in the risk characteristics of the portfolios held by funds in the same objective or style categories. In order to control for portfolio risk characteristics that are not explained by fund level measures, we use variables based on the three DGTW (1997) dimensions. The *Value-weighted Size, B/M and MOM Quintile* variables are the value-weighted average DGTW size, book-to-market and momentum quintiles of the stocks held in a portfolio respectively. *Industry_Herfindahl* is a measure of the industry concentration of the fund portfolio, measured as the Herfindahl (summation of squared-portfolio weights allocated to each industry) across NCIS industry categories held by the fund. The size of a fund family, *Log (# funds in family),* is reported as the natural logarithm of the total number of funds under the investment management company. A pairwise correlation matrix of the explanatory variables used in this study is presented in Table 3.3.

[13] For more details on measures of networks, see Gupta-Mukherjee (2007).

Table 3.3.
Correlation Matrix

The table reports all the pairwise correlation coefficients between variables used in regression analyses. *Log (TNA)* is the natural logarithm of a fund's total net assets reported in $ million. *Log (Age)* is the natural logarithm of the fund age (in years) computed from the fund's first offer date. *Turnover* is the fund's turnover ratio. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past perf.* is the objective-adjusted average monthly return of the fund in the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* for each fund *j* is computed as the natural logarithm of the following:

$$(Network)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Network)_{j,i}$$

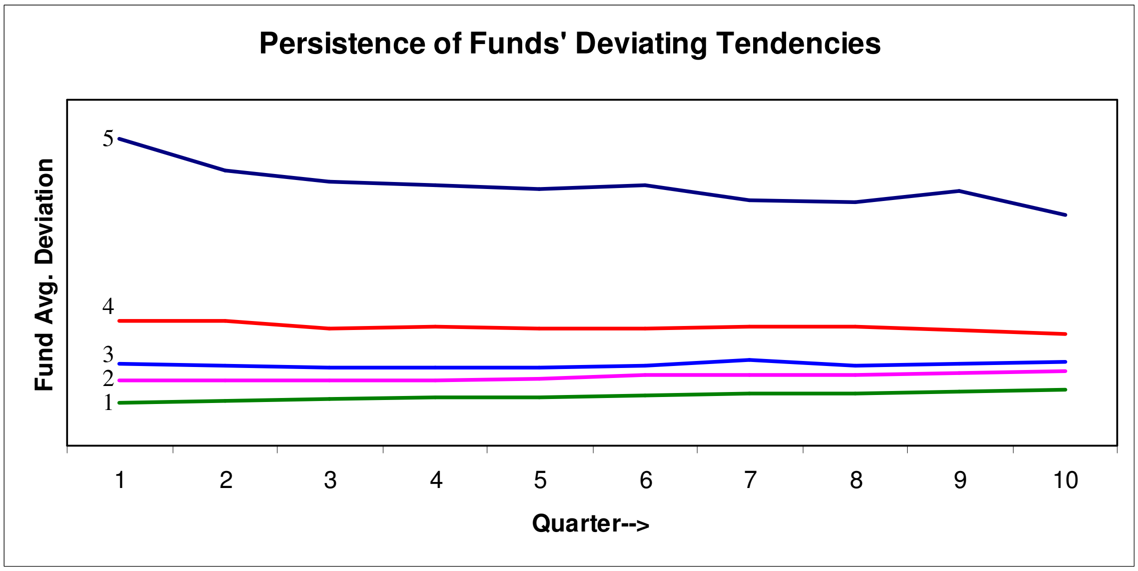
where, $i = 1, \ldots N$ are all funds in the same objective category but not in the same family as fund *j*, $L^{FF}(Network)_{j,i}$ = 1/(1+ $log(Distance_{j,i})$), and $Distance_{j,i}$= distance in km. between city of fund *i* and fund *j*. The *Value-weighted Size, B/M and MOM Quintile* variables are the value-weighted average DGTW size, book-to-market and momentum quintiles of the stocks held in a portfolio respectively. *Log (# funds in family)* is the natural logarithm of the total number of funds under the investment management company.

	Log (TNA)	*Log (Age)*	*Turnover*	*Single manager dummy*	*Past perf.*	*Fund-Fund Networks*	*Value-wt Size Quintile*	*Value-wt B/M Quintile*	*Value-wt MOM Quintile*	*Avg. Fund-Comp Networks*	*Log (# funds in family)*
Log (TNA)	1.00***										
Log (Age)	0.48***	1.00***									
Turnover	-0.13***	-0.12***	1.00***								
Single manager dummy	-0.02**	0.00	-0.01	1.00***							
Past perf.	0.02***	-0.06***	0.01	-0.02**	1.00***						
Fund-Fund Networks	-0.02*	0.02***	-0.07***	0.04***	0.03***	1.00***					
Value-wt Size Quintile	0.09***	0.12***	-0.11***	-0.02*	-0.15***	0.09***	1.00***				
Value-wt B/M Quintile	0.02*	-0.03***	-0.07***	-0.05***	0.17***	-0.11***	0.06***	1.00***			
Value-wt MOM Quintile	-0.06***	-0.04***	0.14***	0.05***	-0.04***	-0.02**	-0.41***	-0.28***	1.00***		
Avg. Fund-Comp Networks	0.04***	0.09***	-0.05***	0.02**	-0.02*	0.20***	0.14***	0.06***	-0.14***	1.00***	
Log (# funds in family)	0.21***	-0.04***	0.02***	-0.04***	-0.00	0.06***	0.09***	-0.05***	0.01	-0.04***	1.00***

*** 1% significance; ** 5% significance; * 10% significance

Figure 3.1. Persistence in Funds' Deviating Tendencies

The figure documents the persistence of fund deviating tendencies over time. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. The case where all funds in the sample are used as a peer group is reported. A fund's deviation is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter. In the first quarter, the funds are ranked into quintiles using fund's deviation. The plot reports the average fund deviation of the quintile groups formed in the first quarter over ten quarters.



3.4. Results

3.4.1. Graphical analysis: Deviations from peer groups

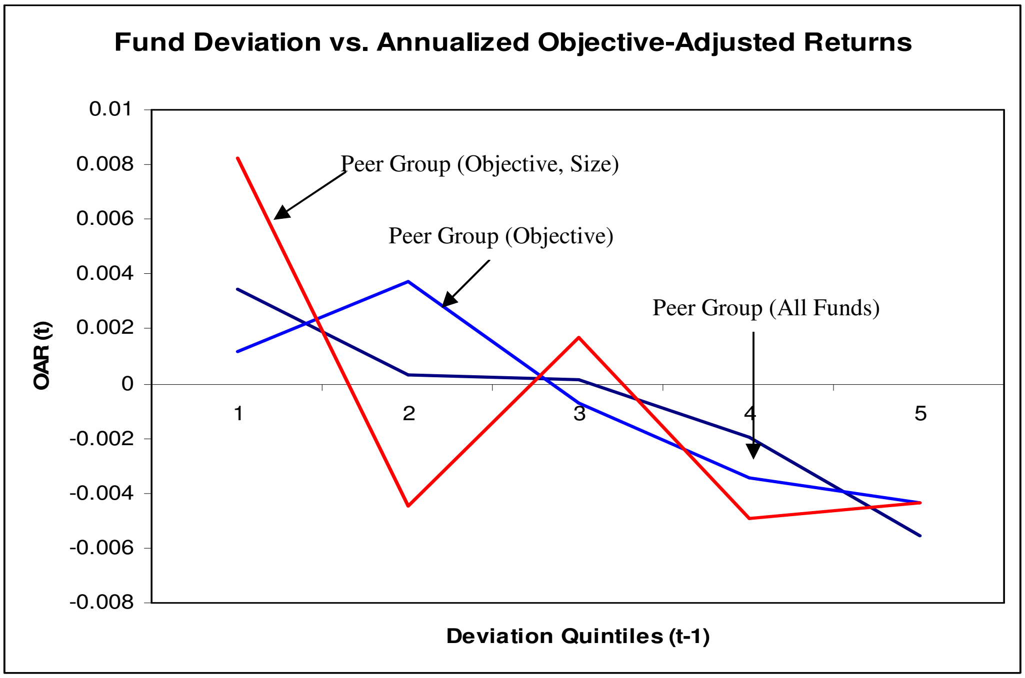
Figure 3.1. reports the persistence in the deviating tendency measures of mutual fund managers, presented as an average across all the funds in our sample. Funds are assigned into quintile portfolios formed based on deviation measures in the first quarter. The average deviations of the funds in the quintile groups are reported for subsequent quarters, and we note a striking persistence in the relative rankings of deviations. In effect, the funds which had highest deviating tendency in the first quarter are also the

Figure 3.2.1. Fund Performance vs. Deviations from Peer Groups

The figure documents the relationship between overall fund performance and fund deviating tendencies over time. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. A fund's deviation is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter. Funds are ranked into quintiles in every quarter *t*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. The quarterly objective-adjusted return (*OAR*) in quarter *t* is computed as:

OAR = (1+Ret_mth1)(1+Ret_mth2)*(1+Ret_mth3) - (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3)*

The median OAR in period *t* is reported for the deviation quintiles formed in period *t-1*.



most likely to show highest relative deviations from their peers' portfolio strategies in subsequent quarters. We present the case where all the funds in the sample are considered the peer group. In unreported robustness checks, we confirm that other definitions of peer groups lead to similar implications.

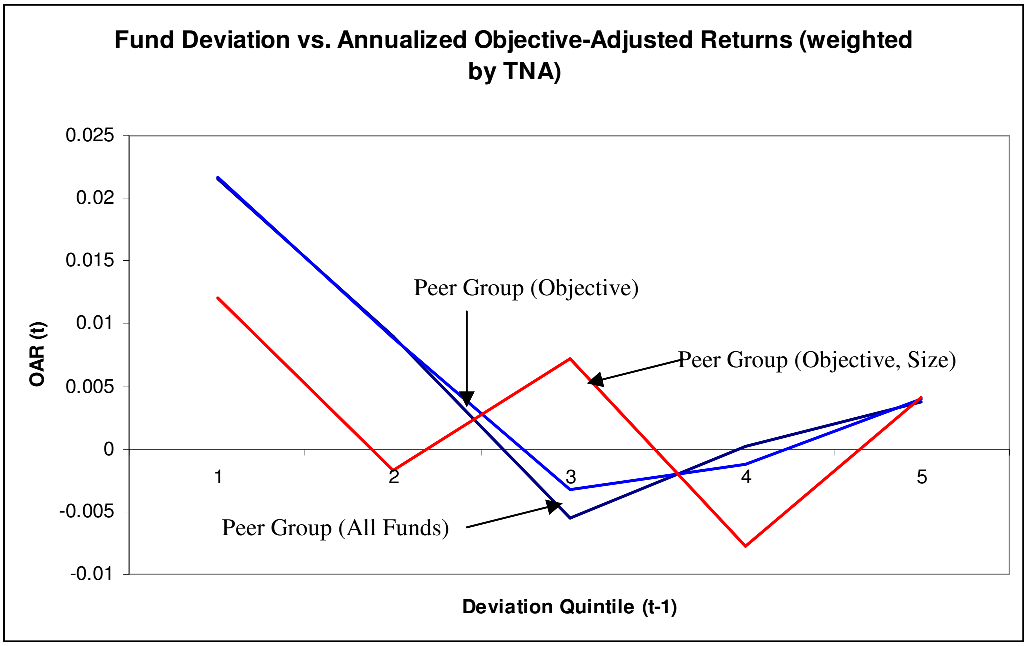
Figure 3.2.1 presents the plot between funds' average objective-adjusted returns (OARs) for the quintile groups of funds, ranked by deviating tendency in the previous quarter to which OAR is measured. The deviating tendency is measured as expressed in

Figure 3.2.2. Fund Performance weighted by TNA vs. Deviations from Peer Groups

The figure documents the persistence of fund deviating tendencies over time. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. A fund's deviation is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter. Funds are ranked into quintiles in every quarter *t*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. The quarterly objective-adjusted return (*OAR*) in quarter *t* is computed as:

OAR = (1+Ret_mth1)(1+Ret_mth2)*(1+Ret_mth3) - (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3)*

The median OAR in period *t* is reported as a TNA-weighted value for the deviation quintiles formed in period *t-1*.



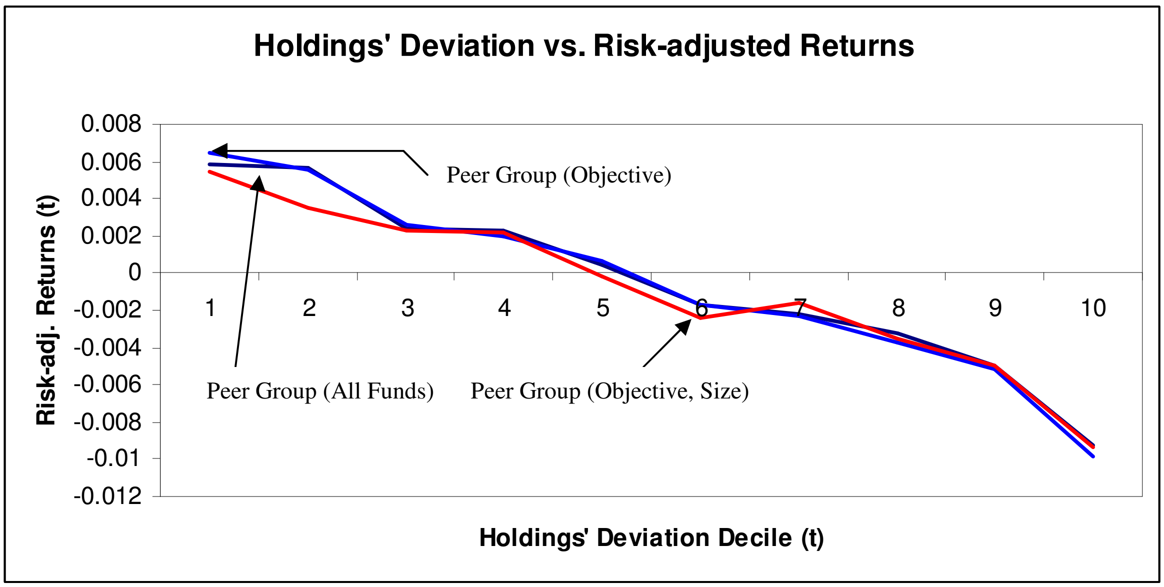
equations (4) and (5). For all definitions of peer groups considered, there is a distinct negative trend in OAR as deviating tendency increases. This alludes to a potential negative relationship between fund performance and the funds' deviations in portfolio strategies relative to peers. In Figure 3.2.2, the reported OAR is weighted by fund TNA, to check whether the relationships are driven only by smaller funds, in which case an observable trend should not exist. However, the previous result that fund performance decreases with deviating tendencies holds.

Figure 3.3. Holdings' Deviation from Peer Groups vs. Risk-adjusted Returns

The figure reports value-weighted risk-adjusted returns of sub-portfolios formed by decomposing a fund's portfolio into deciles based on deviation of portfolio weights from the mean portfolio weight allocated by the fund manager's peer group in the same stock. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. For each fund portfolio, *dev_perctna* is ranked into deciles, with Decile 1 (10) being holdings' which are most underweighted (overweighted) relative to peer funds. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. Risk-adjusted portfolio returns are computed in each quarter for each decile as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns are expressed in annual percentage rates and averaged across quarters.



In Figure 3.3., we employ a portfolio decomposition methodology to identify the holdings in which a fund manager deviates the most, in terms of overweighting or underweighting, relative to their peers in the concurrent quarter. The graphical relationship between the deviations from peers' portfolio allocations, in terms of underweighting and overweighting, and subsequent performance of the holdings is reported. The holdings in a fund's portfolio are ranked into deciles based on $\boldsymbol{Deviation}_{i,t}$ as computed in equation (4), with Decile 1 (Decile 10) representing the sub-portfolio of stocks where the fund manager has chosen to most underweight (overweight) the stock relative to the portfolio weight allocated to that stock by all other fund managers in the peer group. There is an almost monotonic decrease in benchmark-adjusted returns as the relative deviation weights increase, indicating that the average fund managers seems to overweight stocks that underperform in the subsequent quarter, and underweight stocks that show superior performance.

While the graphical results strongly suggest a negative relationship between deviation tendencies of fund managers and performance in an univariate setting, we have not controlled for various other factors that may diminish this relationship. In the next few sections, we conduct a more rigorous empirical investigation using multivariate settings and regression analysis.

3.4.2. Multivariate regressions: Determinants of Deviation from peer groups

Table 3.4. reports results of estimating regression models that explain the overall deviation tendencies exhibited by mutual fund managers. Various fund/family characteristics and portfolio characteristics are included as explanatory variables. Robust standard errors are used to account for the possibility that the standard errors are correlated across observations. Throughout the paper, three alternative methods are considered in the measure of deviating tendency used. The methods differ in the definition of peer groups for a fund manager, with the first being the most general since it

Table 3.4.
Multivariate Regressions (Funds' Deviations from Peer Groups)

The dependent variable in the clustered OLS regressions is the absolute value of average deviation in portfolio weight allocations by a fund manager from their peer groups in a portfolio quarter. The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. A fund's deviation is measured as the average *dev_perctna* across all stocks in a fund portfolio in the quarter. *Turnover* is the turnover ratio, *Log(Age)* is the natural logarithm of fund age, and *Log(TNA)* is the natural logarithm of total net assets. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past fund performance* is the cumulative objective-adjusted return for the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* is a measure of the strength of information networks that a fund manager has with other fund managers, and the details of the variable constructions are given in Appendix A. *Value-weighted Size (B/M, Momentum) Quintile* are the value-weighted average DGTW size (book-to-market, momentum) quintiles in a portfolio, respectively. *Log (# funds in family)* is the natural logarithm of the total number of fund's under the investment management company of the fund. p-values are based on robust standard errors. ***, **, * report significance at the 1%, 5% and 10% levels. *Past fund performance*^{2}

	Peer Groups								
	All Funds (1)			Objective (2)			Objective, Size (3)		
	Coeff.		p-val	Coeff.		p-val	Coeff.		p-val
Intercept	2.360	***	0.00	2.294	***	0.00	2.236	***	0.00
Fund characteristics:									
Log (TNA)	-0.033	***	0.00	-0.034	***	0.00	-0.038	***	0.00
Log (Age)	-0.004		0.69	0.006		0.53	0.007		0.47
Turnover	-0.019	***	0.00	-0.017	***	0.00	-0.013	***	0.00
Single manager dummy	0.090	***	0.00	0.103	***	0.00	0.095	***	0.00
Past fund performance	-0.841	**	0.05	-0.790	**	0.05	-0.752	**	0.05
(Past fund performance)^2	11.592	***	0.00	11.557	***	0.00	11.463	***	0.00
Fund-Fund Networks	-0.110	***	0.00	-0.121	***	0.00	-0.128	***	0.00
Portfolio characteristics:									
Value-weighted Size Quintile	0.122	***	0.00	0.129	***	0.00	0.139	***	0.00
Value-weighted B/M Quintile	0.014		0.57	0.028		0.26	0.034		0.17
Value-weighted Mom Quintile	-0.091	***	0.00	-0.086	***	0.00	-0.079	***	0.01
Avg. Fund-Company Networks	0.334	***	0.00	0.326	***	0.00	0.310	***	0.00
Family characteristics:									
Log (# funds in family)	-0.126	***	0.00	-0.123	***	0.00	-0.117	***	0.00
Time fixed-effects			YES			YES			YES
Objective fixed-effects			YES			YES			YES
N			12260			12260			12260
Adjusted R-sq.			0.14			0.14			0.14

considers the whole sample of actively managed U.S. funds investing in domestic equity. The second peer group considered is all funds in a particular objective, and seems a natural definition since funds are for most purposes compared to other funds in their objective. Lastly, we consider forming a peer group by categorizing funds into objectives and similar size quartiles. All the regression models presented control for time and objective fixed effects.

In model (1), we report the regression estimates when all sample funds are considered as the peer group for a fund manager. Several fund characteristics are significant in explaining the deviating tendency of a fund manager. The deviating tendency of a fund manager decreases with the fund size, family size, fund turnover, and strength of networks with other mutual fund managers.[14] Since our measure of networks is associated with geographical location, our results suggest that managers located in areas with a higher concentration of fund managers are less likely to deviate. In our regressions, we include a measure of past performance and the square of past performance as independent variables. This accounts for a possible non-linear relationship between a manager's deviating tendency and past fund performance. Based on the regression results in Table 3.4., we find a U-shaped relationship between deviating tendency and past performance, supporting the idea that the best and worst performers deviate more than the intermediate performers. These findings are consistent with Zweibel (1995) who suggests that very good and very bad managers have incentives to deviate from the benchmark, while others have incentives to herd. The likelihood of

[14] Since there are some simultaneity problems with using a dependant variable based on fund size (TNA) and fund TNA as an independent variable, we also run regressions where fund TNA is excluded from the models. However, the results remain similar and we do not report these specifications.

deviating from peers also increases if the fund is managed by a single manager as compared to when the fund is team-managed. The deviating tendency is higher for fund managers investing in larger stocks. While the portfolio characteristic in the book-to-market ratio dimension is not significant, the deviating tendency is lower when the manager invests in a portfolio with higher momentum stocks.

Models (2) and (3) in Table 3.4. report regression results for alternative definitions of peer groups using objective, and objective combined with size, respectively. The results are consistent with model (1). All variables that are significant in model (1) retain their significance in models (2) and (3) with similar magnitudes of coefficients. The results suggest that in this case the choice of definition of peer groups for a fund manager does not have a critical impact on the measured relationship between the deviating tendency and the explanatory variables considered.

3.4.3. Relationship between performance and deviation

In this section, we study the relationship between the deviating tendencies, extent of deviation and future performance of the fund and portfolio holdings. The empirical methodology conducts comparisons of fund-level performance in an univariate setting between funds displaying highest and lowest deviating tendencies, and also uncovers the performance-deviation relationship using multivariate regressions. The second part of the empirical investigation analyses within-portfolio differences in performance from holdings where a manager is more bullish than their peers, versus in holdings where they are more bearish than their peers.

A. Fund returns

In Table 3.5., we report multivariate regression results explaining fund performance. The regression coefficients are for various model specifications, include time and objective fixed effects, and the p-values reported are based on robust standard errors.

In Panel (1) of Table 3.5., the peer group considered is the universe of equity funds in our sample. Model (i) studies the relationship between a fund's deviating tendency in period *t*, *Fund Deviation (t),* and performance in the same period *t*. The deviating tendency has a significantly negative impact on performance as reflected in an estimated coefficient of -0.002 on *Fund Deviation (t)* with significance at the 1% level. Other control variables that explain some of the variation in performance are fund size, measured as the natural logarithm of total net assets (*Log (TNA))*, fund's recent performance in the previous six months*, Past fund performance,* and overall portfolio characteristics of the fund. In model (ii), we include the deviating tendency measured in the previous period, *Fund Deviation (t-1)*, to predict performance in the current period *t*. The deviation in the previous period also has a significantly negative impact on fund performance, but the magnitude of the effect is smaller than for contemporaneous deviation-performance relationships. We do not include *Fund Deviation (t)* and *Fund Deviation (t-1)* together because of high degrees of correlation between deviation measures across time. In unreported tests, we find significant correlations between the time series of deviating tendency measures, suggesting substantial persistence in deviating tendencies.

In Panel (2) and (3) of Table 3.5., the regressions are repeated using the alternative measures of peer groups, matched by objective and objective-size respectively. Results

Table 3.5.
Relationship between Fund Performance and Funds' Deviation from Peer Groups

The dependent variable in the regressions is the quarterly objective-adjusted return (*OAR*), the measure of fund performance. The quarterly *OAR* is computed as:
OAR = (1+Ret_mth1)(1+Ret_mth2)*(1+Ret_mth3) – (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3).* The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. A fund's deviation at time *t (t-1)*, *Fund Deviation (t) (Fund Deviation (t-1)),* is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter *t (t-1). Turnover* is the turnover ratio, *Log(Age)* is the natural logarithm of fund age, and *Log(TNA)* is the natural logarithm of total net assets. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past fund performance* is the cumulative objective-adjusted return for the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* is a measure of the strength of information networks that a fund manager has with other fund managers, and the details of the variable constructions are given in Appendix A. *Value-weighted Size (B/M, Momentum) Quintile* are the value-weighted average DGTW size (book-to-market, momentum) quintiles in a portfolio, respectively. *Log (# funds in family)* is the natural logarithm of the total number of fund's under the investment management company of the fund. p-values are based on robust standard errors. ***, **, * report significance at the 1%, 5% and 10% levels.

	Peer Groups											
	All Funds (1)				Objective (2)				Objective, Size (3)			
	Model (i)		Model (ii)		Model (iii)		Model (iv)		Model (v)		Model (vi)	
	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val
Intercept	-0.009	0.27	-0.040 ***	0.00	-0.010	0.26	-0.040 ***	0.00	-0.010	0.26	-0.040 ***	0.00
Fund Deviation (t)	-0.002 ***	0.00			-0.002 ***	0.00			-0.002 ***	0.00		
Fund Deviation (t-1)			-0.001 *	0.06			-0.001 *	0.07			-0.001 *	0.06
Fund characteristics:												
Log (TNA)	0.001 **	0.05	0.001 *	0.07	0.001 **	0.05	0.001 *	0.08	0.001 *	0.05	0.001 *	0.08
Log (Age)	-0.001 *	0.10	-0.001	0.28	-0.001	0.11	-0.001	0.29	-0.001	0.11	-0.001	0.29
Turnover	0.000	0.71	0.000	0.49	0.000	0.72	0.000	0.49	0.000	0.74	0.000	0.50
Single manager dummy	-0.002	0.21	-0.002	0.23	-0.002	0.21	-0.002	0.23	-0.002	0.20	-0.002	0.22
Past fund performance	0.136 ***	0.00	0.111 ***	0.00	0.136 ***	0.00	0.111 ***	0.00	0.136 ***	0.00	0.111 ***	0.00
Fund-Fund Networks	-0.001	0.21	-0.001	0.56	-0.001	0.20	-0.001	0.55	-0.001	0.20	-0.001	0.55
Portfolio characteristics:												
Value-weighted Size Quintile	-0.003 ***	0.00	-0.001	0.27	-0.003 ***	0.00	-0.001	0.28	-0.003 ***	0.00	-0.001	0.29
Value-weighted B/M Quintile	0.007 ***	0.00	0.010 ***	0.00	0.007 ***	0.00	0.010 ***	0.00	0.007 ***	0.00	0.010 ***	0.00
Value-weighted Mom Quintile	0.004 ***	0.00	0.005 ***	0.00	0.004 ***	0.00	0.005 ***	0.00	0.004 ***	0.00	0.005 ***	0.00
Avg. Fund-Company Networks	0.001	0.82	-0.001	0.79	0.001	0.82	-0.001	0.79	0.001	0.83	-0.001	0.78
Industry_Herfindahl	0.012 **	0.03	0.011 **	0.02	0.010 *	0.07	0.012 *	0.09	0.011 **	0.05	0.012 *	0.10
Family characteristics:												
Log (# funds in family)	0.000	0.81	0.000	0.71	0.000	0.81	0.000	0.69	0.000	0.84	0.000	0.69
Time fixed-effects		YES		YES		YES		YES		YES		YES
Objective fixed-effects		YES		YES		YES		YES		YES		YES
N		12255		9921		12225		9921		12225		9921
Adjusted R-sq. (%)		2.68		2.39		3.25		2.39		3.26		2.39

are consistent with the earlier analyses using all funds in the sample as a peer group. Both the magnitudes and significance of explanatory variables are similar across the peer group classifications. There is a significant relationship between the extent of deviating tendency displayed by a fund manager in a portfolio quarter and fund performance. The deviating tendency in a portfolio quarter is also significant in explaining the fund's performance in the next quarter. Various fund/family characteristics and portfolio characteristics are used as control variables in all the model specifications.

Table 3.6. examines the relationship between fund performance and deviating tendencies across different fund size and past performance categories. While Table 3.5. shows that there is a significant relationship between performance and deviations, after controlling for factors like fund size and past performance, the strength of the relationship may be differ depending on the category of funds. In Table 3.6. we compose portfolios of high versus low deviation funds, within fund size and past performance categories, and study the return differences between these hypothetical portfolios.

In Panel A of Table 3.6., we sort the funds into size quartiles based on TNA. It is possible that the information contained in the deviating tendencies of portfolio managers is different across fund size categories. Depending on the fund's size characteristics, which are closely related with the resources a fund manager has at her disposal, the causes of deviations from peers may be strikingly different. A fund manager of a large fund may have better research resources related to small funds, wherein they deviate when they have private information about investment opportunities. Additionally, these fund managers are also likely to be the ones with larger reputation stakes resulting in more incentives to herd. So, when the managers of large funds deviate, it might be based

Table 3.6.
Fund Performance and Deviations from Peer Groups

Panel A reports the annualized objective-adjusted return (*OAR*) for fund that have high versus low deviation tendency from their peers across different fund size categories. The quarterly *OAR* is computed as:
OAR = (1+Ret_mth1)(1+Ret_mth2)*(1+Ret_mth3) – (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3).* The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. A fund's deviation at time *t*, *Fund Deviation (t),* is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter *t.* High (Low) Deviation Funds are the funds in the highest (lowest) quintile ranked by *Fund Deviation (t).* Panel B reports the annualized objective-adjusted return (*OAR*) for funds that have high versus low deviation tendency from their peers across different fund past performance categories. Returns are expressed in annual percentage rates and averaged across quarters. p-values are based on two-sample t test of the hypothesis that the returns have equal means across the high and low deviation fund samples.

	Panel A: Objective-adjusted Return (by Peer Group)					
	All Funds (1)		Objective (2)		Objective, Size (3)	
Fund Size Quartiles	OAR	p-val	OAR	p-val	OAR	p-val
Quartile 1 (Small): Median TNA = 9.73						
High Deviation Fund	-0.038		-0.042		-0.039	
Low Deviation Fund	0.008		0.009		0.034	
High – Low	-0.046	0.20	-0.050	0.20	-0.073	0.17
Quartile 2: Median TNA = 34.20						
High Deviation Fund	-0.010		-0.010		-0.015	
Low Deviation Fund	0.012		-0.023		0.017	
High – Low	-0.021	0.01	0.013	0.68	-0.032	0.00
Quartile 3: Median TNA = 111.40						
High Deviation Fund	-0.008		-0.008		-0.007	
Low Deviation Fund	0.014		0.012		0.013	
High – Low	-0.023	0.00	-0.019	0.00	-0.020	0.00
Quartile 4 (Large): Median TNA = 739.80						
High Deviation Fund	-0.002		-0.001		0.000	
Low Deviation Fund	0.016		0.016		0.011	
High – Low	-0.018	0.00	-0.017	0.00	-0.011	0.01

Table 3.6. (contd.)

	Panel B: Objective-adjusted Return (by Peer Group)					
	All Funds (1)		Objective (2)		Objective, Size (3)	
Fund Previous Performance Quartiles	OAR	p-val	OAR	p-val	OAR	p-val
Quartile 1 (Worst): Median OAR = -4.00%						
High Deviation Fund	-0.046		-0.044		-0.044	
Low Deviation Fund	-0.030		-0.028		-0.029	
High – Low	-0.016	0.06	-0.016	0.05	-0.016	0.06
Quartile 2: Median OAR = -0.95%						
High Deviation Fund	-0.017		-0.016		-0.014	
Low Deviation Fund	0.001		0.001		-0.001	
High – Low	-0.017	0.00	-0.017	0.00	-0.013	0.02
Quartile 3: Median OAR = 1.11%						
High Deviation Fund	0.009		0.010		0.008	
Low Deviation Fund	0.019		0.020		0.017	
High – Low	-0.010	0.08	-0.011	0.14	-0.010	0.07
Quartile 4 (Best): Median OAR = 4.41%						
High Deviation Fund	0.031		0.031		0.030	
Low Deviation Fund	0.044		0.045		0.044	
High – Low	-0.013	0.04	-0.014	0.68	-0.013	0.04

on accurate private information. On the other hand, it is possible that a fund manager of a small fund has relatively poorer resources, and deviates for reasons that do not have positive implications for future performance. Under these circumstances, the relative performance of fund managers who deviate versus those who have portfolio allocations similar to their peers may depend on the fund's resources and reputation.

From the results presented in Panel A of Table 3.6., we conclude that the relationship between fund performance and deviating tendency is similar across all fund size categories and definitions of peer groups. For the peer group definition including all funds, the funds in the highest quintile of deviating tendency underperform the funds in the lowest quintile in all size categories. However, for the sub-sample of small funds, the underperformance of high deviation funds relative to low deviation funds is not significant. For all other fund size categories, the difference in performance is significant at the 1% level. For the sub-sample of large funds, high deviation funds' underperformance relative to their objectives is 1.8% more than low deviation funds. For funds in the second and third size quartile, the underperformance is 2.1% and 2.3% expressed as annualized OAR. For alternative peer group definitions based on objective and objective-size matches, the results are consistent with the findings using all funds as the peer group. When all same-objective funds are considered the peer group, the underperformance of high deviation funds relative to low deviation funds are significant for the two largest size quartiles, but not significant for the smaller size quartiles. For peer group definition using an objective-size matching, the underperformance is significant for the majority of size quartiles, except for the smallest funds in the sample.

In Panel B of Table 3.6., we compare performance of funds across different categories based on recent performance of the funds. A fund's past performance may have an important impact on the motivation to deviate away from peers' portfolio strategies. Brown et al. (1996) posit that fund managers with recent poor performance are more likely to pursue riskier strategies in order to compensate for previous low returns. If the deviating tendency is a way of pursuing riskier strategies, recent poor performers may have more incentives to deviate from their peers.

From Panel B of Table 3.6., the findings suggest that funds with high deviating tendencies underperform funds with low deviating tendencies across all categories of past fund performance. For the first peer group definition, when the sub-sample of worst performers in the previous six months are considered, the high deviation funds underperform by an annualized return of 1.6% relative to low deviation funds, and the difference is significant at the 10% level. For the best performers, comprising the fourth quartile, the high deviation funds underperform the low deviation funds by 1.3%. Interesting, while for the sub-sample of poor performers, both high and low deviation funds underperform their objectives, for the best performers, both outperform their objectives. In the latter case, the high deviation funds outperform their objectives to a lesser extent than the low deviation funds. These results are robust when alternative definitions of peer groups, based on objective and size, are used.

B. Holdings' returns

In the previous sections, we have focused on fund performance in order to study the potential information contained in the deviating tendencies of mutual fund managers. Using a portfolio decomposition approach, we conduct further analyses aiming to understand the implications of a fund manager's decision to deviate away from their peers in portfolio allocation strategies. In this approach, we distinguish between holdings where a fund manager has chosen to deviate from their peers by allocating a higher portfolio weight than their peers, i.e. overweight the asset, and holdings where they underweight relative to their peers. A manager with valuable private information should deviate in the positive direction (i.e., overweight) in assets that are more likely to generate positive risk-adjusted returns in the future, and in the negative direction (i.e., underweight) for assets that are less likely to have good future performance. So, there may be information inferred by comparing the performance of holdings that are overweighted versus holdings that are underweighted by a fund manager. Among the advantages of using this approach is that by examining within-portfolio differences in performance, we can avoid manager-, fund-, family- and time-specific heterogeneities which are the main challenge when comparing performance across funds.

Table 3.7. presents the value-weighted risk-adjusted returns for ten subportfolios formed based on the magnitude of deviation of the holdings' allocated weight and mean weight allocated by peers in the same security. Each fund portfolio is decomposed in deciles based on portfolio weights' deviation and ranked into ten decile portfolios. The reported values in Table 3.7. are sample averages over ten quarters. In addition to equally-weighted averages across funds in the sample, we also compute the portfolios returns for each decile portfolio using value-weighting by fund TNA. TNA-weighted averages are reported in order to eliminate the possibility that the results are primarily driven by small funds and do not hold for larger funds in the sample. It also indicates whether the relationship between returns and deviation in portfolio allocations are important when we look at aggregate dollar returns from the investment management industry. For phenomena that only holds for small funds, the implications in terms of dollar returns may not be substantial.

In Table 3.7., the first definition of peer group used is all funds in the sample. From the results presented in panel (1), the value-weighted returns decrease almost monotonically for the decile portfolios as the magnitude of deviation in portfolio weight increases. Fund managers seem to overweight stocks that underperform and underweight stocks that outperform in the portfolio quarter. The decile portfolio of holdings which the manager

Table 3.7.
Holding-based Returns and Deviations from Peer Groups (Portfolio Decomposition)

The table reports value-weighted risk-adjusted returns of sub-portfolios formed by decomposing a fund's portfolio into deciles based on deviation of portfolio weights from the mean portfolio weight allocated by the fund manager's peer group in the same stock. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. For each fund portfolio, *dev_perctna* is ranked into deciles, with Decile 1 (10) being holdings' which are most underweighted (overweighted) relative to peer funds. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. Risk-adjusted portfolio returns are computed in each quarter for each decile as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns are expressed in annual percentage rates are reported both as equally-weighted as well as value-weighted by fund total net assets (TNA) and averaged across quarters. p-values are based on one-sample t test of the hypothesis that the portfolio risk-adjusted return has a mean of zero.

	Abnormal Returns: Peer Group											
	All Funds				Objective				Objective, Size			
	Not TNA-weighted (1)		TNA-weighted (2)		Not TNA-weighted (3)		TNA-weighted (4)		Not TNA-weighted (5)		TNA-weighted (6)	
	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val
(Lowest weight relative to peers)												
Decile 1	0.018	0.00	0.011	0.31	0.019	0.00	0.011	0.03	0.016	0.00	0.011	0.04
Decile 2	0.017	0.00	0.028	0.02	0.017	0.00	0.020	0.00	0.011	0.00	0.016	0.01
Decile 3	0.007	0.00	0.008	0.59	0.008	0.00	0.016	0.00	0.007	0.00	0.019	0.00
Decile 4	0.007	0.00	0.020	0.08	0.006	0.00	0.013	0.02	0.007	0.00	0.009	0.15
Decile 5	0.001	0.54	0.010	0.43	0.002	0.30	0.008	0.18	-0.001	0.79	0.005	0.40
Decile 6	-0.005	0.01	0.005	0.84	-0.005	0.01	0.004	0.43	-0.007	0.00	0.000	0.98
Decile 7	-0.007	0.00	0.003	0.77	-0.007	0.00	-0.004	0.55	-0.005	0.02	0.000	0.99
Decile 8	-0.010	0.00	0.010	0.50	-0.011	0.00	0.000	0.98	-0.011	0.00	-0.003	0.69
Decile 9	-0.015	0.00	-0.018	0.10	-0.015	0.00	-0.022	0.00	-0.015	0.00	-0.008	0.19
Decile 10	-0.028	0.00	-0.033	0.02	-0.029	0.00	-0.035	0.00	-0.028	0.00	-0.037	0.00
(Highest weight relative to peers)												
2nd Half – 1st Half	-0.023	0.00	-0.022	0.00	-0.024	0.00	-0.025	0.00	-0.021	0.00	-0.022	0.00
5th Quintile – 1st Quintile	-0.039	0.00	-0.045	0.00	-0.040	0.00	-0.044	0.00	-0.035	0.00	-0.036	0.00
10th Decile – 1st Decile	-0.046	0.00	-0.043	0.00	-0.049	0.00	-0.047	0.00	-0.044	0.00	-0.049	0.00

overweight the most relative to peers, i.e. Decile 10, has an annualized return of -2.8% compared to the most underweighted stocks which have a return of 1.8%. The difference in performance between highest and lowest weighted stocks is -4.6%, and statistically significant at the 1% level. The underperformance of overweighted stocks holds for comparisons between the highest and lowest quintiles of deviation in portfolio weights allocated, with a return difference of -3.9%. The results also hold when the higher half according to portfolio weight deviations are compared to the lower half, in which case the difference in returns is -2.3%, and significant at the 1% level. In panel (2), the portfolio returns are reported as TNA-weighted measures. As with the equally-weighted returns, the portfolio of stocks with the highest relative weight underperforms the portfolio of stock with lowest relative weights by -4.3%. Overall, the results are similar whether we weight by fund size or not, indicating that the results are not driven by small funds.

The results are also robust to the three definitions of peer groups considered. In panels (4) and (5) of Table 3.7., we report annualized returns when deviations are calculated based on all funds in the same objective as a peer group. The portfolio annualized return of Decile 10 underperforms the returns of Decile 1 by -4.9% when values are not TNA-weighted, and by -4.7% when values are weighted by fund TNA. In panels (5) and (6), we use all funds in the same objective and same fund size quartile, ranked in each quarter, as the peer group. The portfolio annualized return of Decile 10 underperforms the returns of Decile 1 by -4.4% when values are not TNA-weighted, and by -4.9% when values are weighted by fund TNA. The differences are significant at the 1% level.

In summary, fund managers on average seem to allocate higher weights to stocks that underperform and lower weights to stocks that outperform in the portfolio quarter. So, the evidence does not support the notion that fund managers deviate from their peers in their portfolio weight allocations based on private information. These findings based on holdings' returns are consistent with the conclusions from analyses of fund returns in previous sections. Whether we consider aggregate fund performance or holdings' returns, the decision to deviate from peers does not reflect private information. The fund manager's deviation relative to her peers is related to future underperformance both at the fund and holdings' level.

As further robustness checks, we examine holdings' return and their relationship with deviation in portfolio allocations across different categories of funds, based on fund size and recent performance. In Panel A of Table 3.8., the returns are reported for the portfolios of highest and lowest weights relative to peer groups, across fund size quartiles. The underperformance of the portfolio with highest relative weights compared to the portfolio with lowest relative weights is significant and similar across fund size quartiles. For the smallest (largest) funds, the stocks that were overweighted underperform stocks that were underweighted by -4.3% (-4.2%) annualized return. The findings hold when other definitions of peer groups are considered. So, the relationship between deviation and holdings' returns hold across different fund sizes.

In Panel B of Table 3.8., we present results across different fund performance quartiles, based on fund returns in the six months prior to the portfolio quarter. The results are consistent with overall findings that the portfolio of stocks with highest weight allocations relative to peers significantly underperform stocks assigned the lowest portfolio weight allocations. The portfolio returns of the highest relative weights, i.e. Decile 10, underperform the portfolio of lowest relative weights, i.e. Decile 1, across all

Table 3.8.
Holdings' Performance and Deviations from Peer Groups

Fund Previous Performance Quartiles are formed based on the cumulative objective-adjusted fund return for the six months prior to the beginning of a portfolio quarter. Panel A reports the annualized objective-adjusted return (*OAR*) for fund that have high versus low deviation tendency from their peers. The quarterly *OAR* is computed as:
OAR = (1+Ret_mth1)(1+Ret_mth2)*(1+Ret_mth3) – (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3).*
The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock).* Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. A fund's deviation at time *t*, *Fund Deviation (t),* is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter *t.* High (Low) Deviation Funds are the funds in the highest (lowest) quintile ranked by *Fund Deviation (t).* In Panel B, for each fund portfolio, *dev_perctna* is ranked into deciles, with Decile 1 (10) being holdings' which are most underweighted (overweighted) relative to peer funds. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. Risk-adjusted portfolio returns are computed in each quarter for each decile as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns are expressed in annual percentage rates are reported both as equally-weighted as well as value-weighted by fund total net assets (TNA) and averaged across quarters. p-values are based on one-sample t test of the hypothesis that the portfolio risk-adjusted return has a mean of zero.

	Panel A: Holdings' Return (by Peer Group)					
	All Funds (1)		Objective (2)		Objective, Size (3)	
Fund Size Quartiles	Risk-ad. Ret	p-val	Risk-ad. Ret	p-val	Risk-ad. Ret	p-val
Quartile 1 (Small): Median TNA = 9.73						
Highest relative weight	-0.028		-0.030		-0.029	
Lowest relative weight	0.015		0.013		0.012	
High – Low	-0.043	0.00	-0.043	0.00	-0.041	0.00
Quartile 2: Median TNA = 34.20						
Highest relative weight	-0.027		-0.026		-0.027	
Lowest relative weight	0.017		0.017		0.014	
High – Low	-0.044	0.00	-0.044	0.00	-0.042	0.00
Quartile 3: Median TNA = 111.40						
Highest relative weight	-0.031		-0.031		-0.028	
Lowest relative weight	0.023		0.030		0.021	
High – Low	-0.053	0.00	-0.061	0.00	-0.049	0.00
Quartile 4 (Large): Median TNA = 739.80						
Highest relative weight	-0.026		-0.030		-0.027	
Lowest relative weight	0.016		0.018		0.018	
High – Low	-0.042	0.00	-0.048	0.00	-0.046	0.00

Table 3.8. (contd.)

	Panel B: Holdings' Return (by Peer Group)					
	All Funds (1)		Objective (2)		Objective, Size (3)	
Fund Previous Performance Quartiles	Risk-ad. Ret	p-val	Risk-ad.	p-val	Risk-ad. Ret	p-val
Quartile 1 (Worst): Median OAR = -4.00%						
Highest relative weight	-0.032		-0.030		-0.040	
Lowest relative weight	0.014		0.010		0.012	
High – Low	-0.046	0.00	-0.040	0.00	-0.052	0.00
Quartile 2: Median OAR = -0.95%						
Highest relative weight	-0.027		-0.031		-0.027	
Lowest relative weight	0.018		0.017		0.017	
High – Low	-0.044	0.00	-0.048	0.00	-0.044	0.00
Quartile 3: Median OAR = 1.11%						
Highest relative weight	-0.037		-0.032		-0.036	
Lowest relative weight	0.019		0.010		0.021	
High – Low	-0.056	0.00	-0.042	0.00	-0.057	0.00
Quartile 4 (Best): Median OAR = 4.41%						
Highest relative weight	-0.021		-0.038		-0.027	
Lowest relative weight	0.021		0.018		0.016	
High – Low	-0.041	0.00	-0.056	0.00	-0.043	0.00

fund performance quartiles. The underperformance is -4.6% and -4.1% for the worst and best performing funds, respectively. Results are also robust for alternative definition of peer groups categorized based on fund objective and size, and are presented in panels (2) and (3). The evidence suggests that the results are not driven by poorly performing funds. Even funds that have performed well in the past seem unable to pick the right stocks to overweight and underweight.

C. Robustness Checks

The previous sections have documented the relationship between the deviating tendencies of mutual fund managers away from the portfolio allocation strategies of their peers, and the ability to generate superior performance. However, there is no conclusive definition of what constitutes a peer group for fund managers. In this section, we examine the robustness of the findings to alternative definitions of peer groups based on portfolio characteristics and fund objective definitions other than ICDI objective categories. We have used ICDI objective definitions in all previous analyses.

Table 3.9. presents clustered multivariate OLS regressions explaining the funds' deviating tendency when the deviations are measured relative to peer groups based on the portfolio characteristics of the funds. In order to develop peer group categories based on a fund's portfolio characteristics, we employ the DGTW stock characteristics based on size, book-to-market (B/M) ratios and momentum (MOM). For each fund portfolio in each quarter, we compute a value-weighted quintile measure for each of the DGTW dimensions for the fund portfolio. The value-weighted quintiles of fund portfolios are calculated as

$$(Fund\_DGTW\_sizeQ)_t = \sum_{i=1}^{n_t} w_i (DGTW\_sizeQ)_i \tag{7}$$

$$(Fund\_DGTW\_bmQ)_t = \sum_{i=1}^{n_t} w_i (DGTW\_bmQ)_i \tag{8}$$

$$(Fund\_DGTW\_momQ)_t = \sum_{i=1}^{n_t} w_i (DGTW\_momQ)_i \tag{9}$$

Here, $(DGTW\_sizeQ)_t$, $(DGTW\_bmQ)_t$, $(DGTW\_momQ)_t$ are the DGTW size, B/M, momentum quintile assignments, respectively, for stock *i* in the fund portfolio in quarter *t*; w_i is the portfolio weight invested in stock *i* in quarter *t*.

Next, each fund is assigned into style categories based on the three dimensions. In each quarter, each fund is assigned a quintile based on sorting the measures of $(Fund\_DGTW\_sizeQ)_t$, where each quintile comprises funds in one peer group.

Table 3.9.
Multivariate Regressions (Funds' Deviations from Style-based Peer Groups)

The dependent variable in the clustered OLS regressions is the absolute value of average deviation in portfolio weight allocations by a fund manager from their peer groups in a portfolio quarter. The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock).* Three alternative definitions of peer groups are used: (i) funds in the same quintile based on value-weighted DGTW Size quintiles held, (ii) funds in the same quintile based on value-weighted DGTW B/M quintiles held, and (iii) funds in the same quintile based on value-weighted DGTW Momentum quintiles held. A fund's deviation is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter. *Turnover* is the turnover ratio, *Log(Age)* is the natural logarithm of fund age, and *Log(TNA)* is the natural logarithm of total net assets. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past fund performance* is the cumulative objective-adjusted return for the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* is a measure of the strength of information networks that a fund manager has with other fund managers, and the details of the variable constructions are given in Appendix A. *Value-weighted Size (B/M, Momentum) Quintile* are the value-weighted average DGTW size (book-to-market, momentum) quintiles in a portfolio, respectively. *Log (# funds in family)* is the natural logarithm of the total number of fund's under the investment management company of the fund. p-values are based on robust standard errors. ***, **, * report significance at the 1%, 5% and 10% levels.

	Peer Groups					
	DGTW Size (1)		DGTW B/M (2)		DGTW Momentum (3)	
	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val
Intercept	2.070 ***	0.00	2.144 ***	0.00	2.209 ***	0.00
Fund characteristics:						
Log (TNA)	-0.032 ***	0.00	-0.029 ***	0.00	-0.028 ***	0.01
Log (Age)	0.002	0.95	0.000	0.99	-0.003	0.89
Turnover	-0.022 ***	0.00	-0.020 ***	0.01	-0.023 ***	0.00
Single manager dummy	0.086 ***	0.01	0.082 ***	0.01	0.074 **	0.02
Past fund performance	-0.771 **	0.05	-0.875 **	0.03	-0.889 **	0.02
(Past fund performance)^2	10.950 ***	0.01	9.956 ***	0.01	10.397 ***	0.00
Fund-Fund Networks	-0.100 ***	0.00	-0.103 ***	0.00	-0.106 ***	0.00
Portfolio characteristics:						
Value-weighted Size Quintile	0.128 ***	0.00	0.115 ***	0.00	0.110 ***	0.00
Value-weighted B/M Quintile	0.029	0.51	0.045	0.29	0.031	0.47
Value-weighted Mom Quintile	-0.062	0.15	-0.070 *	0.10	-0.086 **	0.03
Avg. Fund-Company Networks	0.361	0.15	0.382	0.12	0.362	0.13
Family characteristics:						
Log (# funds in family)	-0.119 ***	0.00	-0.118 ***	0.00	-0.113 ***	0.00
Time fixed-effects		YES		YES		YES
Objective fixed-effects		YES		YES		YES
N		12258		12258		12258
Adjusted R-sq.		0.15		0.14		0.14

Similarly, peer groups are also formed by sorting the other two style dimensions: $(\boldsymbol{Fund\_DGTW\_bmQ})_t$ and $(\boldsymbol{Fund\_DGTW\_momQ})_t$. In summary, the goal is to define a fund's peer group based on the characteristics of the stocks held in their portfolio. For instance, all funds in the highest quintile of $(\boldsymbol{Fund\_DGTW\_sizeQ})_t$ ($(\boldsymbol{Fund\_DGTW\_bmQ})_t$) in a portfolio quarter are the funds that invest in large-cap (value) stocks, and belong to the same peer group.

The results reported in Table 3.9. are similar to the findings in previous empirical analyses. Large, high turnover funds and funds belonging to larger fund families have a lower tendency to deviate from their peers. Also, funds located in areas where there are likely to be more interactions with other fund managers (i.e., stronger networks) have lesser tendency to deviate. The evidence on the existence of a U-shaped relationship between previous fund performance and deviating tendency also holds. So, the poorest and best performers show higher deviations from peers. The results are also similar across the three style dimensions of size, B/M and momentum characteristics of the portfolio of stocks.

Table 3.10. reports the multivariate regressions exploring the relationship between performance of the fund, using fund objective-adjuster returns, and the fund's deviations relative to peers. The results from the regression analyses are consistent with previous findings. Ceteris paribus, funds which show a higher deviation tendency have poorer performance. The relationship between contemporaneous deviations and performance is stronger than the predictive relationship, which is not significant in all model specifications. The control variables included are identical to previous analyses.

Table 3.10.
Relationship between Fund Performance and Funds' Deviation from Style-based Peer Groups

The dependent variable in the regressions is the quarterly objective-adjusted return (*OAR*), the measure of fund performance. The quarterly *OAR* is computed as:
OAR = (1+Ret_mth1)(1+Ret_mth2)*(1+Ret_mth3) – (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3).*
The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock).* Three alternative definitions of peer groups are used: (i) funds in the same quintile based on value-weighted DGTW Size quintiles held, (ii) funds in the same quintile based on value-weighted DGTW B/M quintiles held, and (iii) funds in the same quintile based on value-weighted DGTW Momentum quintiles held. A fund's deviation at time *t (t-1)*, *Fund Deviation (t) (Fund Deviation (t-1)),* is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter *t (t-1). Turnover* is the turnover ratio, *Log(Age)* is the natural logarithm of fund age, and *Log(TNA)* is the natural logarithm of total net assets. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past fund performance* is the cumulative objective-adjusted return for the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* is a measure of the strength of information networks that a fund manager has with other fund managers, and the details of the variable constructions are given in Appendix A. *Value-weighted Size (B/M, Momentum) Quintile* are the value-weighted average DGTW size (book-to-market, momentum) quintiles in a portfolio, respectively. *Log (# funds in family)* is the natural logarithm of the total number of fund's under the investment management company of the fund. p-values are based on robust standard errors. ***, **, * report significance at the 1%, 5% and 10% levels.

	Peer Groups											
	DGTW Size (1)				DGTW B/M (2)				DGTW Momentum (3)			
	Model (i)		Model (ii)		Model (iii)		Model (iv)		Model (v)		Model (vi)	
	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val
Intercept	-0.006	0.48	-0.045 ***	0.00	-0.012	0.26	-0.045 ***	0.00	-0.006	0.26	-0.040 ***	0.00
Fund Deviation (t)	-0.001 ***	0.01			-0.002 ***	0.01			-0.002 ***	0.01		
Fund Deviation (t-1)			-0.001	0.21			-0.001 *	0.10			-0.001	0.20
Fund characteristics:												
Log (TNA)	0.001 **	0.06	0.001 *	0.08	0.001 *	0.06	0.001 *	0.08	0.001 *	0.06	0.001 *	0.07
Log (Age)	-0.001	0.11	-0.001	0.28	-0.001	0.11	-0.001	0.28	-0.001 *	0.10	-0.001	0.27
Turnover	0.000	0.91	0.000	0.73	0.000	0.91	0.000	0.73	0.000	0.90	0.000	0.73
Single manager dummy	-0.001	0.25	-0.002	0.27	-0.001	0.25	-0.002	0.27	-0.001	0.25	-0.002	0.26
Past performance	0.141 ***	0.00	0.117 ***	0.00	0.141 ***	0.00	0.116 ***	0.00	0.141 ***	0.00	0.116 ***	0.00
Past fund performance)^2	-0.158	0.12	-0.213 *	0.06	-0.157	0.12	-0.211 *	0.06	-0.157	0.12	-0.213	0.06
Fund-Fund Networks	-0.001	0.14	-0.001	0.44	-0.001	0.13	-0.001	0.43	-0.001	0.13	-0.001	0.43
Portfolio characteristics:												
Value-weighted Size Quintile	-0.003 ***	0.00	-0.001	0.19	-0.003 ***	0.00	-0.001	0.19	-0.003 ***	0.00	-0.001	0.18
Value-weighted B/M Quintile	0.007 ***	0.00	0.010 ***	0.00	0.007 ***	0.00	0.010 ***	0.00	0.007 ***	0.00	0.010 ***	0.00
Value-weighted Mom Quintile	0.003 ***	0.00	0.005 ***	0.00	0.003 ***	0.00	0.005 ***	0.00	0.003 ***	0.00	0.005 ***	0.00
Avg. Fund-Company Networks	0.001	0.76	-0.001	0.80	0.001	0.73	-0.001	0.82	0.001	0.74	-0.001	0.80
Industry_Herfindahl	0.009 **	0.04	0.010 **	0.05	0.008 *	0.10	0.009 *	0.09	0.010 **	0.04	0.007 *	0.09
Family characteristics:												
Log (# funds in family)	0.000	0.72	0.000	0.77	0.000	0.67	0.000	0.82	0.000	0.69	0.000	0.77
Time fixed-effects		YES		YES		YES		YES		YES		YES
Objective fixed-effects		YES		YES		YES		YES		YES		YES
N		12253		9919		12253		9919		12253		9919
Adjusted R-sq. (%)		3.11		2.25		3.12		2.25		3.12		2.39

In Table 3.11., we report within-portfolio deviations from peers and risk-adjusted returns. In general, the value-weighted returns decrease across the decile portfolios (based on holdings' portfolio weight relative to peers) as the magnitude of deviation in portfolio weight increases. This is consistent with our previous finding that fund managers seem to overweight stocks that underperform and underweight stocks that outperform in the portfolio quarter. Overall, the results are similar whether we weight by fund TNA or not, indicating that the results are not driven by small funds.

Table 3.12. presents regressions explaining fund deviations using a different objective classification. In all previous analyses, we have followed other studies in using ICDI objective classifications. We conduct robustness checks where we use Standard & Poor's objective classifications (reported in CRSP MFDB) when we are defining peer groups involving objectives, and accounting for objective fixed-effects in regression analyses. Using alternative objective classifications does not change the overall findings using ICDI objective definitions. Again, large, high turnover funds, and funds belonging to larger fund families and stronger networks have a lower deviations from their peers. The singer manager funds and the extreme performers deviate more, confirming the previously documented U-shaped relationship.

In Table 3.13., we present multivariate regressions examining the relationship between performance and fund deviations, using S&P objective classifications. The negative relationship between fund deviations and performance persists, and the magnitudes of co-efficients are higher than when ICDI objectives are used as fund objective classifications. Overall results also hold across different peer group classifications.

Table 3.11.
Holding-based Returns and Deviations from Style-based Peer Groups (Portfolio Decomposition)

The table reports value-weighted risk-adjusted returns of sub-portfolios formed by decomposing a fund's portfolio into deciles based on deviation of portfolio weights from the mean portfolio weight allocated by the fund manager's peer group in the same stock. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. For each fund portfolio, *dev_perctna* is ranked into deciles, with Decile 1 (10) being holdings' which are most underweighted (overweighted) relative to peer funds. Three Three alternative definitions of peer groups are used: (i) funds in the same quintile based on value-weighted DGTW Size quintiles held, (ii) funds in the same quintile based on value-weighted DGTW B/M quintiles held, and (iii) funds in the same quintile based on value-weighted DGTW Momentum quintiles held. Risk-adjusted portfolio returns are computed in each quarter for each decile as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}),$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintle benchmark portfolio (following Daniel et al. (1997)). Returns are expressed in annual percentage rates are reported both as equally-weighted as well as value-weighted by fund total net assets (TNA) and averaged across quarters. p-values are based on one-sample t test of the hypothesis that the portfolio risk-adjusted return has a mean of zero.

	Abnormal Returns: Peer Group											
	DGTW Size				DGTW B/M				DGTW Momentum			
	Not TNA-weighted (1)		TNA-weighted (2)		Not TNA-weighted (3)		TNA-weighted (4)		Not TNA-weighted (5)		TNA-weighted (6)	
	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val	Risk-ad Ret.	p-val
(Lowest weight relative to peers)												
Decile 1	0.021	0.00	0.018	0.00	0.018	0.00	0.021	0.00	0.017	0.00	0.018	0.00
Decile 2	0.017	0.00	0.015	0.00	0.010	0.00	0.018	0.00	0.015	0.00	0.010	0.03
Decile 3	0.009	0.00	0.014	0.01	0.011	0.00	0.011	0.08	0.009	0.00	0.017	0.00
Decile 4	0.003	0.11	0.003	0.60	0.002	0.26	0.003	0.64	0.004	0.08	0.000	0.99
Decile 5	-0.006	0.01	0.008	0.16	-0.001	0.51	0.003	0.51	-0.001	0.65	0.002	0.69
Decile 6	-0.006	0.01	-0.002	0.77	-0.002	0.40	0.007	0.16	-0.003	0.20	0.005	0.37
Decile 7	-0.006	0.00	0.004	0.53	-0.007	0.00	-0.006	0.34	-0.009	0.00	0.003	0.62
Decile 8	-0.011	0.00	-0.009	0.19	-0.012	0.00	-0.003	0.62	-0.013	0.00	-0.004	0.49
Decile 9	-0.013	0.00	-0.013	0.04	-0.012	0.00	-0.012	0.03	-0.014	0.00	-0.018	0.00
Decile 10	-0.030	0.00	-0.037	0.00	-0.029	0.00	-0.032	0.00	-0.028	0.00	-0.032	0.00
(Highest weight relative to peers)												
2nd Half – 1st Half	-0.022	0.00	-0.023	0.02	-0.019	0.03	-0.026	0.00	-0.022	0.00	-0.024	0.04
5th Quintile – 1st Quintile	-0.041	0.00	-0.042	0.01	-0.038	0.00	-0.044	0.00	-0.036	0.01	-0.045	0.00
10th Decile – 1st Decile	-0.052	0.00	-0.050	0.00	-0.048	0.00	-0.057	0.00	-0.049	0.00	-0.053	0.00

Table 3.12.
Multivariate Regressions (Funds' Deviations from Peer Groups using S&P Objectives)

The dependent variable in the clustered OLS regressions is the absolute value of average deviation in portfolio weight allocations by a fund manager from their peer groups in a portfolio quarter. The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock).* Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. A fund's deviation is measured as the average *dev_perctna* across all stocks in a fund portfolio in the quarter. *Turnover* is the turnover ratio, *Log(Age)* is the natural logarithm of fund age, and *Log(TNA)* is the natural logarithm of total net assets. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past fund performance* is the cumulative objective-adjusted return for the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* is a measure of the strength of information networks that a fund manager has with other fund managers, and the details of the variable constructions are given in Appendix A. *Value-weighted Size (B/M, Momentum) Quintile* are the value-weighted average DGTW size (book-to-market, momentum) quintiles in a portfolio, respectively. *Log (# funds in family)* is the natural logarithm of the total number of fund's under the investment management company of the fund. p-values are based on robust standard errors. ***, **, * report significance at the 1%, 5% and 10% levels. S&P objective codes in sample are: AGG, FLX, GMC, GRI, GRO, ING, and SCG.

	Peer Groups					
	All Funds		Objective		Objective, Size	
	(1)		(2)		(3)	
	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val
Intercept	2.377 ***	0.00	2.278 ***	0.00	2.209 ***	0.00
Fund characteristics:						
Log (TNA)	-0.012 *	0.06	-0.013 ***	0.00	-0.017 ***	0.01
Log (Age)	-0.005	0.84	0.005	0.85	0.007	0.78
Turnover	-0.027 **	0.05	-0.025 ***	0.00	-0.022 ***	0.01
Single manager dummy	0.082 ***	0.02	0.083 ***	0.01	0.076 **	0.02
Past fund performance	-0.579	0.13	-0.534	0.15	-0.507	0.15
(Past fund performance)^2	8.867 **	0.02	8.632 **	0.02	8.538 ***	0.01
Fund-Fund Networks	-0.121 **	0.03	-0.120 **	0.03	-0.134 ***	0.01
Portfolio characteristics:						
Value-weighted Size Quintile	0.047	0.38	0.044	0.40	0.061	0.23
Value-weighted B/M Quintile	0.031	0.48	0.043	0.32	0.049	0.26
Value-weighted Mom Quintile	-0.080 *	0.08	-0.077 *	0.08	-0.071 *	0.10
Avg. Fund-Company Networks	0.278	0.30	0.246	0.34	0.237	0.35
Family characteristics:						
Log (# funds in family)	-0.114 ***	0.00	-0.111 ***	0.00	-0.105 ***	0.00
Time fixed-effects		YES		YES		YES
Objective fixed-effects		YES		YES		YES
N		12258		12258		12258
Adjusted R-sq.		0.16		0.17		0.16

Table 3.13.
Relationship between Fund Performance and Funds' Deviation from Peer Groups (using S&P Objectives)

The dependent variable in the regressions is the quarterly objective-adjusted return (*OAR*), the measure of fund performance. The quarterly *OAR* is computed as: *OAR = (1+Ret_mth1)*(1+Ret_mth2)*(1+Ret_mth3) – (1+ObjR_mth1)*(1+ObjR_mth2)*(1+ObjR_mth3).* The sample includes actively managed equity mutual funds and spans ten quarters during 2003 to 2005. For each stock holding in a fund's portfolio in a given quarter, the deviation from peer group is computed as: *dev_perctna = (percent_tna – mean percent_tna of all other funds in the peer group holding the same stock)*. Three alternative definitions of peer groups are used: (i) all funds in the sample, (ii) all same objective funds, and (iii) all same objective and same size quartile funds. A fund's deviation at time *t (t-1)*, *Fund Deviation (t) (Fund Deviation (t-1)),* is measured as the average |*dev_perctna*| across all stocks in a fund portfolio in the quarter *t (t-1)*. *Turnover* is the turnover ratio, *Log(Age)* is the natural logarithm of fund age, and *Log(TNA)* is the natural logarithm of total net assets. *Single Manager dummy* is a dummy variable assuming a value of 1 if the fund managed by one manager and 0 otherwise. *Past fund performance* is the cumulative objective-adjusted return for the six months prior to the beginning of a portfolio quarter. *Fund-Fund Networks* is a measure of the strength of information networks that a fund manager has with other fund managers, and the details of the variable constructions are given in Appendix A. *Value-weighted Size (B/M, Momentum) Quintile* are the value-weighted average DGTW size (book-to-market, momentum) quintiles in a portfolio, respectively. *Log (# funds in family)* is the natural logarithm of the total number of fund's under the investment management company of the fund. p-values are based on robust standard errors. ***, **, * report significance at the 1%, 5% and 10% levels. S&P objective codes in sample are: AGG, FLX, GMC, GRI, GRO, ING, and SCG.

	Peer Groups											
	All Funds (1)				Objective (2)				Objective, Size (3)			
	Model (i)		Model (ii)		Model (iii)		Model (iv)		Model (v)		Model (vi)	
	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val	Coeff.	p-val
Intercept	-0.043	0.27	-0.040 ***	0.00	-0.020	0.26	-0.040 ***	0.00	-0.010	0.45	-0.053 ***	0.00
Fund Deviation (t)	-0.023 ***	0.01			-0.025 **	0.03			-0.019 **	0.04		
Fund Deviation (t-1)			-0.018 *	0.06			-0.019	0.20			-0.020 *	0.06
Fund characteristics:												
Log (TNA)	0.005 *	0.07	0.004 *	0.09	0.003 ***	0.01	0.001 *	0.08	0.002 *	0.07	0.004 *	0.09
Log (Age)	-0.001	0.11	-0.001	0.29	-0.001	0.12	-0.001	0.54	-0.001	0.13	-0.001	0.50
Turnover	0.000	0.86	0.000	0.90	0.000	0.85	0.000	0.87	0.000	0.93	0.000	0.85
Single manager dummy	-0.001	0.33	-0.001	0.35	-0.002	0.33	-0.002	0.40	-0.002	0.31	-0.002	0.43
Past performance	0.142 ***	0.00	0.115 ***	0.00	0.142 ***	0.00	0.111 **	0.03	0.121 **	0.02	0.111 *	0.10
(Past fund performance)^2	-0.135	0.19	-0.179	0.11	-0.136	0.18	-0.111	0.20	0.112 *	0.09	0.114	0.12
Fund-Fund Networks	-0.010	0.45	-0.015	0.93	-0.001	0.45	-0.001	0.88	-0.001	0.20	-0.001	0.93
Portfolio characteristics:												
Value-weighted Size Quintile	-0.002	0.15	0.001	0.46	-0.002	0.15	-0.001	0.43	-0.003	0.42	-0.001	0.36
Value-weighted B/M Quintile	0.007 ***	0.00	0.010 ***	0.00	0.007 ***	0.00	0.010 ***	0.00	0.011 ***	0.00	0.010 ***	0.00
Value-weighted Mom Quintile	0.003 ***	0.00	0.005 ***	0.00	0.003 ***	0.00	0.005 ***	0.00	0.004 ***	0.00	0.005 ***	0.00
Avg. Fund-Company Networks	0.002	0.60	-0.001	0.88	0.002	0.61	-0.001	0.79	0.001	0.83	-0.001	0.65
Industry_Herfindahl	0.009 **	0.03	0.011 **	0.02	0.010 *	0.08	0.012 *	0.09	0.011 **	0.05	0.012 *	0.10
Family characteristics:												
Log (# funds in family)	0.000	0.47	0.000	0.72	0.000	0.46	0.000	0.69	0.000	0.84	0.000	0.73
Time fixed-effects		YES		YES		YES		YES		YES		YES
Objective fixed-effects		YES		YES		YES		YES		YES		YES
N		12253		9919		12225		9919		12225		9921
Adjusted R-sq. (%)		3.09		2.29		3.08		2.28		3.26		3.01

3.5. Conclusion

The main findings in the paper are summarized as follows. Our study uncovers a significantly negative relationship between fund managers' deviating tendencies in their portfolio allocation strategies relative to their peers, and fund performance relative to their objectives. This finding has an important bearing on the frequent discussion about the tendency of money managers to follow similar strategies. The negative relationship documented in this study suggests that the average fund manager does not deviate based on valuable private information.

There also exists a striking persistence in deviating tendencies over time. We find a U-shaped relationship between deviating tendency and past performance, suggesting that the best and worst performers deviate more than the intermediate performers in subsequent periods. In further empirical analyses using portfolio decompositions, it is documented that the average fund manager overweights stocks that subsequently underperform compared to the stocks that the manager underweights. The underperformance is significant and the magnitude is an annualized benchmark-adjusted return of about -4.6%. The results are robust across peer group definitions, fund size categories, objective definitions and fund past performance categories.

The findings in this study have several important implications and raise some interesting questions. Results seem to indicate that mutual fund investors may do better by avoiding funds which have higher disparity in portfolio allocations relative to comparable funds, since it is a challenge to identify the managers with superior ability. Also, the persistence in deviating tendencies, which have a negative impact on performance, suggests potential conflicts of interest between fund managers and mutual fund investors. Further, this study has not attempted to disentangle what causes the detrimental impact of deviating tendencies and performance. The relationship may be driven by agency problems where the manager is willing to take rational risks that are not beneficial for the fund's investors, or by irrational biases like managerial overconfidence, where the manager overestimates her skill and private information. We leave this is an interesting avenue for future research.

CHAPTER 4

WHAT DRIVES HOME BIAS IN CORPORATE INVESTMENTS? EVIDENCE FROM U.S. DOMESTIC M&A

4.1. Introduction

"Everything is related to everything else, but near things are more related than distant things."

-Waldo Tobler's "First Law of Geography" (1970)

The overarching goal of this paper is to shed light on the factors that impact choices made by acquiring firm managers during corporate investment in domestic M&A. We do so by focusing our attention on one intriguing facet of investment choice: the tendency of economic agents to show proximity preference. Our motivation to study this aspect of investment is rooted in the recent renaissance of literature that relates geographical location to various factors that impact business interactions and outcomes, like information asymmetry, familiarity, networks and economic spillovers. We first document a substantial proximity preference (or 'home bias') in corporate investment choices in M&A that is not satisfactorily explained by industrial agglomeration, and then identify some factors that impact the geography of these corporate investments. Our findings suggest that home bias in M&A is impacted by proximate economic opportunities, antitakeover legal regimes, herding behavior and acquiring firm characteristics. Unexpectedly, the target's characteristics (i.e., asset attributes) are not among the prominent drivers of home bias.

Our study is most closely related to two main streams of literature. The first is the growing body of research that documents and explores home bias in portfolio investments, a phenomenon that continues to intrigue financial economists. While initial studies focused on home bias in international portfolio investments[15], a significant extension of the literature were studies like Coval and Moskowitz (1999, 2001) and Grinblatt and Keloharju (2001) which documented investors' home bias even in domestic investments. Specifically, Coval and Moskowitz show that U.S. investment managers exhibit a strong preference for locally headquartered firms, particularly small and highly levered firms producing nontraded goods. The authors interpret their findings as suggesting that information advantage of local over non-local investors drives the preference for investing in geographically proximate assets. Similarly, Grinblatt and Keloharju (2001) show that Finnish investors are more likely to hold and trade the stocks of Finnish firms that are located close to the investor, communicate in the investor's native language, and have chief executives of the same cultural background. Although a definite accounting is still elusive, the home bias in domestic portfolio holdings is likely to be related to information asymmetry and/or a cognitive bias towards the familiar as argued by Huberman (2000). In the context of international portfolio investments, Chan, Covrig, and Ng (2005) find that the home bias is not confined to U.S. investors, but is universally exhibited by portfolio

[15] See for example, French and Poterba (1991) who show the lack of diversified international portfolios held by U.S. investors. Most early studies attributed this home bias to the existence of barriers to international investment such as legal restrictions, withholding taxes, etc. However, in recent years formal barriers to international investment have largely been dismantled.

investors around the world and has persisted after the elimination of most formal barriers to international investments.

The second body of research related to our study is that on corporate investments, and more specifically on mergers and acquisitions. A vast number of studies have explored various aspects of M&A, both cross-border and domestic, since M&A form a significant part of corporate economic activity. Additionally, M&A have retained attention because the overall results point to the fact that acquirers do not create wealth for their shareholders on an average[16], but it remains among the primary channels of corporate investment. Most gains go to the target firm's shareholders. Considerable research has been geared towards finding determinants of successful acquirer performance in M&A[17].

During 1990-2003, domestic M&A activity of publicly traded U.S. firms accounted for more than $6 trillion in corporate investments. Clearly, M&A are an important form of corporate investments and have major implications for the industry, shareholders as well as policy makers. In this paper, we take a step back from stock-price based studies on M&A performance. In peeling another layer off the evidence found in performance studies, we try to shed light on one issue that may influence deals in the decision-making stage and determine the choice set of prospective target

[16] Bruner (2002) surveys the literature on M&A and reviews the findings of 130 studies during the period 1971-2001. In summary, Bruner states that acquirers fail to benefit from synergies in the deal when short-term stock price reactions are considered, albeit with considerable cross-sectional variations.

[17] See for example, Rau and Vermaelen (1998) who find that long-term post-merger performance is better for tender offers than mergers, and poor for 'glamour' bidders with low book-to-market ratios. Loughran and Vijh (1997) find that long-term performance is higher for bidders using cash as method of payment compared to bidders paying with stock.

firms: the issue of target firm location relative to acquirer. If acquiring firms limit the scope of search for potential targets, what are the reasons that drive this behavior? Acquirers involved in acquisitive activities identify attractive target firms based on their information about the potential targets. This situation gives rise to the possibility that acquirers may have differential information and awareness about potential targets, depending on geographical proximity to the acquirer. By exploring the geographical distribution of domestic M&A deals we also draw attention to an important aspect of the market for corporate control, namely, the national versus segmented scope of the M&A market. We aim to disentangle the effect of industrial agglomeration from home bias, an aspect which has clear implications for corporate investments unlike for portfolio investments.

To the extent that firms have greater resources and capacity for collecting and processing information than the majority of portfolio investors, firms may not exhibit a significant home bias in their investments if at all. Further, unlike portfolio investors who often need to collect information in a timely fashion to counter efficient markets, firms often face imperfect competition for the investment projects and thus may devote more time to information gathering and analysis. So, the influence of information asymmetry can be much less pronounced in corporate investments than in portfolio investments. Also, being an impersonal organization with pecuniary mandates and collective decision-making processes, firms may be less prone to psychological biases than portfolio investors. In other words, geography may not be as important a factor in corporate investments as in portfolio investments.

However, the literature on economic geography, a study of spatial location of economic activity, suggests otherwise. Studies such as von Thünen (1826), Marshall (1920), and Krugman (1991), suggest that economic activities may cluster naturally as a result of interactions of transportation costs, market potentials, and technical externalities. Marshall and Krugman similarly argue that there can be spatial boundaries to knowledge spillovers among the firms, as the cost of transmitting knowledge increases with distance. In the same vein, Audretsch and Feldman (2001) document that R&D activities and innovation tend to cluster geographically due to the existence of knowledge externalities. In summary, the literature on economic geography broadly suggests that geographical proximity may play an important role in corporate investments. Additionally, unlike for portfolio investors, acquisitions are investments in real assets. So, corporate acquirers may prefer proximate targets due to the ease of post-deal monitoring. Since there can be opposite forces influencing the spatial distribution of corporate investments, the question then can only be answered empirically. We use a large sample of successfully completed domestic M&A deals in the U.S. in order to bear on the questions relating geography to target choices in corporate M&A investments.

We examine a sample of about 10,300 successfully completed U.S. domestic M&A deals, of at last $10 million in value, announced by publicly traded firms during the period 1990-2003. We are mainly concerned with (i) documenting acquirers' limited scope of target search arising out of proximity preference in domestic corporate M&A investments, and (ii) the factors driving the observed proximity preference. We study the distribution pattern of M&A based on two alternative observation units: the states where acquirers and targets are headquartered and the geographical distance between targets and acquirers. There are several reasons supporting the use of states as primary geographical units in the domestic context. Some of the main reasons are (i) many policy decisions about businesses and law are made at the state level, (ii) M&A activities are regulated mostly by the state, and (iii) states are intuitive geographical categories for economic agents during decision-making. The key findings and hypotheses presented in our paper are summarized below.

Firstly, our results show that firms exhibit a strong proximity preference in M&A deals, with the frequency of the deals declining sharply as the geographical distance between targets and acquirers increases. Specifically, about 34% of acquired targets are 'local', i.e, located within a 100 kilometer (km) radius from the headquarters of acquiring firms. After adjusting for industry agglomeration, acquirers invest in targets that are approximately 34% (or 580 km) nearer than the average potential target in the sample, almost four times the 9% (or 160 km) local bias shown by U.S. mutual fund managers in Coval and Moskowitz (1999). We adjust for industrial clustering by constructing the benchmark (or 'unbiased') target distance from each acquirer as the mean distance from a portfolio of potential targets firms operating in the same industry as the actual target. This pattern of local bias holds across deal size quintiles, but is somewhat less for largest (≈ 462 km or 28%; mean deal size = $1,999 mill) as compared to smallest size quintile (≈ 655 km or 37.5%; mean deal size = $13 mill). Overall, firms are found to exhibit proximity preference that is strikingly similar to the well documented behavior of portfolio investors, and is considerably more compelling in magnitude. Our results allude to a much more magnified home bias in case of investment in real assets versus in financial securities.

Second, when the state is used as an observation unit instead of geographical distance, we again observe a strong home bias in corporate M&A activities. On an average, while acquirers choose 23.2% targets in their home state, the benchmark or unbiased sample weight of target firms in a state is 2%. For example, while Wisconsin-domiciled targets account for 1.2% of the total number of sample targets during the period 1990-2003, they account for 30.5% of the total acquisitions made by Wisconsin firms. Targets based in Wisconsin, Illinois, and Minnesota, together account for more than half (55.5%) of acquisitions made by Wisconsin-based firms. Another example of home bias is exhibited by Washington-based firms that primarily acquire targets on the West coast (27.9% in-state, 26.7% in California and 5.2% in Oregon). The examples of Wisconsin and Washington are representative of a wide-spread tendency of acquiring firms to show preference for home state targets, and are not explained solely by economic concentration.

Thirdly, our goal is to explain the considerable variation in the degree of home bias displayed by acquiring firms. Our hypotheses outline six categories of factors that may relate to home bias: (i) economic opportunities, (ii) legal environment, (iii) herd behavior, (iv) acquiring firm characteristics, (v) target firm characteristics, and, (vi) deal characteristics. While the first three categories of factors are external to the firms, the remaining factors capture internal firm-specific situations. We expect that greater economic opportunities in the acquirer's vicinity will induce localization of target choices in M&A. The aspect of corporate law most pertinent to takeovers, namely state antitakeover laws, should discourage M&A in states authorizing higher protection of target firm managers via adoption of antitakeover statutes. Firms' acquisition strategies may be influenced by the strategies of a peer group of managers they are likely to be compared with by the media and shareholders, interact more with or are more likely to compete with. This may manifest itself in correlated or 'herd' behavior[18]. In our context, if the managers in the peer group are showing a tendency for localized M&A, the acquirer may have a higher likelihood of displaying localized target choices. We form two peer groups for each acquirer in each year: first, all the acquiring firm managers based in the same city and in the same industry; second, all the acquirers not located in the same city but operating in the same industry. This method allows us to separate industry-wide effects from location-dependent herding effects. Additionally, acquiring firm characteristics like size, book-to-market, debt in capital structure, R&D intensity and undistributed free cash flows may be vital in determining target choices. These acquirer characteristics reflect the firm's business resources, network, risk attitudes, strategic considerations and financial health, all of which may impact M&A decisions. Target firm characteristics like size, book-to-market and leverage reflect the degree to which information asymmetries play a role in takeovers. In case of deal characteristics, while we cannot overreach in interpreting causality, we hypothesize that deal features like cash versus stock payment, hostile

[18] For example, Scharfstein and Stein (1990) develop a model of herd behavior among managers, where managers tend to mimic each others decisions because a manager is less likely to be answerable for a wrong strategy when other managers in the industry also followed the wrong strategy (i.e., a "sharing-the-blame" effect protects managers from being held responsible). Hong, Kubik and Stein (2005) find that mutual fund managers located in the same city herd in and out of the same stocks.

versus friendly attitude, same-industry versus inter-industry and tender offer to shareholders are related to information asymmetry and prior familiarity between acquirer and target, the same factors which are expected to be related to distance between the firms.

Our first set of regression analyses, based on state-level choices, show that the propensity to acquire in-state targets is positively related to the size of the state where the acquiring firm is headquartered, reflecting the opportunities at home. It is noted that during our sample period, California- (North Dakota) based firms acquired 50.7% (0%) of their targets in-state, reflecting ample (scarce) acquisition opportunities at home. On the other hand, the propensity to acquire in-state is negatively related to the severity of anti-takeover statutes in the home state of the acquirer. Especially, the statutes regarding control shares, number of freeze-out years and fair price significantly discourage in-state acquisitions. Thus, state-level laws matter in determining where M&A takes place. Considering that home bias, regardless of its causes, tends to reflect segmented markets, anti-takeover statutes can be seen as having an unexpected effect of integrating the market for corporate control by countering the home bias in M&A. Acquirers display substantial herding behavior with managers located in their city and operating in the same industry in their tendency to display home bias while choosing targets. Interestingly, acquirer behavior is not impacted by same-industry managers in other cities, or other-industry managers in the same city. Some firm-level factors help in explaining the degree of proximity preference shown by acquirer. The propensity to acquire in-state is negatively related to the acquirer firm size and book-to-market ratio, showing that large, value firms have a lower propensity for home bias than small, growth firms. Perhaps unexpectedly, publicly-traded targets are more likely to be acquired by home-state firms than private targets, possibly due to the political resistance to out-of-state takeover of public firms that tend to be more visible and vital to the state economy than private firms. Target firm characteristics are insignificant in explaining home bias in M&A when the acquirer characteristics are accounted for. We also conduct parallel analyses involving proximity preference measures based on distance instead of state-level geographical choices and the empirical evidence holds.

While our study is by no means comprehensive in terms of finding the determinants of corporate investment choices, our paper provides new insights into corporate decision-making processes. By focusing our attention on the geography of investment choices, we have been able to distinguish some factors that directly or indirectly play a substantial role in the outcomes of the decision processes. Our findings, along with other studies similarly indicating that 'home' lies within a 100 km radius, are perhaps suggestive of the limited human capacity for managing complex social interactions, information sharing and processing, factors that may be at the root of the so-called home bias puzzle. The evidence that state laws can have a considerable impact on the location and nature of corporate strategies deserves further attention, since it uncovers the role of legal structures in the development of businesses and regional economies. Finally, the notion that acquirer managers care more about or are influenced more by the strategies of managers they are likely to be compared with by the local media and shareholder base, have more word-of-mouth communication with, or compete locally with deserves further consideration in order to examine the drivers of corporate behavior and their subsequent implications for success.

The paper is organized as follows. Section 4.2. discusses the data and sample construction used in the study. Section 4.3. documents the geographical distribution of M&A deals in the United States and provides evidence on the existence of a strong home bias in acquiring firms. Section 4.4. discusses the variables and hypotheses related to the factors that may affect home bias in acquiring firms. Empirical results are reported in section 4.5. Section 4.6. concludes.

4.2. Data and Sample Selection

The primary source of our data is Securities Data Corporation (SDC) Platinum's Mergers and Acquisitions (M&A) database. We construct a sample of successfully completed domestic M&A deals in the U.S. that were announced during 1990-2003 and use various criteria to select our final dataset. There were 91,274 domestic acquisition announcements by U.S. acquirers during this period. From this sample, we choose M&A deals that have deal value of at least $10 million, were completed and where the acquirer owned 100% of the target's shares post-acquisition. This reduces the sample to 25,010 deals. Further, we choose acquiring firms that are publicly traded and targets which have either public or private status, and have 11,885 deals that satisfy these criteria. Finally, we exclude U.S. territories and islands from our sample in order to prevent outliers from driving the results. Although we include Alaska and Hawaii in our analysis, the results are not affected by their exclusion. Our final sample consists of 10,379 M&A deals in the U.S. during 1990-2003. The SDC M&A database is our main source of data for deal and firm characteristics.

We supplement the firm-level data provided by SDC with data obtained from Center for Research on Security Prices (CRSP) and COMPUSTAT databases for U.S. publicly traded firms. Monthly stock price and shares outstanding data are obtained from CRSP to compute market value of acquirers in the month prior to the acquisition announcement where available. COMPUSTAT annually updated financial data were used to compute firm book-to-market equity values, leverage, research and development (R&D) expenses and undistributed free cash flows. Similar data for target firms were obtained for the subsample of targets that were publicly traded at the time of the acquisition announcement.

Our study uses publicly available economic and geographical data on states provided by the U.S. government. A widely accepted measure of a state's economy is the gross state product (GSP) in current dollars which is obtained from the Bureau of Economic Analysis (BEA), U.S. Department of Commerce (http://www.bea.doc.gov/). GSP is defined as the value added in production by the labor and property located in a state. GSP for a state is computed as the aggregated gross state product originating in all industries in a state. BEA prepares GSP estimates for 63 industries and aggregates these industries' GSP to compute the aggregated state-level Gross State Product. We also collect information on the standard antitakeover statutes adopted by each state to define antitakeover legal regimes. Appendix A summarizes some of the variables used in our study.

Geographical location of firms is obtained by matching firms' city of headquarters with the latitude-longitude co-ordinates provided by the U.S. Geological Survey (USGS). We then compute the great circle distance between each target '*i*' and acquirer '*j*' pair by calculating the arc length 'd_{ij}' as[19]:

$$d_{ij} = arc\,cos\{cos(lat_i)cos(long_i)cos(lat_j)cos(long_j) + cos(lat_i)sin(long_i)cos(lat_j)sin(long_j) + sin(lat_i)sin(lat_j)\} * 2\pi r/360 \quad (1)$$

where lat and $long$ are the latitudinal and longitudinal coordinates of the target and acquirer headquarters' cities in degrees, and r is the radius of the earth ($\approx 6378\ kilometers$).

We use returns on the S&P 500 composite index and interest rate as macroeconomic variables that capture the overall business conditions under which the firms were operating at the time of the deal. CRSP is our source of stock index returns. The Federal Reserve Board of Governors provides the data on annual average prime interest rate levels. We do not consider monthly prime rate fluctuations since the deviations of monthly rates from the annual average in a given year are negligible.

4.3. Geographical Distribution of M&A

In this section we document geographical patterns in domestic M&A activity and provide evidence on the propensity of M&A to occur in spatial clusters within the United States. However, in order to understand and interpret the spatial distribution of

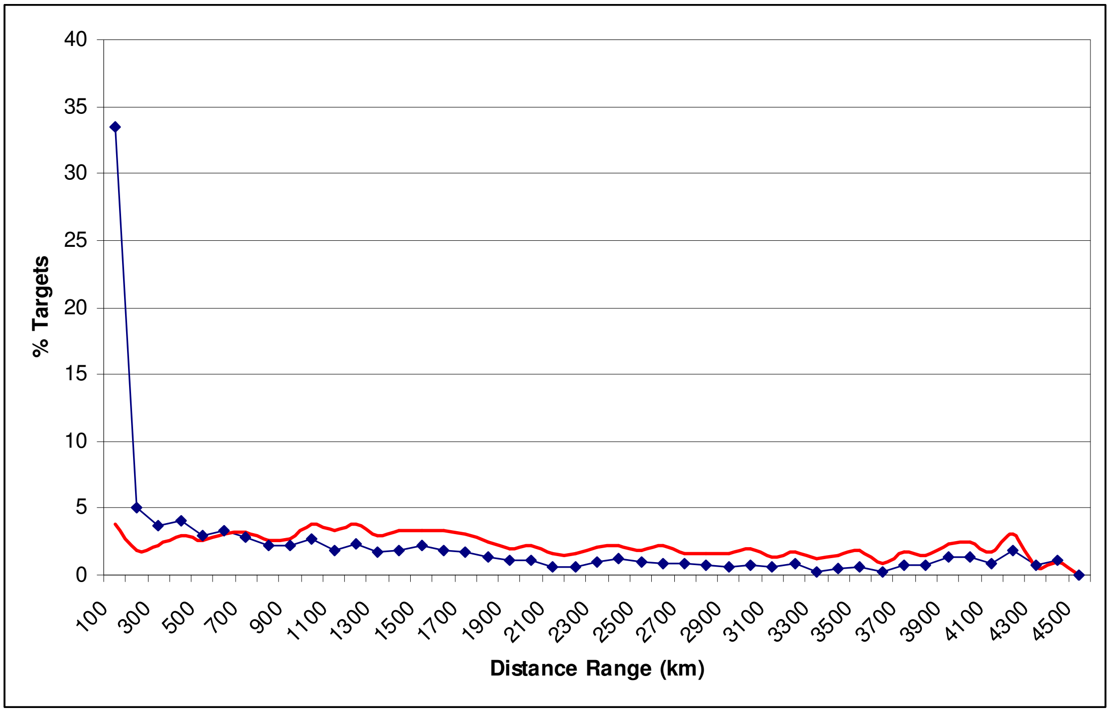
[19] The great-circle distance is the shortest distance between any two points on the surface of a sphere measured along a path on the surface of the sphere (as opposed to going through the sphere's interior).

M&A, it is imperative to take into account industrial agglomeration and urban clustering. These phenomena by definition put more potential targets clustered around an acquirer, since industries and populations tend to develop in agglomerated geographic spaces. For example, Ellison and Glaeser (1999) in their study of U.S. manufacturing industries confirm the conventional wisdom that most industries are somewhat localized (extreme examples being Silicon Valley and Detroit's auto industry). However, their empirical results show that the degree of localization is slight for many of the industries in their sample.

Figure 4.1. shows plots of the actual and benchmark frequency distributions of M&A deals versus the geographical distance ranges between the target and acquiring firms. Urban and industrial clustering lead to a skewed geographical distribution of firm locations, because they cause more potential targets to be located in proximity to an acquirer. So, in order to estimate what an ex-ante or "unbiased" target spatial frequency distribution should be, we have to take into account urban and industrial agglomeration. We use a simplistic frequency distribution of the universe of sample target firms based on distance from each acquirer, which accounts for spatial clustering of firms. For ease of presentation, we aggregate the ex-ante distribution of targets across all acquirers. While this measure of ex-ante expected target distribution may not be ideal, it is impossible to determine a perfect ex-ante target distribution since we would then have to know the universe of firms that each acquirer considers as potential targets. Our benchmark measure should at least partially reflect the effect of agglomeration. Using this method, the ex-ante probability that an acquired target is located within 100 km of the acquirer (or 'local') is 4%. However, using the actual or

Figure 4.1. Frequency of M&A and Distance between Acquirers and Targets

The figure shows the geographical frequency distribution of targets acquired and the benchmark target distribution. Actual target distribution plots the % of targets acquired lying in the corresponding x-axis distance range from the acquirer. Benchmark target distribution is computed as the % of target firms in the sample which lie in the corresponding distance range to an acquiring firm. The values plotted are averaged across all acquirers in the sample. The distance ranges are in 100km units between acquirer and target firms. The x-axis is the distance range at which the frequency of deals is computed: 0-100 km, 101-200 km, 201-300 km etc. The plot after 4500 km is truncated due to negligible frequency.



ex-post target distribution, the probability that a target is within 100 km from the acquirer is 34%. So, the actual probability of deals involving a local target is more than eight times the expected probability.

Figure 4.1. also illustrates that the frequency of M&A deals with proximate targets is much higher than those involving distant targets. The frequency of M&A deals falls precipitously with distance between acquirers and targets. Till around 650 km distance from acquirer, the actual target frequency exceeds the benchmark

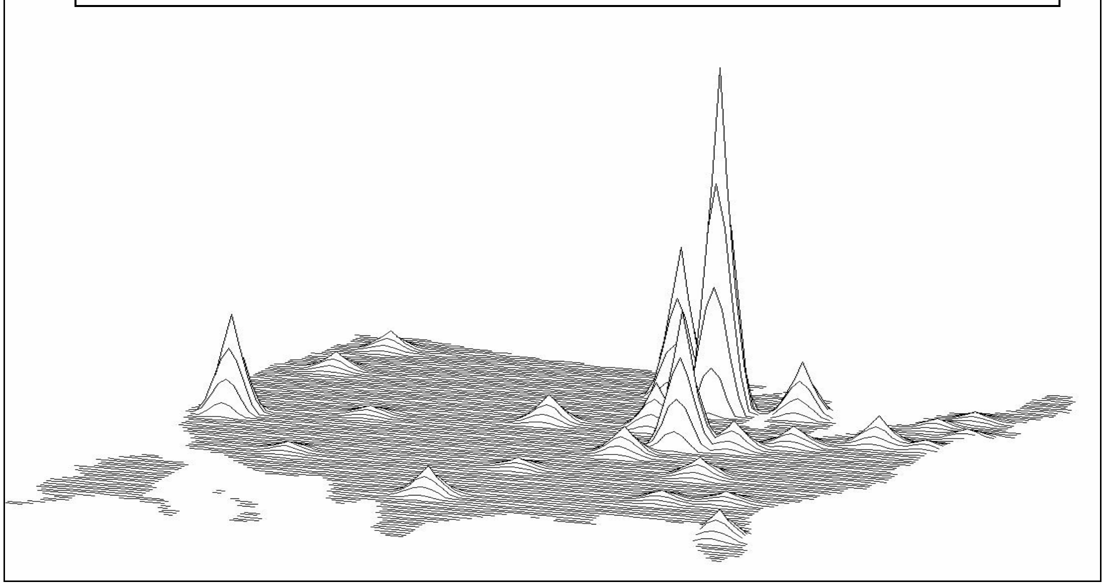
frequency. However, for distances greater than 650 km, the benchmark target frequency is higher than the actual frequency through all distance ranges. The effect of distance on the propensity of M&A deals to occur becomes negligible after approximately 1800 km. Large states like California, New York, Massachusetts and Texas are likely to have a high degree of business exchange, which would be reflected in greater geographical distances between acquirers and targets in these states. This fact gets reflected in the distance ranges 3800-4400 km, where there is a slight increase in frequency of M&A. We also run additional checks with a sub-sample where we exclude acquirers and targets from these four states, but the frequency plot looks very similar to the results for the full sample and we do not report it.

To introduce our state-level analyses of target choices, we consider acquirers from two states, namely, Wisconsin and Washington. Figure 4.2. illustrates the phenomenon of proximity preference in M&A, by presenting surface maps of the distribution of target firms acquired by companies from Wisconsin (Panel A) and Washington (Panel B). As we will demonstrate in the later part of this section, the behavior of Washington and Wisconsin acquirers is typical of firms from most states. Panel A presents a contour map of the geographical frequency distribution of takeovers by Wisconsin acquirers. It clearly shows that there is a strong proximity preference shown by Wisconsin acquirers in the choice of where to make investments in M&A. The contour peaks are highest in the home state and contiguous states like Illinois and Minnesota, and fall away with distance. Also representative of several other states in the sample, Wisconsin acquirers venture to acquire in industrially

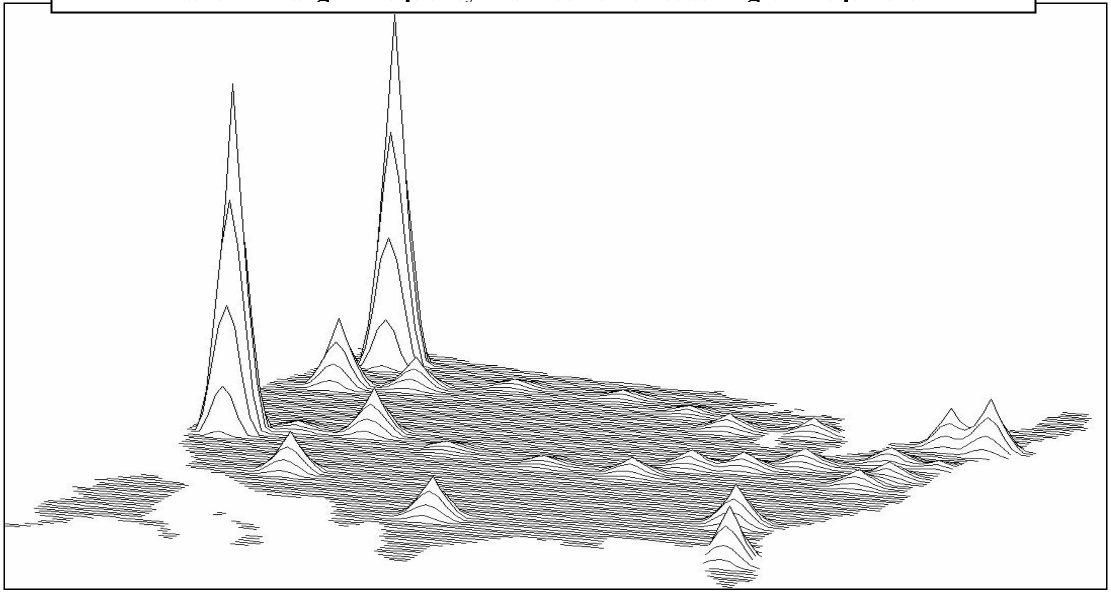
Figure 4.2. Geographical Distribution of Target firms

Panel A shows a contour map of the distribution of M&A activity conducted by Wisconsin acquirers, based on frequency of targets in a state. Panel B shows a contour map of the distribution of M&A activity conducted by Washington acquirers, based on frequency of targets in a state.

Panel A: Target Frequency Distribution of Wisconsin Acquirers



Panel B: Target Frequency Distribution of Washington Acquirers



concentrated regions like California, Florida and the Northeast in spite of distance. Panel B presents an equivalent contour map for takeovers by Washington acquirers. We clearly see that Washington acquirers primarily acquire in their home state and nearby states on the West coast, like California and Oregon. The other regions where Washington acquirers show some activity are Texas, Florida and the Northeast.

Overall, the spatial patterns in target firms' locations provide strong evidence that the home state and contiguous states are preferred by acquirers during acquisitive activity, thereby showing a home as well as near-home bias. In order to understand whether the phenomenon of proximity preference universally holds across the spectrum of acquiring firms in the U.S., we study the distribution of M&A activity involving acquirers and targets from all U.S. states.

Table 4.1. provides descriptive statistics on the geographical distribution of M&A activity using states as units of observations. Business activity, as reflected by the proportion of targets and acquirers in a state, is clearly not distributed uniformly between states and large inequalities are evident. California is by far the biggest state, accounting for approximately 18% of acquirers and 19% of target firms. Some other states that account for a considerable portion of the acquirers and targets in the sample are Texas (8.5% of acquirers, 7.7% of targets), New York (7.8% of acquirers, 6.3% of targets) and Massachusetts (5% of acquirers, 5.1% of targets), together accounting for around 21% of the acquirers and 19% of target firms.

One of the most important things evident from Table 4.1. is that the geographical distribution of M&A deals is not explained solely by the concentration of business

Table 4.1.
Summary Statistics of Domestic M&A Activity by State

The table reports summary statistics for the 50 U.S. states and the District of Columbia. The *% of Targets* (*Acquirers*) in a state is the number of deals involving targets (acquirers) located in the state as a percentage of the total number of deals in the sample. *Home Acquirers (%)* is the percentage of targets in the state acquired by in-state acquirers. The *Top three Out-of-State Acquirers* for a target state are the three states which acquired the highest number of targets in the state. When more than one acquirer state has the same number of acquisitions, we rank according to the mean value of the deal. *Home Targets (%)* is the percentage of acquisitions conducted by acquirers in the state involving in-state targets. *Top three Out-of-State Targets* for an acquiring state are the three states which had the maximum number of targets involved in deals conducted by acquirers in the state.

				Acquirer State				*Target State*			
State	*State Code*	*% of Acquirers*	*% of Targets*	*Home Acquirers (%)*	*Top three Out-of-State Acquirers (As % of Targets In Target State)*			*Home Targets (%)*	*Top three Out-of-State Targets (As % of Acquisitions By Acquirer State)*		
Alabama	AL	1.87	0.86	24.72	GA: 12.36	TN: 10.11	CA: 8.99	11.40	FL: 25.39	GA: 14.51	TX: 11.40
Alaska	AK	0.02	0.09	0.00	CA: 44.44	AR: 11.11	MI: 11.11	0.00	WA:50.00	CA: 50.00	-
Arizona	AZ	1.06	1.50	10.32	CA: 18.06	TX: 8.39	FL: 6.45	14.55	CA: 13.64	NY: 9.09	TX: 7.27
Arkansas	AR	0.58	0.49	31.37	TX: 15.69	MO: 11.76	TN: 9.80	26.67	TX: 15.00	IL: 8.33	CA: 8.33
California	CA	17.97	19.13	47.57	MA: 6.12	NY: 6.12	TX: 5.71	50.65	MA: 6.78	TX: 5.33	NY: 3.55
Colorado	CO	2.10	2.40	15.73	CA: 16.13	TX: 11.29	NY: 6.85	17.97	CA: 11.98	TX: 9.68	VA: 5.07
Connecticut	CT	2.09	2.05	22.64	NY: 12.26	CA: 11.32	NJ: 7.55	22.22	CA: 12.04	MA: 7.87	NY: 7.87
D.of Columbia	DC	0.54	0.35	11.11	NY: 16.67	CA: 8.33	VA: 5.56	7.14	NY: 10.71	VA: 8.93	GA: 8.93
Delaware	DE	0.17	0.30	0.00	CO: 12.90	MD: 9.68	PA: 9.68	0.00	PA: 27.78	IL: 16.67	CA: 16.67
Florida	FL	4.06	5.31	25.68	AL: 8.93	NC: 6.92	CA: 6.92	33.57	CA: 10.95	TX: 7.14	NY: 6.67
Georgia	GA	3.74	3.77	25.64	CA: 11.03	AL: 7.18	FL: 5.90	25.84	CA: 9.56	FL: 8.01	TX: 5.68
Hawaii	HI	0.07	0.15	26.67	CA: 26.67	TX: 20.00	TN: 6.67	57.14	CA: 28.57	WA: 14.29	-
Idaho	ID	0.17	0.18	0.00	WA: 21.05	OH: 15.79	UT: 10.53	0.00	CA: 16.67	FL: 11.11	MT: 5.56
Illinois	IL	4.21	4.37	21.24	CA: 8.63	MO: 6.64	NY: 5.53	22.07	CA: 11.49	TX: 6.44	NY: 6.21
Indiana	IN	1.49	1.65	34.50	OH: 11.70	MI: 6.43	TX: 5.26	38.31	IL: 13.64	OH: 5.84	KY: 4.55
Iowa	IA	0.42	0.65	20.90	MO: 13.43	NE: 10.45	WI: 7.46	32.56	MI: 9.30	TX: 6.98	SD: 4.65
Kansas	KS	0.41	0.49	7.84	MO: 25.49	CA: 11.76	TX: 9.80	9.52	OK: 19.05	FL: 9.52	CO: 7.14
Kentucky	KY	0.73	0.81	25.00	OH: 21.43	IN: 8.33	TN: 7.14	27.63	OH: 11.84	CA: 11.84	TN: 5.26
Louisiana	LA	0.85	1.35	28.57	TX: 27.14	MS: 7.14	AL: 6.43	45.45	TX: 17.05	TN: 3.41	NM: 2.27
Maine	ME	0.23	0.30	16.13	PA: 9.68	NY: 9.68	VT: 6.45	20.83	MA: 29.17	CT: 12.50	NH: 8.33
Maryland	MD	2.11	1.96	24.14	CA: 11.82	TX: 6.90	NJ: 6.40	22.48	CA: 12.84	VA: 10.55	MA: 6.42
Massachusetts	MA	5.04	5.14	28.76	CA: 23.68	NY: 6.02	TX: 4.32	29.37	CA: 23.22	IL: 4.41	TX: 4.41
Michigan	MI	1.64	2.01	25.48	OH: 8.65	IL: 7.69	NY: 7.69	31.18	IL: 12.35	CA: 10.59	IN: 6.47
Minnesota	MN	2.18	1.87	17.10	CA: 14.51	WI: 8.81	NY: 7.25	14.67	CA: 16.44	MA: 5.33	NJ: 4.89

Table 4.1. (contd.)

State	*State Code*	*% of Acquirers*	*% of Targets*	*Acquirer State* *Home Acquirers (%)*	*Top three Out-of-State Acquirers (As % of Targets In Target State)*			*Target State* *Home Targets (%)*	*Top three Out-of-State Targets (As % of Acquisitions By Acquirer State)*		
Mississippi	MS	0.63	0.44	34.78	TN: 8.70	GA: 6.52	FL: 6.52	24.62	LA: 15.38	TN: 9.23	AR: 4.62
Missouri	MO	1.89	1.32	26.47	IL: 8.09	CA: 7.35	TX: 6.62	18.46	IL: 15.38	TX: 12.31	CA: 7.18
Montana	MT	0.08	0.13	30.77	NY: 15.38	ID: 7.69	WV: 7.69	50.00	ND: 12.50	ID: 12.50	WA: 12.50
Nebraska	NE	0.71	0.35	19.44	CA: 16.67	WI: 8.33	IL: 8.33	9.59	IA: 9.59	TX: 9.59	NJ: 6.85
Nevada	NV	0.50	0.63	23.08	CA: 18.46	TX: 9.23	UT: 7.69	28.85	CA: 15.38	OR: 5.77	NY: 5.77
New Hampshire	NH	0.38	0.55	19.30	CA: 19.30	MA: 14.04	CT: 7.02	28.21	MA: 25.64	CA: 7.69	IL: 5.13
New Jersey	NJ	3.76	3.42	24.29	NY: 14.69	CA: 11.02	PA: 9.60	22.11	CA: 16.20	NY: 12.60	PA: 6.68
New Mexico	NM	0.26	0.38	0.00	MA: 23.08	CA: 10.26	CT: 7.69	0.00	MA: 14.81	CA: 14.81	FL: 11.11
New York	NY	7.82	6.31	35.68	CA: 10.11	NJ: 7.50	TX: 5.82	28.80	CA: 14.96	NJ: 6.43	TX: 4.57
North Carolina	NC	2.95	2.25	35.19	TX: 7.73	CA: 7.30	GA: 6.44	26.89	FL: 12.46	VA: 7.54	CA: 6.89
North Dakota	ND	0.12	0.05	0.00	MT: 20.00	MI: 20.00	WA: 20.00	0.00	CA: 25.00	AZ: 16.67	NE: 8.33
Ohio	OH	3.60	3.27	30.77	NY: 8.28	CA: 6.51	TX: 5.03	27.96	CA: 8.06	IN: 5.38	PA: 5.38
Oklahoma	OK	0.58	0.89	22.83	TX: 19.57	KS: 8.70	NY: 7.61	35.00	TX: 25.00	CO: 6.67	KS: 3.33
Oregon	OR	0.77	1.02	12.26	CA: 30.19	WA: 8.49	NJ: 4.72	16.25	CA: 33.75	MA: 8.75	WA: 7.50
Pennsylvania	PA	4.48	3.97	37.47	CA: 7.30	NJ: 6.33	NY: 5.84	33.26	CA: 8.86	NY: 7.56	NJ: 7.34
Rhode Island	RI	0.21	0.22	13.04	TX: 26.09	IL: 17.39	MA: 8.70	13.64	CA: 18.18	OH: 13.64	NY: 13.64
South Carolina	SC	0.47	0.80	20.48	NC: 15.66	VA: 7.23	AL: 6.02	34.69	FL: 16.33	GA: 8.16	NC: 6.12
South Dakota	SD	0.04	0.08	0.00	IA: 25.00	NV: 12.50	DC: 12.50	0.00	CO: 50.00	IL: 50.00	-
Tennessee	TN	1.95	1.43	22.97	TX: 8.78	GA: 6.76	AL: 5.41	16.83	FL: 6.93	TX: 6.93	CA: 6.44
Texas	TX	8.55	7.74	36.13	CA: 12.38	NY: 4.63	FL: 3.75	32.69	CA: 12.78	LA: 4.30	NY: 4.30
Utah	UT	0.74	0.87	11.11	CA: 13.33	CO: 8.89	WA: 6.67	12.99	CA: 20.78	CO: 12.99	WA: 7.79
Vermont	VT	0.15	0.10	30.00	PA: 20.00	ME: 10.00	IA: 10.00	20.00	MA: 26.67	ME: 13.33	NH: 13.33
Virginia	VA	2.35	2.96	24.18	CA: 11.11	MD: 7.52	NC: 7.52	30.45	CA: 12.76	TX: 6.17	MD: 4.53
Washington	WA	1.66	1.99	23.30	CA: 21.36	NY: 7.77	MA: 4.85	27.91	CA: 26.74	OR: 5.23	MA: 4.07
West Virginia	WV	0.36	0.37	52.63	OH: 15.79	NC: 10.53	TN: 5.26	54.05	VA: 18.92	OH: 5.41	CA: 5.41
Wisconsin	WI	1.24	1.23	30.71	IL: 11.81	MN: 7.87	NY: 5.51	30.47	MN: 13.28	IL: 11.72	CA: 8.59
Wyoming	WY	0.02	0.05	0.00	TX: 40.00	OK: 20.00	CO: 20.00	0.00	UT: 50.00	CA: 50.00	-
Mean		1.96	1.96	21.73	16.61	9.57	7.61	23.23	18.47	11.56	6.37
(Median)		(0.77)	(0.89)	(23.30)	(15.38)	(8.39)	(6.85)	(24.62)	(15.38)	(8.93)	(6.21)

activity in certain large states like California, Texas, New York and Massachusetts, among a few others. The pattern of higher propensity for in-state M&A is observed for a vast majority of states. On average, only about 2% of sample targets are located in a given state but acquiring firms from the state choose in-state targets 23% of the time. For 35 states, the majority of acquisitive activities involving targets from the state were conducted by home state acquirers.

The geography of M&A documented in Table 4.1. also provides evidence that proximity preference does not imply only in-state business transactions. It is also observed even when we consider "near-home" or neighboring states. The top (i.e, most frequent) acquirer and target states for most of the 50 states include either the economically dominant states like California, or proximate states. Several top acquiring states are contiguous with the target state. For example, Georgia and Tennessee acquirers account for approximately 22% of the acquisitions in Alabama. This phenomenon is not restricted to states in any particular region. Target firms from Iowa in the Midwest have a majority of acquirers from Missouri, Nebraska and Wisconsin, together accounting for 31% of the acquisitions of Iowa firms. A large proportion (30%) of target firms in Vermont in the Northeast gets acquired by out-of-state acquirers from Pennsylvania and Maine. Approximately, 26% of Nevada targets in the West region of the U.S. get acquired by out-of-state acquirers from California and Utah, both of which are contiguous to Nevada. Another fact that is apparent from Table 4.1. is the importance of California as a center for business activity. California is the predominant exception to the pattern of proximity preference, and the state is a leading hub of M&A activity for a majority of states, irrespective of their geographical distance.

Tables 4.2. and 4.3. report statistical significance tests based on two alternative measures of home bias. Table 4.2. reports our first measure based on the degree to which acquirers overweight their home state targets in M&A, in comparison to the benchmark, or “unbiased”, weight of the state’s potential target firms. The geographical units of observation used in this measure are states. An ideal measure of benchmark weight of a state’s targets would reflect the firms located in the state that are potential targets for an acquirer, relative to the universe of firms in the U.S. However, the distribution of potential target firms is unknown. We construct two alternative benchmark weights that are likely to be good proxies of the distribution of unbiased benchmark target weights across states.

The first method of computing benchmark weights uses the distribution of all target firms across states in our sample of consummated M&A deals. In using the full sample of target firms, this measure avoids assumptions about likelihood of inter- versus intra-industry deals, and allows for the possibility that acquirers are as likely to acquire unrelated targets as they are to acquire related targets[20]. We measure home bias as the degree to which acquirers overweight their home state targets during M&A, compared to the benchmark sample weight of targets located in the state. The home bias measure is positive and significant for most states. All except seven states

[20] Relatedness of acquirer and target is measured at the 2-digit SIC code level. If the 2-digit SIC codes match between two firms, they are classified as being related, and are otherwise considered unrelated.

Table 4.2.
Test of Home Bias in Domestic M&A Activity

The table reports the degree of home bias in acquirers, using acquirer states as units of observation. The benchmark weight of home state targets is computed (i) as the weight of home state targets in sample, or (ii) the sample weight of Compustat firms located in the acquirer's home state. The actual weight of targets in the home state is the % of acquisitions by the acquirer state involving home state targets. Home bias is measured as the difference in actual weight and benchmark weight of home state targets and t-tests use the binomial probability test: The null hypothesis is that the probability of acquisition in the home state by an acquirer is equal to the sample weight of firms in the acquirer's home state. ***, ** denote significance at the 1%, 5% level respectively.

Acquirer State	*Code*	*Sample Tgt. Bench. Wt. (%)*	*Compustat Tgt. Bench. Wt. (%)*	*Actual Weight (%)*	*Home Bias (%) (Sample Targets)*	*Home Bias (%) (Compustat)*
Alabama	AL	0.86	0.63	11.40	10.54***	10.77***
Alaska	AK	0.09	0.04	0.00	-0.09	-0.04
Arizona	AZ	1.50	1.14	14.55	13.05***	13.41***
Arkansas	AR	0.49	0.41	26.67	26.18***	26.26***
California	CA	19.13	13.84	50.65	31.52***	36.81***
Colorado	CO	2.40	2.23	17.97	15.57***	15.74***
Connecticut	CT	2.05	2.04	22.22	20.17***	20.18***
D. of Columbia	DC	0.35	0.28	7.14	6.79***	6.86***
Delaware	DE	0.30	0.38	0.00	-0.30	-0.38
Florida	FL	5.31	4.42	33.57	28.26***	29.15***
Georgia	GA	3.77	2.16	25.84	22.07***	23.68***
Hawaii	HI	0.15	0.21	57.14	56.99***	56.93***
Idaho	ID	0.18	0.22	0.00	-0.18	-0.22
Illinois	IL	4.37	3.60	22.07	17.70***	18.47***
Indiana	IN	1.65	1.27	38.31	36.66***	37.04***
Iowa	IA	0.65	0.50	32.56	31.91***	32.06***
Kansas	KS	0.49	0.48	9.52	9.03***	9.04***
Kentucky	KY	0.81	0.56	27.63	26.82***	27.07***
Louisiana	LA	1.35	0.66	45.45	44.10***	44.79***
Maine	ME	0.30	0.18	20.83	20.53***	20.65***
Maryland	MD	1.96	1.50	22.48	20.52***	20.98***
Massachusetts	MA	5.14	3.89	29.37	24.23***	25.48***
Michigan	MI	2.01	1.72	31.18	29.17***	29.46***
Minnesota	MN	1.87	2.77	14.67	12.80***	11.90***
Mississippi	MS	0.44	0.26	24.62	24.18***	24.36***
Missouri	MO	1.32	1.49	18.46	17.14***	16.97***
Montana	MT	0.13	0.09	50.00	49.87***	49.91***
Nebraska	NE	0.35	0.35	9.59	9.24***	9.24***
Nevada	NV	0.63	0.85	28.85	28.22***	28.00***
New Hampshire	NH	0.55	0.44	28.21	27.66***	27.77***

Table 4.2. (contd.)

Acquirer State	*Code*	*Sample Tgt. Bench. Wt. (%)*	*Compustat Tgt. Bench. Wt. (%)*	*Actual Weight (%)*	*Home Bias (%) (Sample Targets)*	*Home Bias (%) (Compustat)*
New Jersey	NJ	3.42	4.39	22.11	18.69***	17.72***
New Mexico	NM	0.38	0.15	0.00	-0.38	-0.15
New York	NY	6.31	8.34	28.80	22.49***	20.46***
North Carolina	NC	2.25	1.53	26.89	24.64***	25.36***
North Dakota	ND	0.05	0.07	0.00	-0.05	-0.07
Ohio	OH	3.27	3.26	27.96	24.69***	24.7***
Oklahoma	OK	0.89	0.73	35.00	34.11***	34.27***
Oregon	OR	1.02	0.83	16.25	15.23***	15.42***
Pennsylvania	PA	3.97	3.92	33.26	29.29***	29.34***
Rhode Island	RI	0.22	0.27	13.64	13.42***	13.37***
South Carolina	SC	0.80	0.65	34.69	33.89***	34.04***
South Dakota	SD	0.08	0.11	0.00	-0.08	-0.11
Tennessee	TN	1.43	1.05	16.83	15.40***	15.78***
Texas	TX	7.74	7.84	32.69	24.95***	24.85***
Utah	UT	0.87	0.82	12.99	12.12***	12.17***
Vermont	VT	0.10	0.18	20.00	19.90***	19.82***
Virginia	VA	2.96	2.07	30.45	27.49***	28.38***
Washington	WA	1.99	1.51	27.91	25.92***	26.4***
West Virginia	WV	0.37	0.17	54.05	53.68***	53.88***
Wisconsin	WI	1.23	1.18	30.47	29.24***	29.29***
Wyoming	WY	0.05	0.13	0.00	-0.05	-0.13
Mean(Median)		1.96 (0.89)	1.72 (0.82)	23.23 (24.62)	21.27 (22.07)	21.51 (20.98)

have a statistically significant home bias measure based on population weights of sample targets. Excluding Hawaii[21], the acquirers displaying the highest degree of home bias based on this measure are West Virginia, Montana, Louisiana, Indiana and Oklahoma. Perhaps surprisingly, these are not states which have a high level of business activity, showing that proximity preference is not related solely to acquisition opportunities in the home state. On an average, acquiring firms make 23% acquisitions in the home state, as compared to the approximately 2% average sample acquisition is more than 11 times higher than the ex-ante 'unbiased' probability. The

[21] Hawaii is a non-continental state and therefore may have geographically unusual reasons for showing a home bias.

Table 4.3.
Test of Home Bias using Coval-Moskowitz Local Bias Measure

The table reports measures and significance of local bias (*LB*) following Coval-Moskowitz (1999). The reported values are averages across all acquirers in a state. Actual Distance is the distance in km between the acquirer and target. *Unadj. Benchmark Distance* for an acquirer is the mean distance in km between all the targets in the sample and the acquirer. *Industry-adj. Benchmark Distance* is the mean distance of the acquirer from all target firms in the sample having the same 2-digit SIC code as the target firm acquired. *LB in km (%)* is the local bias measured as difference between actual and benchmark distances (% of benchmark distance). *t-statistics* are reported for tests of the null hypothesis that *LB* is zero. ***, ** denote significance at the 1%, 5% level respectively.

Panel A					
Acquirer State	*Actual Dist. (km)*	*Unadj. Bench. Dist. (km)*	*Unadj. LB (km)*	*Unadj. LB (%)*	*t-stat (Unadj.)*
Alabama	783.31	1562.77	779.47	49.79	15.99***
Alaska	2275.27	4674.32	2399.05	51.32	-
Arizona	1846.54	2198.90	352.36	16.03	2.90***
Arkansas	822.09	1529.01	706.92	46.03	6.86***
California	1584.13	2583.79	999.65	38.54	24.39***
Colorado	1459.31	1808.13	348.82	19.25	5.36***
Connecticut	1270.60	1871.62	601.01	31.99	5.53***
D. of Columbia	1125.27	1650.09	524.83	31.81	3.19***
Delaware	1226.79	1713.40	486.62	28.42	1.45
Florida	1412.17	2096.09	683.92	32.58	10.43***
Georgia	962.42	1572.03	609.61	38.60	11.19***
Hawaii	890.53	6418.61	5528.08	86.13	6.21***
Idaho	1934.22	2378.84	444.62	18.84	1.57
Illinois	1037.59	1459.74	422.15	28.93	9.45***
Indiana	544.77	1435.36	890.59	62.10	14.28***
Iowa	788.57	1513.53	724.96	47.62	6.13***
Kansas	1122.38	1531.87	409.49	26.37	3.16***
Kentucky	740.98	1441.90	700.92	48.51	6.49***
Louisiana	665.99	1717.33	1051.34	61.10	12.66***
Maine	776.04	2112.19	1336.16	63.05	5.04***
Maryland	1034.53	1650.32	615.79	37.40	6.34***
Massachusetts	1766.56	1994.91	228.35	11.47	2.80***
Michigan	827.61	1516.30	688.69	45.45	8.17***
Minnesota	1328.03	1626.41	298.38	18.38	5.18***
Mississippi	659.37	1597.71	938.34	58.92	10.48***
Missouri	984.51	1564.26	579.75	37.47	11.98***
Montana	729.04	2382.87	1653.83	69.35	4.55***
Nebraska	1097.33	1560.54	463.21	29.69	5.61***
Nevada	1264.63	2307.19	1042.57	44.80	5.46***
New Hampshire	1001.11	1998.08	996.97	50.18	4.21***
New Jersey	1129.90	1771.42	641.52	36.18	7.62***
New Mexico	1839.54	1920.33	80.79	4.22	0.44

Table 4.3., Panel A **(contd.)**

Acquirer State	*Actual Dist. (km)*	*Unadj. Bench. Dist. (km)*	*Unadj. LB (km)*	*Unadj. LB (%)*	*t-stat (Unadj.)*
North Carolina	847.15	1625.41	778.26	47.86	13.13***
North Dakota	1528.51	1799.07	270.56	15.08	1.21
Ohio	812.68	1484.59	671.91	45.01	12.42***
Oklahoma	616.39	1581.04	964.65	61.05	11.55***
Oregon	1555.05	2757.16	1202.11	43.71	7.54***
Pennsylvania	917.98	1658.09	740.11	44.36	12.32***
Rhode Island	1817.35	1968.65	151.31	7.78	0.40
South Carolina	759.06	1630.36	871.30	53.50	5.57***
South Dakota	879.66	1836.21	956.54	52.09	4.34***
Tennessee	900.58	1480.55	579.97	39.07	8.96***
Texas	1221.61	1742.85	521.24	29.58	14.90***
Utah	1019.35	2099.22	1079.88	51.43	11.12***
Vermont	474.82	1943.81	1468.99	75.67	5.39***
Virginia	1098.43	1644.65	546.22	33.39	6.17***
Washington	1484.67	2761.16	1276.49	46.49	11.56***
West Virginia	439.66	1510.80	1071.15	70.77	6.91***
Wisconsin	681.11	1519.24	838.13	55.04	10.33***
Wyoming	783.18	2099.55	1316.37	62.70	0.92
Mean	1210.60	1962.63	685.46	36.08	
(Median)	(731.02)	(1717.33)	(600.92)	(35.36)	

weight of targets in the state. Therefore, the actual probability of a home state only states which do not show significant home bias are Alaska, Delaware, Idaho, New Mexico, North Dakota, South Dakota and Wyoming. The lack of in-state business opportunities may be causing the absence of home bias in states like Alaska and Idaho. Delaware, on the other hand, is an outlier in terms of the corporate law regime in the state and while it attracts a majority of incorporations, it does not have many domiciled firms.

The second measure of benchmark weights uses the universe of Compustat firms located in the U.S. While our sample includes domestic M&A involving public and private targets, the Compustat database only includes publicly traded companies. However, the geographical distribution of publicly traded firms within the U.S. is

Table 4.3., Panel B

Acquirer State	*Actual Dist. (km)*	*Industry-adj. Bench. Dist. (km)*	*Industry-adj. LB (km)*	*Industry-adj. LB (%)*	*t-stat (adj.)*
Alabama	783.31	1293.99	512.56	40.39	11.07***
Alaska	2275.27	4788.80	2513.54	52.49	-
Arizona	1846.54	2096.49	242.39	12.41	2.07**
Arkansas	822.09	1437.08	629.53	45.02	6.89***
California	1584.13	2374.96	785.79	32.37	19.00***
Colorado	1459.31	1706.76	258.54	15.19	4.12***
Connecticut	1270.60	1938.17	604.96	34.92	5.90***
D. of Columbia	1125.27	1680.07	567.17	34.70	3.60***
Delaware	1226.79	1658.69	416.69	28.05	1.29
Florida	1412.17	2062.71	656.55	32.30	10.25***
Georgia	962.42	1542.36	580.72	40.38	11.57***
Hawaii	890.53	6661.39	5913.39	86.91	6.64***
Idaho	1934.22	2238.15	303.93	11.72	1.01
Illinois	1037.59	1428.84	388.21	28.70	9.25***
Indiana	544.77	1248.10	706.84	61.23	13.57***
Iowa	788.57	1459.69	672.20	47.01	6.05***
Kansas	1122.38	1397.63	291.06	22.67	2.53***
Kentucky	740.98	1206.81	461.43	38.73	4.42***
Louisiana	665.99	1529.12	845.81	55.10	10.45***
Maine	776.04	1887.79	1111.76	62.67	4.78***
Maryland	1034.53	1588.01	562.80	37.42	6.04***
Massachusetts	1766.56	2117.40	356.00	17.64	4.46***
Michigan	827.61	1364.47	526.36	40.37	6.49***
Minnesota	1328.03	1633.40	302.96	18.30	5.29***
Mississippi	659.37	1434.58	766.08	55.48	9.07***
Missouri	984.51	1485.96	493.10	34.38	10.74***
Montana	729.04	2512.35	1783.31	70.24	4.68***
Nebraska	1097.33	1529.16	428.20	28.31	5.34***
Nevada	1264.63	2216.30	980.34	44.09	5.20***
New Hampshire	1001.11	1992.50	1002.38	54.94	4.85***
New Jersey	1129.90	1733.34	614.71	37.83	7.63***
New Mexico	1839.54	1918.39	77.00	3.72	0.41
New York	1285.78	1771.66	489.21	30.05	9.13***
North Carolina	847.15	1431.93	573.32	43.86	10.64***
North Dakota	1528.51	1775.20	239.27	13.99	1.10
Ohio	812.68	1299.49	477.40	39.34	9.40***
Oklahoma	616.39	1175.76	539.48	45.05	6.34***
Oregon	1555.05	2648.53	1096.40	38.95	6.31***
Pennsylvania	917.98	1536.99	611.23	41.01	10.55***
Rhode Island	1817.35	1907.89	115.09	7.50	0.32
South Carolina	759.06	1412.09	637.41	49.70	4.50***
South Dakota	879.66	1623.59	743.93	47.79	6.45***
Tennessee	900.58	1347.71	444.91	33.44	7.06***
Texas	1221.61	1561.81	350.81	22.54	10.61***
Utah	1019.35	2144.66	1159.16	52.39	11.25***
Vermont	474.82	1581.17	1087.70	74.76	4.89***
Virginia	1098.43	1607.11	513.80	34.22	6.09***
Washington	1484.67	2699.57	1214.69	44.35	10.65***
West Virginia	439.66	1138.84	685.06	62.65	4.62***
Wisconsin	681.11	1403.17	718.14	53.81	9.75***
Wyoming	783.18	1913.53	1130.35	59.74	2.87***
Mean	**1210.60**	**1790.46**	**579.28**	**33.64**	
(Median)	**(731.02)**	**(1743.29)**	**(825.23)**	**(54.28)**	

likely to be highly correlated with the overall distribution of companies across states. We compute the second measure of benchmark target weights for states using the distribution of Compustat firms. The Compustat benchmark weights tend to be a reflection of the sample target weights in a state. Not surprisingly, the results are very similar whether we use the sample of target firms or Compustat firms. For almost all the states, the measure for degree of home state bias is qualitatively indistinguishable whether we use sample targets or Compustat to determine benchmark weights.

In order to verify the generality of these patterns, we conduct further robustness checks across deal size quintiles. It may be expected that smaller acquirers who do not have the resources to make big acquisitions find it unfeasible to take over, monitor and integrate distant targets. Additionally, small targets may not provide sufficient synergies that offset cost of a distant acquisition. So, the size of both acquirer and target may play a crucial role in determining whether an acquirer displays proximity preference. We use deal size as a proxy for size effects of firms. Interestingly, 32% of acquisitions in the smallest size quintile (mean deal size= $13 mill) are in-state, while 30% in the largest size quintile (mean deal size= $1,999 mill) are in-state, the difference being statistically insignificant. Our evidence indicates that home bias is displayed across the spectrum of deal sizes.

A caveat is in order when we interpret the results of state-level home bias in Table 4.2. The benchmark weights used do not adjust for industrial agglomeration. In the extreme case where most industries are clustered into a limited geographical space, the proximity preference observed may be simply due to the higher likelihood of potential targets being clustered around an acquirer in the same industry. Our following empirical tests attempt to capture the impact of industrial agglomeration and whether this explains the observed home bias in M&A deals.[22]

Table 4.3. reports the local bias measures based on geographical distance between acquirers and targets, following the methodology of Coval and Moskowitz (1999). For ease of reporting, we use states as units of observation by aggregating acquiring firm bias measures to the corresponding domicile state level. We compute ex-ante benchmark distance of targets from acquirers both as unadjusted and industry-adjusted measures. The unadjusted benchmark distance for an acquirer is the mean distance of an acquiring firm from all target firms in the sample. The unadjusted local bias (*LB*) measures are the difference in actual and unadjusted benchmark distance. The *LB* measures are significant at the 1% or 5% level for most states, except Alaska, Delaware, Idaho, New Mexico, North Dakota, Rhode Island and Wyoming. In terms of significant *LB* (%) measures, the states showing highest bias (excluding Hawaii) are Vermont, West Virginia, Louisiana and Indiana. Among the states showing least local bias are Massachusetts, Arizona, Minnesota and Colorado. On an average, acquiring firms show a local bias of 685 km (36% of benchmark distance) while choosing targets. In other words, actual targets acquired by firms are on an average 685 km (≈ 425 miles) nearer than the benchmark target in the sample.

In Table 4.3., the industry-adjusted benchmark distance for an acquirer is computed as the mean distance between all targets in the sample having matching 2-digit SIC codes with the target acquired. In effect, this benchmark captures the ex-

[22] In unreported results we also replicate Table 2 using benchmark weights for each industry (based on 2-digit SIC and GICS) in each state, and the results are similar to the unadjusted results. However, these empirical tests were not amenable to presenting as a concise table that could be intuitively interpreted.

ante expected distance of a potential target from an acquirer making an acquisition in the target's industry. While for most states the industry-adjusted local bias is smaller than the corresponding unadjusted measure, for 13 states it is in fact larger than the unadjusted local bias. On an average, acquiring firms display an industry-adjusted local bias of around 580 km (33% of benchmark distance). Perhaps surprisingly, while the mean values for *LB* are smaller for industry-adjusted benchmarks compared to unadjusted *LB,* but the median values (825 km and 600 km respectively) are much higher. Even within one target industry, acquirers choose targets that are significantly more proximate than the average target in the sample. Alternatively, we also used the Global Industry Classification System (GICS) industry classifications to match targets in the sample while computing benchmarks and the results remain robust to which classification system is used.[23] These results do not support the notion that industrial agglomeration satisfactorily explains the tendency for localized choice of target firms in M&A deals.

As another dimension for benchmark adjustment, we ran robustness checks with size-adjusted benchmark distance. While we cannot directly observe the target size (due to presence of private targets in the sample), deal size is a good reflection of target size. We rank the deals in our sample into size quintiles. For each acquirer, we compute benchmark distance as the mean distance of the firm from all target firms in the same size quintile as the target actually acquired. The results for size-adjusted

[23] GICS is a system developed by Morgan Stanley Capital International (MSCI) and Standard and Poor's (S&P), and was created to form globally applicable standard industry classifications. More information on the GICS classification can be found at http://www.msci.com/equity/gics.html

local bias were qualitatively indistinguishable from the ones reported and we do not present them.

Additional robustness checks to uncover whether industrial clustering drives home bias in M&A are conducted by examining deals involving acquirers and targets from different industries. If industrial agglomeration is the primary cause of what is perceived as home bias in M&A, then the subsample of related (i.e., same industry) deals should be driving the findings. We replicate the measures reported in Table 4.2. and 3 for the subsample of acquisitions that involve acquirers and targets which do not have two-digit matching SIC codes.[24] These deals can be viewed as "conglomerate" acquisitions involving firms from different industries. This includes about 40% of the 10,342 deals in the full sample used in our study. The results were similar for the subsample of unrelated deals, with slightly lower local bias than that documented for the full sample. However, both measures of home bias continue to be significantly positive, and the difference from the full sample results is not dramatic.

In summary, the significantly positive home bias shown by acquiring firms during M&A activity is not sufficiently explained by industrial agglomeration and pertains to intra- as well as inter-industry deals. The clustering is not limited to the economically dominant states within the U.S. However, there also exist considerable variations in the degree of home bias across acquiring firms. Considering the negligible role of speed of information gathering in M&A and corporations' higher capacity to incur search costs as compared to most portfolio investors, these findings may indicate a stronger and more compelling proximity preference in corporate M&A investments.

[24] We cross-check the results using GICS industry classifications.

On the other hand, given that M&A is an investment in real assets by an acquirer, necessary post-deal monitoring by the acquirer may be facilitated when the target is geographically proximate. In the following sections of the paper, we seek to uncover some of the factors that may give rise to the contours in the economic geography of M&A and influence the propensity of acquiring firms to display proximity preference in choosing targets.

4.4. Factors Affecting Home Bias in M&A

The considerable proximity preference in corporate investment decisions vis-à-vis domestic M&A, documented in section 4.3., may be driven by several different factors. The evidence in previous sections also uncovers substantial cross-sectional variations in the degree of home bias that acquiring firms show in their choice of target firms. An understanding of the factors that cause these variations sheds light on the drivers of M&A in general, and the determinants of home bias in domestic M&A activity in particular. Additionally, identifying the factors that impact the choice of M&A investments facilitates a deeper understanding of the decision-making processes in other forms of corporate investment.

We identify some factors that are potentially related to home bias and are divided into six categories: (1) economic environment, (2) legal environment, (3) herd behavior, (4) acquiring firm characteristics, (5) target firm characteristics, and, (6) deal characteristics. While the first three categories of factors are related to factors external to the firms, the remaining factors capture firm-specific situations. We do not treat the potential drivers of home bias as mutually exclusive, since the existence of one cause of home bias does not preclude other factors also amplifying this phenomenon. In this section we discuss the hypotheses related to various factors that may have a relationship with the geographical distribution of M&A.

4.4.1. Economic opportunities: State economies

The degree of development and growth where a firm is located can be among the primary factors affecting the propensity of localized business exchanges. The economy of a state is an indication of the size of the market of potential targets in the state. Therefore, an acquirer located in a large state has a bigger choice set of attractive target firms which are geographically proximate. In effect, larger states can induce spatial clustering in M&A deals of firms located in the state.

We use state GSP (Gross State Product) as the measure of a state's economic size. The GSP is the sum of three components: compensation of employees, indirect business tax and non-tax liability (IBT), and property-type income. It provides the most aggregate measure of a state economy, and is computed as the sum of value added in production in each industry by the labor and property located in the state. An industry's GSP is conceptually equivalent to its gross output (sales or receipts and other operating income, commodity taxes, and inventory change) minus its intermediate inputs (consumption of goods and services purchased from other U.S. industries or imported). By definition, GSP is equivalent to the Gross Domestic Product (GDP) at the national level. We expect that an acquirer's tendency to choose proximate targets will be positively impacted by the GSP of the state where it is located.

4.4.2. Environment: State antitakeover laws

Antitakeover laws are one aspect of law that can substantially impact domestic M&A activity. In general, antitakeover mechanisms are viewed as being detrimental to shareholders. Legal research shows a strong consensus about the heterogeneity of state antitakeover regimes. Between the years 1980 to 1987, there was effectively no antitakeover legislation at the state or federal levels. Most standard antitakeover statutes, also known as the "second generation" statutes, have been adopted by states after 1987 when the Supreme Court upheld the Indiana law.[25]

Table 4.4. lists the standard antitakeover statutes adopted by the states and the years in which they became effective. There are five standard antitakeover statutes that can be adopted by states: control share, fair price, freezeout, poison-pill endorsement and constituency. Appendix A describes each of these antitakeover statutes. Some of these statutes, like poison-pills, are rarely used in most states other than Delaware, but they signal to the acquirer that the target is legally authorized to use these defensive tactics and therefore, contributes to defining the legal regime.[26] A

[25]Refer Romano (1992) for more information on the adoption of antitakeover statutes.

[26] Bebchuk and Ferrell (2002) note that Delaware is the only state that has a well-developed case law on the use of poison-pill defensive tactics.

Table 4.4.
State Antitakeover Statutes

The table reports state-level antitakeover law characteristics. The year of endorsement of the five standard antitakeover statutes are reported. *Constituency* statute requires a potential acquirer to win approval from a majority of outstanding disinterested shares, before it is allowed to acquire control of the target firm. *Control Share* Requires a potential acquirer to win approval from a majority of outstanding disinterested shares, before it is allowed to acquire control of the target firm. *No. Freezeouts p*rohibits acquirers, under certain conditions, from merging with the target for a certain number of years (typically 3-5 years). *Fair Price* ensures that acquirers do not pay a premium for control of the target and then after acquiring control, buy remaining shares at lower prices. *Poison Pill* explicitly authorizes use of poison pills as a defensive tactic by the target firm. *Number of Statutes* is the total number of statutes endorsed by the state.

State	*Effective Year of Statute*					*Freezeouts (# years)*	*Number of Statutes*
	Constituency	*Control Share*	*No. Freezeouts*	*Fair Price*	*Poison Pill*		
Alabama						0	0
Alaska						0	0
Arizona	1987	1990	1987	1987		3	4
Arkansas						0	0
California						0	0
Colorado					1989	0	1
Connecticut	1997		1988	1985		5	3
D. of Columbia						0	0
Delaware			1987			3	1
Florida	1990	1987		1987	1990	0	4
Georgia	1989		1988	1985	1989	5	4
Hawaii	1989	1985			1988	0	3
Idaho	1988	1988	1988	1988	1988	3	5
Illinois	1985		1989	1985	1989	3	4
Indiana	1989	1986	1986	1986	1986	5	5
Iowa	1989		1997		1989	3	3
Kansas		1988	1989			3	2
Kentucky	1989		1988	1988	1984	5	4
Louisiana	1988	1987		1984		0	3
Maine	1986		1988			5	1
Maryland	1999	1989	1989	1983	1999	5	5
Massachusetts	1989	1987	1989		1989	3	4
Michigan		1988	1984	1984		5	3
Minnesota	1987	1987	1987	1991		4	4
Mississippi	1990	1991		1985		0	3
Missouri	1986	1987	1986	1986		5	4
Montana						0	0
Nebraska		1988	1988			5	2
Nevada	1991	1987	1991	1991	1989	3	5
New Hampshire						0	0
New Jersey	1989		1986	1986	1989	5	4
New Mexico	1987					0	1
New York	1987		1985	1985	1986	5	4
North Carolina		1987		1987	1990	0	3

Table 4.4. (contd.)

State	*Effective Year of Statute*					*Freezeouts (# years)*	*Number of Statutes*
	Constituency	*Control Share*	*No. Freezeouts*	*Fair Price*	*Poison Pill*		
North Dakota	1993					0	1
Ohio	1984	1982	1990	1990	1986	3	5
Oklahoma		1987	1991			3	2
Oregon	1989	1987	1991		1989	3	4
Pennsylvania	1990	1990	1988	1988	1989	5	5
Rhode Island	1990		1990	1990	1990	5	4
South Carolina		1988	1988	1988		2	3
South Dakota	1990	1990	1990	1990	1990	4	5
Tennessee	1988	1988	1988	1988	1989	5	5
Texas			1997			3	1
Utah		1987			1989	0	2
Vermont	1998					0	1
Virginia		1989	1988	1988	1990	3	4
Washington			1987	1987	1998	5	3
West Virginia						0	0
Wisconsin	1987	1986	1987	1987	1972	3	5
Wyoming	1990	1990	1989			3	3

higher number of statutes in place provide more legal channels for target firm managers to resist takeovers if they choose to, making it less shareholder-friendly. For example, while California has maintained its pro-shareholder stance over the decades and not endorsed any antitakeover statutes, states like Ohio and Pennsylvania are viewed as having strong antitakeover legal environments with all five statutes in place since 1990. As a consequence, the heterogeneity in state antitakeover laws can cause segmentation of the legal regimes affecting domestic M&A activity.

Acquirers that are prone to display home bias in the absence of other offsetting effects may be driven to out-of-state acquisitions if the home state's laws provide higher protection to target firm's management. The expected difficulties for the acquirer may be higher if the target is from a stronger antitakeover legal regime. These expected and realized costs can be especially high when the deal is not friendly or solicited. So, quite intriguingly, heterogeneity in antitakeover laws can possibly have the unexpected effect of offsetting geographical clustering of M&A.

In summary, we expect that higher legal protection of a potential target firm's management from takeovers in the acquirer's state, in the form of more potent antitakeover regimes, will decrease the propensity for in-state M&A. Strong antitakover laws in the acquiring firm's state, therefore, may mitigate home bias during takeover decisions.

4.4.3. Herd behavior: Competitive responses

Scharfstein and Stein (1990) develop among the first models on herd behavior among managers and its potential implications for various aspects of finance like corporate investment, stock markets, and intra-firm decision making. In their model, managers tend to mimic each others' decisions because a manager is less likely to be penalized for a wrong strategy when other managers in the industry also followed the wrong strategy (i.e., a "sharing-the-blame" effect is implied). Morck, Shleifer and Vishny (1989) find empirical evidence suggesting that corporate boards are inclined to assign blame to the manager if the poor performance is relative to the industry, rather than when there is industry-wide underperformance.

Herd behavior has distinct implications for M&A decision making by managers. In the context of localized M&A, whether or not a manager is predisposed to display home bias in choosing a target, she may tend to herd towards the behavior of other managers in the industry. In light of the existing literature on herding, the manager is less likely to be questioned for her strategies if other managers in the industry are following the same strategy. This herding effect may be exaggerated for the managers geographically located near each other and operating in the same industry since they are more likely to be compared to each other by an overlapping shareholder base and local media. Alternatively, proximately located managers may be more likely to be influenced by each others' strategies due to interactions via social or business networks, and a "keeping-up-with-the-Joneses" effect might be in play. An example of same-city effects in portfolio investments is Hong, Kubik and Stein (2005) who find that money managers located in the same city tend to buy and sell the same stocks, interpreted as word-of-mouth effects in trading behavior. In our context, competitive strategies of firms may be more correlated at the local rather than the national level.

In summary, if there is a herding tendency of managers in the manner in which they choose targets, they are more likely to conduct localized M&A when other managers who form the peer group display a propensity to choose local targets. This correlated behavior is likely to be more enhanced for managers in the same industry located in geographical proximity. We construct two home bias measures for the peer group of an acquirer: (1) the ratio of the number of in-state acquisitions conducted by same-city, same-industry managers to the total number of acquisitions by same-city, same-industry managers, (2) the ratio of the number of in-state acquisitions conducted by other-city, same-industry managers to the total number of acquisitions by other-city, same-industry managers, in the year of the acquisition announcement. By "other-city" we mean firms located in any city other than the headquarter location of the acquirer.[27] These home bias measures are unadjusted since they do not capture the notion of "abnormal" proximity preference over and above the benchmark based on industrial agglomeration in the acquirer's industry. An alternative adjusted measure of peer group proximity preference is constructed using geographical distance between acquirer and target, a framework more amenable to measuring 'bias'. We use the industry-adjusted local bias measures as presented in Table 4.3., where the benchmark expected distance is based on the portfolio of sample targets in the same industry as the actual target. For the peer groups' local bias, we then use the following measures: (1) the natural logarithm of the mean local bias (in km) of same-city, same-industry acquiring firm managers, (2) the natural logarithm of the mean local bias (in km) of other-city, same-industry acquiring firm managers. We primarily use 2-digit SIC codes as industry classifications for industry matching, and also verify results using the GICS system.

4.4.4. Acquirer characteristics: Resources, growth and risk attitudes

A number of acquirer firm-specific factors can help explain the propensity to display home bias in its corporate investments. Factors like business resources, growth prospects and financial slack can all affect the degree to which geography impacts a firm's decisions and also the proclivity of acquirers to search for attractive targets irrespective of geography. To the extent that distant targets are associated with

[27] We also conduct robustness tests by including only cities in other states, and not other cities in the same state as the acquirer.

a higher perceived or real information asymmetry, risk attitudes of the acquirer may rationally play a role in the choice of targets when higher information asymmetry is related to higher perceived risk. Some firm characteristics, in conjunction with macroeconomic conditions, may proxy for the overall risk attitude of an acquiring firm and arise out of the contemporaneous business conditions in the economy and the financial health of the firm. Firm characteristics are also related to the cost of capital for a firm, and its willingness to incur search costs and pursue investments perceived as more risky. Firm characteristics may therefore explain some of the cross-sectional variation in the degree of home bias.

Firstly, the size of an acquirer is likely to have a significant effect on home bias. Large firms tend to be less localized in their product markets as well as their human capital. These firms are likely to have access to a wider social network and infrastructure through which they can obtain information generated from geographically distant sources. Additionally, larger firms may also be more willing to incur search costs that are related to geographical distance in order to obtain business information. Therefore, we expect geography to pose fewer obstacles during the corporate decisions made by large firms as compared to smaller firms. We use the total market capitalization of the acquirer in the month prior to the acquisition announcement as a measure of the firm size, and expect a negative impact of firm size on home bias of the acquirer during takeovers.

Secondly, the strategic considerations during M&A can be significantly different for value versus growth firms. High-growth acquirers may be more likely to seek small high-growth targets as compared to value firms. These growth targets have assets that are less tangible and give rise to higher information asymmetries between firm insiders and outsiders, on average. Geographical distance from the target can further exacerbate these information asymmetries. Growth targets are also more likely to require close monitoring. Therefore, proximity to the target firm is a mechanism by which acquirers can alleviate information asymmetries through social or business networks and interaction and facilitate monitoring. Additionally, growth firms may also be more likely to acquire same-industry targets than value firms with limited growth opportunities, leading to a higher likelihood of proximate M&A in presence of industrial clustering for growth acquirers. We expect that high book-to-market firms (i.e, value firms) show less home bias compared to low book-to-market firms (i.e, growth firms) in M&A decisions.

Finally, we examine the impact of the extent of debt in an acquirer's capital structure on home bias in M&A decisions. Highly leveraged firms are more likely to exercise financial caution and be more risk-averse relative to firms with low debt in their capital structure. The takeover of a distant target potentially associated with more information asymmetry between the acquirer and target may be perceived as a risky investment by highly-leveraged acquiring firms. Therefore, these acquirers may decide to make an acquisition when they are more confident about their knowledge of a potential target firm. We hypothesize that leverage has a positive impact on the home bias of an acquirer, where leverage is measured as the ratio of total assets minus the book value of equity to the total assets.

4.4.5. Target characteristics: Information asymmetries and growth

We hypothesize that some target characteristics may be important factors that impact the likelihood of the firm being acquired by a proximate acquirer. Unfortunately, data available for the target firms is limited since our sample comprises of public as well as private targets. Financial data on target firms is available only for the subsample of publicly traded targets and our analyses cannot be conducted for the full sample.

Among the publicly traded targets, we may expect the smaller firms to be less visible and associated with less information availability. We hypothesize that, in the subsample of public targets, smaller firms are more likely to be acquired by proximate acquirers who have prior familiarity with these firms.

The second target characteristic we examine is the firm’s book-to-market ratio. Previous studies have shown the considerable differences in performance and operations of value versus growth firms. Growth targets may be associated with more information asymmetry, exacerbated with geographical distance between the acquirer and target. However, acquiring firms looking for high-growth target firms may also be more inclined to incur search costs, thereby offsetting the impact of a priori information asymmetries.

Lastly, we examine the impact of a target firm’s leverage on likelihood of proximate deals. Coval and Moskowitz (1999) find that fund managers exhibit strong proximity preference especially for highly levered firms. They argue that local knowledge may be especially valuable while investing in these firms. Analogously, in case of M&A, we conjecture that acquirers exploit local knowledge and familiarity more while acquiring highly-levered target firms.

4.4.6. Deal characteristics: Information asymmetries and familiarity

Deal characteristics in M&A, like deal attitude and method of payment, among others, are likely to be influenced by the degree of information asymmetry and relationship between the acquiring firm and the target prior to the deal. However, geographical distance between the firms influences the degree of information asymmetry or prior familiarity between an acquirer and a target. Given that similar factors may help define the spatial distribution of M&A as well as the deal characteristics, we expect a significant relationship between geographical proximity of a target to the acquirer and the nature of the deal, without any assumptions about causality. For example, to the extent that firms cluster due to 'industry-specific' technical and knowledge spillovers, acquisitions in the same industry are more likely to take place proximately. Some of the deal characteristics we examine in our empirical investigation are the public vs. private nature of the target, relatedness of the firms, method of payment, hostile vs. friendly attitude and whether a tender offer was extended by the acquirer.

4.4.7. Macroeconomic control variables

Macroeconomic conditions can proxy for the component of firm management's attitude towards risk that is influenced by the overall business environment. We may expect that stronger macroeconomic conditions increase risk-taking propensity of the acquiring firm's management, and make them more tolerant of potential search costs and screening costs of identifying attractive targets. Additionally, macroeconomic conditions may impact cost of capital and consequently the nature of corporate investments. Therefore, we include S&P500 stock index returns and prime interest rates as macroeconomic control variables in our regressions.

Additionally, there can be time trends in the degree to which information asymmetry plays a role in driving home bias. Peterson and Rajan (2000) find that distance is playing a decreasing role in small business lending activity, primarily due to advancement in communication technologies and decrease in information asymmetry associated with distance. The revolution in communication technology has affected almost all business sectors, albeit perhaps to different extents. To examine whether there is a time trend in the role played by distance in M&A deals, we regress the mean distance between acquirers and targets involved in M&A deals each quarter during 1990-2004 with the macroeconomic conditions and a time variable. The estimated OLS regression is (p-values are in parentheses):

$$\begin{aligned}\mathbf{(Mean\_Dist)}_t = 7541 + \underset{(0.00)}{6.80}\mathbf{^*\,(Time)} + \underset{(0.74)}{80.90}\mathbf{^*\,(S\,\&\,P500Ret(12\text{-}mth))}_t \\ + \underset{(0.05)}{3374}\mathbf{^*\,(InterestRate)}_t\end{aligned} \qquad (2)$$

Here, **Time** is the quarter time variable, taking values 1, 2,..,56 for the years 1990-2003. The R-square for the regression is 3%. The co-efficient of the time variable is positive and significant, indicating an increasing trend in mean distance over time. The estimated regression shows that, *ceteris paribus*, the mean distance between acquirers and targets increases by 374 (=6.8x56) kilometers during the 14 years between 1990 and 2003. This evidence is consistent with decreasing information asymmetry over time due to improvements in communication technology and decreasing transportation costs. We use simple year dummy variables to control for time trends in information asymmetry due to communication and transportation costs.

4.5. Regression Results

We conduct empirical tests to identify some of the determinants of the proximity preference in corporate M&A that has been documented in earlier sections. Our empirical analyses use two alternative dependent variables measuring acquirer's propensity to show home bias. The first measure is a dichotomous variable indicating the in-state versus out-of-state nature of the target firm relative to the acquirer. The second measure is based on the geographical distance between the acquiring firm's city of headquarters and target's city of headquarters.

4.5.1. Propensity for In-state M&A: Logistic Regressions

Table 4.5. presents the state economy, state-level antitakeover laws and herding effects as determinants of home bias in acquirers. In these logistic regressions, we use the binary outcome of in-state versus out-of-state M&A as the dependent variable. The dependent variable assumes a value of one when the target is headquartered in the home state of the acquiring firm, and zero otherwise. We report the estimated coefficients of the explanatory variables and their marginal effects, with all other independent variable is held at median values. We also include announcement year-, state- and industry-fixed effects. The baseline regressions separately include each category of factors that have been outlined in section 4.4. with macroeconomic control variables and appropriate fixed-effects, and finally with all variables together.

The coefficient of state GSP is positive and highly significant at the 1% level, indicating that in-state M&A is more likely when the acquirer is located in a state with a large economy, as reflected in a larger GSP. A one standard deviation increase in GSP increases a home state acquirer's home bias by around 29%. Larger states have more companies headquartered in the state and offer more opportunities for a potential acquirer, thereby augmenting localization of M&A.

Antitakeover statutes have a negative and significant impact on the likelihood of in-state acquisitions. A one standard deviation change in number of antitakeover statute endorsed by a state decreases the likelihood of in-state M&A by 3.6%. The dummy variables for each of the standard antitakeover statutes are negative and significant in most specifications. The evidence supports the hypothesis that stronger antitakeover laws partially nullify home bias by making targets in the state less

Table 4.5.
Propensity for In-state M&A: Effects of Macroeconomic Conditions, State Law and Herd Behavior

The dependent variable in the logistic regressions is the dummy variable (*In-state*) which assumes a value of one if the target is headquartered in the same state as the acquirer, and value of zero otherwise. *Log (GSP)* is the natural logarithm of the acquirer state's Gross State Product in $million in the year when the acquisition is announced. *No. of Antitakeover Statutes* is the number of antitakeover statutes that have been endorsed by the acquirer state. There are five types of standard antitakeover statutes. *Control Shares Statute* is a dummy variable with value one when the state endorses a statute which requires a potential acquirer to win approval from a majority of outstanding disinterested shares, before it is allowed to acquire control of the target firm, and value of zero otherwise. *Fair Price Statute* is a dummy variable with value one when the state ensures that acquirers do not pay a premium for control of the target and then after acquiring control, buy remaining shares at lower prices, and assumes a value of zero otherwise. *No Freezeouts Statute* is a variable with values 0, 3 or 5, indicating the number of years for which the state prohibits acquirers, under certain conditions, from merging with the target. This variable has value zero when the state has not adopted a no-freezeouts statute, and otherwise indicates the number of years for which the prohibition holds in the statute. *Poison Pill Statute* is a dummy variable with value one when a state endorses poison-pills as defensive tactics, explicitly authorizing the use of these tactics by the target firm, and has value zero otherwise. *Constituencies Statute* is a dummy variable with value one when a state authorizes the target's management to use defensive tactics in the name of non-shareholder constituencies, such as employees etc., and has value zero otherwise. *Home Bias of Same City Mgrs.* is computed as (No. of Instate Acquisitions)/(Total No. of Acquisitions) conducted by same industry (matched by 2-digit SIC codes) managers headquartered in the same city as the acquirer, in the year that an acquisition was announced. *Home Bias of Other City Mgrs.* is computed as the (No. of Instate Acquisitions)/(Total No. of Acquisitions) conducted by same industry (matched by 2-digit SIC codes) managers not headquartered in the same city as the acquirer, in the year that an acquisition was announced. *S&P500 Ret.(12-month)* is the twelve-month compounded return on the S&P500 composite index prior to the month of acquisition. *Interest Rate* is the annual average interest rate in year t. $\%\Delta p$ is the marginal effect measured as percent change in the probability of occurrence of the dependent variable (at median values for all variables excluding dummy variables which are discrete). [a, b, c] denote significance at the 1%, 5% and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Independent Variables	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.
	[%Δp]	[%Δp]	[%Δp]	[%Δp]	[%Δp]	[%Δp]	[%Δp]	[%Δp]	[%Δp]	[%Δp]
Intercept	-10.62[a]	-1.04[a]	-1.05	0.26	-1.01	-1.00	-1.03	-1.05	-0.97	-0.99[a]
Log (GSP)	1.52[a]									1.23[a]
	[29.28]									[24.95]
No. of Antitakeover Statutes		-0.18[a]								-0.10[a]
		[-3.57]								[-2.04]
Control Shares Statute			-0.48[a]					-0.29[a]		
			[-10.96]					[-5.72]		
Fair Price Statute				-0.59[a]				-0.26[a]		
				[-13.06]				[-5.78]		
No. Freezeouts Statute					-0.12[a]			-0.06[a]		
					[-2.67]			[-1.34]		
Poison Pill Statute						-0.46[a]		-0.06		
						[-10.57]		[-1.37]		
Constituencies Statute							-0.52[a]	-0.04		
							[-11.78]	[-0.79]		
Home Bias of Same City Mgrs.									1.14[a]	1.39[a]
									[26.06]	[28.04]
Home Bias of Other City Mgrs.									-0.73[a]	-0.70[a]
									[-16.67]	[-14.18]
S&P500 Ret.(12-month)	0.05	0.01	-0.02	-0.02	0.02	-0.02	0.02	0.01	0.17	0.11
	[0.97]	[0.15]	[-0.55]	[-0.39]	[0.48]	[-0.41]	[0.38]	[0.15]	[3.97]	[2.15]
Avg. Interest Rate	0.15[a]	0.09[b]	0.09[b]	0.09[b]	0.09[b]	0.08[b]	0.08[b]	0.09[b]	0.08	0.11[b]
	[2.97]	[1.75]	[2.15]	[2.06]	[1.92]	[1.82]	[1.78]	[1.94]	[1.74]	[2.23]
Ann. Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo-R^2 (%)	10.70	8.14	7.22	7.63	7.45	7.20	7.41	8.17	14.29	12.76
No. of Obs.	10,323	10,323	10,323	10,323	10,323	10,323	10,323	10,323	7,351	7,408

attractive to home state acquirers. Therefore, antitakeover laws have the unexpected effect of mitigating the tendency of acquiring firms to exhibit home bias.

We find a positive and highly significant coefficient on the same-city, same-industry peer group's tendency towards home bias. The propensity of managers in the same city and industry as an acquirer to choose in-state targets increases the acquirer's likelihood of acquiring an in-state target, and is consistent with our hypothesis on herding behavior. A 30%, or one standard deviation, increase in the same-city, same-industry managers' degree of in-state acquisitions relative to total acquisitions increases the acquirer's likelihood of in-state M&A by 26%. The industry fixed effects are included to separate the impact of herding in in-state acquisitions from the effect of localization in M&A due to agglomeration in certain industries and other industry-wide strategic considerations. These results hold both for 2-digit SIC (reported in Table 4.5.) and GICS (unreported) codes used for classifying acquirers into industries. We also find a negative and significant effect of other-city, same-industry managers' propensity to conduct localized acquisitions when we use 2-digit SIC codes for industry classification.[28] However, these results for other-city, same-industry managers are not robust to the industry classification system used. The coefficient becomes insignificant when GICS codes are used to classify acquirer industries. So, we do not find any strong evidence to support the idea that herding exists in the propensity for home bias among acquirers located in different cities. In further unreported robustness checks, the results remain similar when we drop all cities

[28] While this finding is somewhat puzzling, it may in some way reflect the location of good acquisition opportunities for acquirers. If other-city acquirers are choosing local targets, it may indicate that greater economic opportunities are located near these other cities. So, acquirers distant to these cities may also seek out attractive targets in these other cities, thereby causing the observed negative relationship in the tendency for localized M&A.

located in the same state as the acquirer while considering other-city managers. Additionally, we did not observe any herding among acquirers not operating in the same industry whether located in the same city or not, and we do not present these results. Interestingly, this evidence suggests that location of an acquirer matters more in herding behavior than the acquirer industry.

Table 4.6. reports regressions examining the relationship between firm characteristics, deal characteristics and likelihood of in-state acquisitions. The coefficient of acquirer size is negative and significant at the 1% level for all specifications, including regressions controlling for year, state and industry fixed effects. Larger acquiring firms are more geographically diversified in their infrastructure, networks and markets. They are also more likely to be prepared to incur potential search costs associated with obtaining information about distant and unfamiliar targets. The negative impact of size on proximity preference substantiates these notions. The results for acquirer book-to-market ratio indicate that value firms exhibit lower proximity preference than growth firms, as reflected in the negative and significant coefficients in three of the four model specifications including the variable. Acquiring firm's debt in capital structure, on the other hand, has a significantly positive impact on the propensity for in-state acquisitions, at 1% level of significance in almost all specifications of the regression model. If distant targets are associated with higher information asymmetries and perceived risk, a financially cautious acquirer will be more averse towards distant deals. The estimated regression

Table 4.6.
Propensity for In-state M&A: Firm and Deal Characteristics

The dependent variable in the logistic regressions is the dummy variable (*In-state*) which assumes a value of one if the target is headquartered in the same state as the acquirer, and value of zero otherwise. *Acquirer Log (MV)* is a measure of the acquirer size and is the natural logarithm of the market value (in $mill) of the acquiring firm in the month prior to the acquisition announcement. *Acquirer Log(BE/ME)* is the natural logarithm of the ratio of book-value of equity to market-value of equity of the acquirer in the month prior the acquisition announcement. *Acquirer Debt/Assets* is a ratio of debt to total assets of acquirer. *Target Public Dummy* is a dummy variable assuming a value of one if the target is publicly traded, and zero otherwise. *Related Dummy* is a dummy variable assuming a value of one if the acquirer and target have the same two-digit SIC code, and zero otherwise. *Cash Dummy* is a dummy variable assuming a value of one if the method of payment is 100% cash, and zero otherwise. *Hostile Dummy* assumes a value of one is the deal attitude is stated as hostile, and zero otherwise. *Tender Dummy* assumes a value of one if the acquirer made a tender offer, and zero otherwise. *Log(Deal Value)* is the natural logarithm of the value of the deal in $million. *Target Log (MV)* is a measure of the target size and is the natural logarithm of the market value (in $mill) of the target firm in the month prior to the acquisition announcement. *Target Log(BE/ME)* is the natural logarithm of the ratio of book-value of equity to market-value of equity of the target in the month prior the acquisition announcement. *Target Debt/Assets* is a ratio of debt to total assets of target. *Log (GSP)* is the natural logarithm of the acquirer state's Gross State Product in $million in the year when the acquisition is announced. *No. of Antitakeover Statutes* is the number of antitakeover statutes that have been endorsed by the acquirer state. *Home Bias of Same City Mgrs.* is computed as the (No. of Instate Acquisitions)/(Total No. of Acquisitions) conducted by same industry (matched by 2-digit SIC codes) managers headquartered in the same city as the acquirer, in the year that an acquisition was announced. *Home Bias of Other City Mgrs.* is computed as the (No. of Instate Acquisitions)/(Total No. of Acquisitions) conducted by same industry (matched by 2-digit SIC codes) managers not headquartered in the same city as the acquirer, in the year that an acquisition was announced. *S&P500 Ret.(12-month)* is the twelve-month compounded return on the S&P500 composite index prior to the month of acquisition. *Avg. Interest Rate* is the annual average interest rate in year t-1. $\%\Delta p$ is the marginal effect measured as percent change in the probability of occurrence of the dependent variable (at median values for all variables excluding dummy variables which are discrete).

Independent Variables	(1) Co-eff. [%Δp]	(2) Co-eff. [%Δp]	(3) Co-eff. [%Δp]	(4) Co-eff. [%Δp]	(5) Co-eff. [%Δp]	(6) Co-eff. [%Δp]
Intercept	1.77	0.54	-0.95	-1.91[c]	0.36	-3.21[b]
Acquirer Log(MV)	-0.19[a]			-0.20[a]	-0.19[a]	-0.19[a]
	[-4.47]			[-1.10]	[-3.37]	[-1.25]
Acquirer Log(BE/ME)	-0.07[b]			-0.08[b]	0.13	-0.11[b]
	[-1.58]			[-0.05]	[2.25]	[-0.70]
Acquirer Debt/Assets	0.19			0.14	2.08[a]	1.54[a]
	[4.38]			[0.74]	[5.36]	[7.25]
Target Log (MV)[†]		0.04[c]			-0.05	
		[0.98]			[-0.94]	
Target Log(BE/ME) [†]		0.18[a]			-0.03	
		[4.46]			[-0.53]	
Target Debt/Assets[†]		1.58[a]			0.16	
		[17.33]			[2.71]	
Target Public Dummy			0.34[a]	0.20[a]		0.18[a]
			[5.85]	[1.19]		[1.11]
Related Dummy			0.11[b]	0.05	0.36[a]	0.04
			[1.83]	[0.26]	[5.50]	[0.26]
Cash Dummy			-0.20[a]	-0.00	0.11	-0.06
			[-2.44]	[0.03]	[1.86]	[-0.41]
Hostile Dummy			0.65[b]	0.34	0.23	0.15
			[9.84]	[2.12]	[4.11]	[0.96]
Tender Dummy			-0.26[b]	-0.08	-0.61[a]	-0.22
			[-3.04]	[-0.43]	[-8.75]	[-1.60]
Log(Deal Value)			-0.16[a]			
			[-2.50]			
Log(GSP)						1.41[a]
						[9.26]
No. of Antitakeover Statutes						-0.12[a]
						[-1.57]
Home Bias of Same City Mgrs						0.95[a]
						[6.29]
Home Bias of Other City Mgrs						-1.34
						[-8.86]
S&P500 Ret.(12-month)	0.18	-0.54	-0.41	-0.51	-0.53	-0.15
	[4.24]	[-13.27]	[-11.27]	[-8.27]	[-9.17]	[1.00]
Avg. Interest Rate	0.01	0.15[c]	0.14[c]	0.13[b]	0.11	0.07
	[0.21]	[3.57]	[3.33]	[2.47]	[3.57]	[0.43]
Ann. Year Fixed Effects	YES	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES	NO
Industry Fixed Effects	YES	YES	YES	YES	NO	YES
Pseudo-R^2 (%)	16.32	16.63	13.79	16.44	15.38	15.75
No. of Obs.	6,729	2,390	10,240	6,728	1,635	4,658

results support this notion since highly levered acquirers are likely to exercise more caution and show more home bias.[29]

Some additional acquirer-level variables we examine but do not report are R&D intensity and undistributed free cash flow of acquirers. R&D intensity is measured as the ratio of R&D expenses to assets. Undistributed free cash flows of an acquirer are computed prior to the acquisition announcement following Lehn and Poulsen (1979). These variables may potentially impact the strategic considerations during M&A decisions. However, neither R&D intensity nor free cash flows have a significant impact on proximity preference, and are not reported in the table.

Certain target firm characteristics were studied for the subsample of public targets for which CRSP/COMPUSTAT data was available in the month prior to the acquisition announcement. As expected, size of target has a negative impact on likelihood of an in-state deal. The size variable is significant at the 1% level in Model (2), where acquiring firm characteristics are not included. Larger targets are more visible, have lower information asymmetries and require less search costs incurred by an acquirer prior to a deal. The negative impact of target size on likelihood of proximate deals shows that geography decreases in importance for the acquisition of larger, more visible targets. Targets' leverage variable is significantly positive at the 1% level in Model (2). Highly levered firms may have greater information asymmetries and proximate acquirers potentially have information advantage in assessing these targets. Targets' book-to-market ratio has a significantly positive

[29] We also conduct robustness checks by excluding banks and utility firms which operate in relatively regulated industries with leverage structures that are different from most other industries. However, the results remain unchanged when banks and utility firms are dropped from the regression sample.

coefficient, indicating that value firms are more likely to be acquired by home state acquirers. Based on the need for monitoring, the evidence on target book-to-market ratio is somewhat counterintuitive. Growth targets might need relatively greater monitoring by the acquirer than value targets, and proximate acquirers are more suited for extensive monitoring. Our results may also reflect that acquirers investing in growth are more aggressive in their search for attractive targets, and distance is not considered a crucial factor.

Finally, several deal characteristics show a significant relationship with the geographical proximity of the target firm to an acquirer. While a causal relationship is unlikely, deal characteristics may be related to some common factors that also drive the geographical distribution of M&A activity (e.g, information asymmetry and prior familiarity). In Model (3), several deal characteristics are statistically significant. The variable representing public versus privately-owned status of the target firm is significantly positive at the 1% level. Ceteris paribus, a public target is 5.85% more likely to be acquired by a home state acquirer, as compared to privately-owned target firms. This result may be unexpected in light of the fact that information asymmetries are much lower for publicly traded targets as compared to private targets, making their acquisition less risky for distant acquirers. However, public targets may be more likely to be in-state acquisitions possibly due to political resistance to takeovers of visible firms that are important to a state's economic welfare and visibility.[30] Our evidence supports the latter hypothesis since we find a higher likelihood of in-state acquisition when the target is public. Related acquisitions are around 1.8% more

[30] A recent example is the resistance of the Massachusetts state government to the takeover of Boston-based Gillette by Cincinnati's Proctor & Gamble.

likely to be in-state than out-of-state, potentially driven by industrial agglomeration within regions. Cash payments are around 2.4% more likely for out-of-state acquisitions, supporting the notion that cash is more likely to be used when the information asymmetry about firm valuations is higher. Hostile takeover are 9.8% more likely to be in-state, potentially due to the prior familiarity and information the acquirer has about a proximate target, making the co-operation of the target's management less critical in the post-merger integration phase. Tender offers are about 3% more likely for out-of-state M&A, ceteris paribus. We also include deal value, which is a reflection of target size and is correlated with acquirer size. As expected based on information asymmetries, larger deals are associated with less proximity preference of acquirer, since these are likely to be more visible targets. In model (4) when acquirer characteristics are included with deal variables, only the target's public versus private status dummy remains significant.

In model (5), where acquirer characteristics are included as explanatory variables, target characteristics become insignificant.[31] Interestingly, the acquirer's characteristics seem to be more instrumental in defining home bias in M&A than target firm characteristics. Extrapolating to the area of portfolio investments, this is analogous to the notion that investor characteristics matter more in directing home bias behavior than the characteristics of assets they invest in. Related and tender offer dummies are the only deal characteristics that are significant in this specification.

[31] The target firm characteristics and acquirer characteristics are not significantly correlated, so the regressions including both sets of variables do not suffer from multicollinearity.

In Model (6), we include acquirer characteristics, deal characteristics, state GSP, antitakeover law, herding measures and control variables. Deal characteristics become less important when acquirer characteristics are included in the regression models, except for the public status of a target firm which remains significantly positive. From the various specifications of models reported in Table 4.6., the most important determinants of home bias in M&A are acquirer characteristics, state economic environment, state antitakeover laws and home bias of peer group managers.

4.5.2. Propensity for Local Bias: Multivariate Regressions

Table 4.7. contains multivariate analyses explaining the local bias (in km) displayed by an acquirer in the choice of the target firm during M&A deals. We use the industry-adjusted local bias to factor in industrial agglomeration and are computed using the methodology reported in Table 4.3. The dependent variable is measured as the natural logarithm of the industry-adjusted local bias (in km) of an acquirer. We control for macroeconomic conditions, year-, state- and industry-fixed effects in the different specifications of the model.

Economic size of the home state (GSP) has a positive and highly significant impact on the local bias of an acquirer. Acquirers from larger states with greater business opportunities are less likely to search for and invest in targets that are further away. It is possible that the marginal benefits for these acquirers of finding good targets that happen to be distant is not high enough to justify ignoring proximate

Table 4.7.
Factors Impacting Local Bias of Acquirer

The dependent variable in the regressions is *log(local_bias(km))*, where *local_bias(km)* is the industry-adjusted local bias computed as the difference between benchmark target distance (=mean distance from matched 2-digit SIC as actual target) and actual target distance; logarithm is for natural log. *Log (GSP)* is the natural logarithm of the acquirer state's Gross State Product in $million in the year when the acquisition is announced. *No. of Antitakeover Statutes* is the number of antitakeover statutes that have been endorsed by the acquirer state. *Log(Mean Local Bias Same City Mgrs)* is computed as the natural logarithm of the mean industry-adjusted local bias in all M&A conducted by same industry managers (matched by 2-digit SIC codes) headquartered in the same city as the acquirer, in the year that the acquisition was announced. *Log(Mean Local Bias Other City Mgrs)* is computed as the natural logarithm of the mean industry-adjusted local bias in all M&A conducted by same industry managers (matched by 2-digit SIC codes) headquartered in all cities other than the acquirer's city, in the year that the acquisition was announced. *Acquirer Log(MV)* is a measure of the acquirer size and is the natural logarithm of the market value (in $mill) of the acquiring firm in the month prior to the acquisition announcement. *Acquirer Log(BE/ME)* is the natural logarithm of the ratio of book-value of equity to market-value of equity of the acquirer in the month prior the acquisition announcement. *Acquirer Debt/Assets* is a ratio of debt to total assets of acquirer. *Target Public Dummy* is a dummy variable assuming a value of one if the target is publicly traded, and zero otherwise. *Related Dummy* is a dummy variable assuming a value of one if the acquirer and target have the same two-digit SIC code, and zero otherwise. *Cash Dummy* is a dummy variable assuming a value of one if the method of payment is 100% cash, and zero otherwise. *Hostile Dummy* assumes a value of one is the deal attitude is stated as hostile, and zero otherwise. *Tender Dummy* assumes a value of one if the acquirer made a tender offer, and zero otherwise. *Log(Deal Value)* is the natural logarithm of the value of the deal in $million. *Target Log(MV)* is a measure of the target size and is the natural logarithm of the market value (in $mill) of the target firm in the month prior to the acquisition announcement. *Target Log(BE/ME)* is the natural logarithm of the ratio of book-value of equity to market-value of equity of the target in the month prior the acquisition announcement. *Target Debt/Assets* is a ratio of debt to total assets of target. *S&P500 Ret.(12-month)* is the twelve-month compounded return on the S&P500 composite index prior to the month of acquisition. *Avg. Interest Rate* is the annual average interest rate in year t-1. The table reports t-statistics in parentheses.

Independent Variables	(1) Coeff. (t-stat)	(2) Coeff. (t-stat)	(3) Coeff. (t-stat)	(4) Coeff. (t-stat)	(5) Coeff. (t-stat)	(6) Coeff. (t-stat)	(7) Coeff. (t-stat)
Intercept	3.32[a] (4.08)	5.74[a] (7.13)	6.67[a] (6.38)	7.80[a] (7.45)	5.71[a] (6.21)	7.55[a] (6.86)	4.66[a] (5.68)
Log(GSP)	0.37[a] (13.87)						0.36[a] (10.06)
No. of Antitakeover Statutes		-0.06[a] (-9.74)					-0.05[a] (-6.23)
Log(Mean Local Bias Same City Mgrs)			0.01[a] (2.75)				0.01[a] (2.66)
Log(Mean Local Bias Other City Mgrs)			0.03 (0.33)				0.01 (0.87)
Acquirer Log(MV)				-0.03[a] (-4.16)			-0.05[a] (-5.51)
Acquirer Log(BE/ME)				-0.02 (-1.30)			-0.05[a] (-3.12)
Acquirer Debt/Assets				0.13[c] (1.90)			-0.05 (-0.67)
Target Public Dummy					0.05[b] (2.01)		0.04[c] (1.92)
Related Dummy					0.01 (0.48)		0.02 (0.56)
Cash Dummy					-0.02 (-0.95)		0.04 (1.20)
Hostile Dummy					0.15 (1.61)		0.25[c] (1.76)
Tender Dummy					-0.01 (-0.22)		0.00 (0.08)
Log(Deal Value)					-0.03[a] (-4.32)		
Target Log(MV)[†]						0.01 (1.46)	
Target Log(BE/ME)[†]						0.03 (1.41)	
Target Debt/Assets[†]						0.58[a] (4.01)	
S&P500 Ret.(12-month)	-0.09 (-0.71)	-0.08 (-0.65)	0.06 (0.23)	-0.06 (-0.86)	-0.06 (-0.45)	-0.28 (-1.14)	-0.07 (-0.70)
Avg. Interest Rate	0.04[a] (2.60)	0.03[c] (1.71)	0.02 (1.41)	0.00 (0.01)	0.02 (1.13)	0.02 (0.70)	0.03 (1.44)
Ann. Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
State Fixed Effects	NO	NO	YES	YES	YES	YES	NO
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Adj.-R^2 (%)	12.21	10.91	24.51	25.44	23.49	25.15	15.66
No. of Obs.	6,599	6,599\	5,611	4,400	6,599	1,757	3,747

opportunities that are easier to evaluate and monitor. The degree of antitakeover protection offered by a state to potential target firm managers has a significantly negative impact on propensity for local bias shown by the state's acquirers. Ceteris paribus, Acquirers domiciled in states that have adopted more antitakeover statutes are more likely to invest in M&A involving targets that are further away from its headquarters. While the distance-based local bias measure is less intuitively related to state-level laws and economic development, the results confirm the overall impact documented in earlier sections. The contemporaneous local bias shown by other same-city, same-industry managers during M&A has a statistically and economically significant positive impact on the observed local bias of an acquirer. For a more quantitative interpretation, a 1% increase in local bias of the same-city, same-industry peer group causes a 0.1% (= $e^{0.01*\ln(1.01)}$) increase in local bias of an acquirer, ceteris paribus.

Acquirer size, as measured by the market capitalization in the month prior to the acquisition announcement, has a significantly negative impact on the propensity for localized M&A. The results for book-to-market ratio are somewhat weak. The results point towards the fact that value acquirers may show less local bias, which is consistent with the notion that growth acquirers operate in sectors where the levels of intangible knowledge and uncertainty are relatively higher and may be exacerbated by distance. Additionally, the impact of acquirer leverage on propensity for local bias is also not robust to model specification. Public targets are more likely to be acquired by local acquiring firms. For deals where the target is publicly traded, the acquirer shows 5% more local bias than if the target is privately-owner, ceteris paribus. No other deal characteristics in the regressions are significantly related to the local bias shown by the acquirer. There is some evidence to suggest that hostile takeovers are more likely for more localized deals. This may be driven by the fact that a local acquirer may have better knowledge about the target and the cooperation of target firm's management in the post-deal functioning may not seem vital to the acquirer. Additionally, there may be a lower degree of political resistance to in-state hostile bidders.

By using an alternative measure of proximity preference based on geographical distance we verify the impact of factors related to home bias of acquirers. Both the local bias measures and home bias measures based on states as geographical units have different pros and cons. While distance-based local bias measures are less narrow, they form less intuitive decision categories in terms of legal and economic environment and make it harder to examine the impact of segmentation in state-level factors. On the other hand, using in-state versus out-of-state target choices as measures of home bias downplays the significance of geographical distance which may be a critical factor during economic decisions. However, on conducting parallel analyses for both measures of proximity preference, our overall findings are consistent. We conclude that the key results of our study are robust to the alternative spatial definitions of "home" (i.e., geographically close or in-state).

4.6. Conclusions

This paper focuses on documenting and explaining the propensity of acquirers to show home bias in choosing targets during domestic acquisitions. We show that firms exhibit a strong proximity preference in their investment behavior, consequently limiting their choice set of assets, in a manner that is very similar and even more compelling than that documented for portfolio investors. Industrial agglomeration, concentration of economic activity and acquirer size constraints do not substantially explain the observed proximity preference.

We find that nearly 34% of completed acquisitions involve local targets, while firm spatial clustering possibly explains only about 4% of local deals. We define local as being within a 100 km radius of the headquarters of acquirers. The frequency of deals declines sharply with distance. Our findings converge with other studies similarly indicating that 'home' lies within a 100 km radius, seemingly suggesting that the limited human capacity for managing complex social interactions, information sharing and processing may be at the root of the so-called home bias puzzle. Shedding light on the state-level geography, firms acquire in-state targets about 11 times as frequently as one may expect in the absence of home bias. Local bias measures based on geographical distance uncover acquirers' proximity preference of about 580 km when choosing a target, as compared to the mean distance from a portfolio of potential targets in the industry of the actual target.

Our empirical tests show that states with larger economic size encourage in-state M&A, thereby inducing localized consolidation of businesses. State-authorized protection of target managers via antitakeover regimes dissuades acquisitions by home state acquirers and, as a result, has the unexpected effect of offsetting home bias. Acquirers display substantial herding behavior with managers located in their city and operating in the same industry in their tendency to display home bias while choosing targets. Interestingly, acquirer behavior is not impacted by same-industry managers in other cities, or other-industry managers in the same city. We interpret this finding as suggesting that acquirer managers care more about or are influenced more by the strategies of managers they are likely to be compared with by the local media and shareholder base, have more word-of-mouth communication with, or compete locally with. Additionally, large, value acquirers show less home bias compared to small, growth acquirers. Target firms' characteristics pale in importance once the acquirers' characteristics are accounted for, indicating that at least in case of M&A the investor characteristics drive home bias more than asset characteristics. Public targets are more likely to be in-state acquisitions, alluding to potential political or managerial resistance to out-of-state takeovers of visible, publicly traded firms.

Our findings have important implications for the study of economic geography and corporate investments. Results suggest that home bias in M&A cannot be fully explained by the 'localized' knowledge or pecuniary spillovers that necessitate economic agglomeration. The corporate home bias is attributable, at least in part, to information asymmetries, cognitive bias and economic opportunities, the same factors perceived as responsible for the home bias of portfolio investors. Factors that influence corporate investment behavior clearly have implications for policy-making geared towards attracting or retaining corporate capital in states. Additionally, given that the nature of the domestic market for corporate control is segmented, further research could explore the efficiency implications of this phenomenon on takeovers as a corporate governance mechanism. The suggestion of herding in acquirers' proximity preference alludes to possible behavioral drivers of corporate strategy and deserves further attention. In the absence of frictions like currency risk, political risk, significant transaction costs and communication barriers which may exist in international investments, the high degree of segmentation in economic activities into regional clusters within a nation remains intriguing.

CHAPTER 5

THESIS CONCLUSION

Information is pivotal to all decisions and choices in financial markets. Due to the rapid strides the world has made in communication technology and the advent of the internet, among other innovations heralding in the 'information age', it may be expected that the cost of information acquisition is small, and often negligible. However, a growing body of research documents that markets are informationally imperfect. In the presence of information heterogeneities, we cannot ignore the substantial human element to information flows in markets. Recent research shows that there are various informal factors that have an important impact on economic decision-making, but have been overlooked in classical economic theory. The existence of social networks, word-of-mouth interactions, peer effects etc., are being increasingly acknowledged as having a significant impact on economic behavior. For example, as residents of Atlanta, we often keep an eye on Coca Cola's stock prices. It is a large publicly traded company headquartered in Atlanta, with most public information being made easily available through electronic and print media. However, if a friend expresses a strong opinion about the prospects of the company that diverges from the public information, are we not tempted to allocate more value to her opinion than to public information?

This dissertation is driven by the notion that the ease of information availability via formal channels does not substitute for factors like social information networks, peer effects, familiarity etc., which continue to impact decision-making by investors. The first essay considers information channels among mutual fund managers (*fund-fund networks*), and between holding companies and fund managers (*fund-company networks*). Results show that (1) fund-fund (fund-company) information networks help in generating positive risk-adjusted returns from holdings in absence of fund-company (fund-fund) networks; (2) fund-company networks create information advantage only when the networks are relatively exclusive. Superior networks seem to pick stocks which outperform beyond the quarter. The second essay examines mutual fund managers' tendency to deviate from the strategies of their peers. Results indicate a significantly negative relationship between the managers' deviating tendency and fund performance, suggesting that the average fund manager is more likely to make erroneous decisions when they deviate from their peers. The third essay investigates the determinants of target choices in corporate acquisitions. Results reveal the influence of various factors, including information asymmetries, which may drive this behavior, including economic opportunities, anti-takeover regimes, competitive responses to other managers, and acquirers' size and book-to-market ratios.

The intent of this dissertation is to study and characterize some of the informal interactions and socio-legal processes that play a role in the investment choices and outcomes of economic players in markets. Several interesting avenues for future research are suggested. For instance, the role of these informal drivers of decisions on economic and market efficiency is not clear. Additionally, the motivations and mechanism by which information sharing occurs in markets is still understudied. This research has important implications for all players in financial markets, including investors, corporate executives and policy makers.

APPENDIX A

Description of Macroeconomic and Antitakeover Law Variables

Name of Variable	Description
Log(GSP)	Natural logarithm of the annual Gross State Product (GSP). GSP is defined as the value added in production by the labor and property located in a state, and comprises of three components: compensation of employees, indirect business tax and non-tax liability (IBT), property-type income. *Source:* Bureau of Economic Analysis, U.S. Department of Commerce
Antitakeover Statutes	Total number of standard antitakeover statutes endorsed by a state. The five standard antitakeover statutes are control share, fair price, no freezeout, poison-pill endorsement and constituency.
Control Shares Statute	Requires a potential acquirer to win approval from a majority of outstanding disinterested shares, before it is allowed to acquire control of the target firm.
Fair Price Statute	Ensures that acquirers do not pay a premium for control of the target and then after acquiring control, buy remaining shares at lower prices.
No. Freezeouts Statute	Prohibits acquirers, under certain conditions, from merging with the target for a certain number of years (typically 3-5 years).
Poison Pill Statute	Explicitly authorizes use of poison pills as a defensive tactic by the target firm.
Constituencies Statute	Authorizes the target's management to use defensive tactics in the name of non-shareholder constituencies, such as employees etc.
S&P500 Ret.(12-month)	One-year return on the S&P500 composite index compounded monthly ending the month prior to the announcement of the acquisition by acquirer. *Source:* CRSP (Center for Research on Security Prices)
Interest Rate	Annual average of monthly interest rates in year t-1, where t is the year of announcement of the acquisition. *Source:* Federal Reserve Board of Governors

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