Distribution Agreement

THREE ESSAYS IN BEHAVIORAL FINANCE

By

Byoung-Hyoun Hwang
Doctor of Philosophy

Business

Jay A. Shanken, Ph.D.
Advisor

Tarun Chordia, Ph.D.
Committee Member

Amit Goyal, Ph.D.
Committee Member

T. Clifton Green, Ph.D.
Committee Member

Narasimhan Jegadeesh, Ph.D.
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the Graduate School

Date

THREE ESSAYS IN BEHAVIORAL FINANCE

By

Byoung-Hyoun Hwang
Dipl., European School of Business, 2004
B.Sc., Indiana University, 2004

Advisor: Jay A. Shanken, Ph.D., Carnegie-Mellon University, 1983

An abstract of a dissertation submitted
to the Faculty of the Graduate School of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

Business

2009

Abstract

THREE ESSAYS IN BEHAVIORAL FINANCE

By

Byoung-Hyoun Hwang

While not devoid of sentiment, self-interested rational decision makers in traditional economic models are assumed to be immune to its influence. The purpose of this dissertation is to explore whether financial markets can be better understood when relaxing this important (but questionable) assumption and allowing subjects to be influenced by sentiment. In the first essay ("It pays to have friends" – co-authored with Seoyoung Kim), we examine whether actions of corporate directors with social ties to CEOs are determined by communal norms, which promote mutual caring and trust, as opposed to pure self-interested exchange-based norms. Consistent with our conjecture, the results suggest that boards with more social ties to the CEO award compensation packages that are both higher in level and less sensitive to performance; boards with social ties are also less likely to fire the CEO. In the second essay ("Country-specific sentiment and security prices"), I add to the growing body of evidence suggesting that sentiment, while irrelevant to the decision at hand, has an important influence on decision making and market outcomes. Specifically, my findings imply that sentiment towards certain countries affects demand for financial securities from these countries and causes security prices to deviate from their fundamental values. In the third essay ("Distinguishing behavioral models of momentum"), I test the implications of two of the most prominent, recently proposed, sentiment-based models. I provide evidence consistent with one, but inconsistent with the other.

THREE ESSAYS IN BEHAVIORAL FINANCE

By

Byoung-Hyoun Hwang
Dipl., European School of Business, 2004
B.Sc., Indiana University, 2004

Advisor: Jay A. Shanken, Ph.D., Carnegie-Mellon University, 1983

A dissertation submitted
to the Faculty of the Graduate School of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

Business

2009

Dedication

To my family.

Acknowledgements

I am indebted to my dissertation committee members: Tarun Chordia, Amit Goyal, Clifton Green, Narasimhan Jegadeesh; and, in particular, my advisor, Jay Shanken. Their strong understanding of empirical research methodologies and excellent economic intuition have made them invaluable resources in the development of my dissertation. In addition, their experience publishing research has been extremely helpful in making my research accessible and interesting to a broad audience.

I would also like to thank John Doukas, Wayne Ferson, David Hirshleifer, Josh Pollet, Jeffrey Pontiff, Jeremy Stein, Jeffrey Wurgler, and seminar participants at Emory University, Georgetown University, Georgia Institute of Technology, Harvard University, Indiana University, New York University, Notre Dame University, Ohio State University, Purdue University, University of Chicago, University of Michigan, University of Southern California, and Washington University for helpful comments on parts of my dissertation. Special thanks to Seoyoung Kim for many insightful discussions (from which I have benefited tremendously).

Table of Contents

	Page
Introduction	1
First essay: It pays to have friends	
1. Introduction	3
2. Motivation, hypotheses, and identification of social ties	7
3. Data description	13
4. Empirical results	22
5. Contribution and discussion	39
6. Conclusion	42
Second essay: Country-specific sentiment and security prices	
1. Introduction	43
2. Data	45
3. Iraq war	48
4. Main analysis	49
5. Additional analysis	54
6. Conclusion	63
Third essay: Distinguishing behavioral models of momentum	
1. Introduction	64
2. Relative investor group size and correlation in signal noise terms	68
3. Evidence using the average correlation in analysis' forecast errors	78
4. Additional analysis	85
5. Earnings momentum	92
6. Conclusion	93
Conclusion	95
Appendices	96
References	127
Tables	143
Figures	171

List of Tables

		Page
Table 1:	Proportions of directors with conventional or social ties	143
Table 2:	CEO and board characteristics	144
Table 3:	Determinants of social dependence	145
Table 4:	Firm characteristics and CEO compensation	146
Table 5:	Board independence and CEO compensation	147
Table 6:	Compensation differential within subsample of conventionally independent boards	149
Table 7:	Excess compensation and subsequent operating performance	150
Table 8:	Pay-performance differential within subsample of conventionally independent boards	151
Table 9:	Turnover differential within subsample of conventionally independent boards	152
Table 10:	Bonus differential within subsample of conventionally independent audit committees	153
Table 11:	Sensitivity tests	154
Table 12:	Country closed-end fund premia/(discounts) and countries' popularities	156
Table 13:	Country closed-end fund premia/(discounts) and countries' popularities – Alternative aggregation of country popularity	157
Table 14:	ADR premia/(discounts) and countries' popularities	158
Table 15:	Fund flows and countries' popularities	159
Table 16:	Institutional holdings and countries' popularities	160
Table 17:	Subsequent monthly $\hat{\rho}_{FE}$ for portfolios sorted on past 6 months returns and $\hat{\rho}_{FE}$	161
Table 18:	Monthly returns for portfolios sorted on past 6 months returns	162

Table 19: Monthly returns and alphas for portfolios sorted on past 6 months returns and $\hat{\rho}_{FE}$ 163

Table 20: Monthly returns for portfolios based on past returns, $\hat{\rho}_{FE}$, and firm characteristics 164

Table 21: Returns for portfolios sorted on past 6 months returns and institutional holdings 167

Table 22: Returns for portfolios sorted on past 6 months returns and turnover 168

Table 23: Fama-MacBeth regression estimates 169

Table 24: Monthly returns and alphas for portfolios sorted on SUE and $\hat{\rho}_{FE}$ 170

List of Figures

		Page
Figure 1:	Evolution of social dependence surrounding the appointment of a new CEO	171
Figure 2:	Long-run horizon results	172

Introduction

While not devoid of sentiment, decision makers in traditional economic models are assumed to be immune to its influence (Barberis and Thaler 2005).[1] However, a growing body of empirical evidence has uncovered phenomena that are difficult to understand within a framework built on dispassionate subjects (e.g., Barberis and Thaler 2005). These empirical challenges raise the question of whether decision making and market outcomes can be better understood when allowing behavior to be affected by sentiment. The purpose of this dissertation is to explore this question. The dissertation consists of three essays.

In the first essay ("It pays to have friends" – co-authored with Seoyoung Kim), we argue that agents' actions are governed not only by self-interested, exchange-based norms, which promote dispassionate reciprocation, but also by communal norms, which promote mutual caring and trust (Mills and Clark 1982; Silver 1990); and we contend that, as a result, social ties are a potentially rich source of a director's dependence on the CEO. We measure social ties via similarities in background between the director and the CEO. Consistent with our conjecture, we find that boards with more social ties to the CEO award compensation packages that are both higher in level and less sensitive to performance. Boards with social ties are also less likely to fire the CEO. Because both regulatory and academic settings currently only consider financial and familial ties (but not social ties) when classifying a director as "independent," our results suggest that a considerable percentage of boards classified as "independent" are substantively not.

[1] Sentiment is defined to be irrelevant to the decision at hand (Baker and Wurgler 2007).

In the second essay ("Country-specific sentiment and security prices"), I provide evidence on a specific new dimension of sentiment-driven demand. In particular, I provide evidence that a country's popularity among US investors affects their demand for securities from that country and causes security prices to deviate from their fundamental values. Moreover, the results suggest that country popularity primarily affects retail investors' investment decisions and that, while institutional investors take the other side of "unsophisticated demand," they are unable to eliminate its price effect.

When departing from the strict rationality assumption underlying the traditional economics framework and allowing for sentiment, one must specify the structure of these deviations. Several "behavioral" models take up this challenge (Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999; 2007). These behavioral models generally differ in their approach and reliance on cognitive biases. The third essay ("Distinguishing behavioral models of momentum") conducts an initial exploration into which of these competing behavioral models best explains financial markets. Specifically, I test the implications of two prominent models – those of Hong and Stein (2007) and Daniel, Hirshleifer, and Subrahmanyam (1998) – to see which one better explains the momentum phenomenon, the most significant empirical challenge to the traditional asset-pricing paradigm (Fama and French 2008). Daniel, Hirshleifer, and Subrahmanyam (1998) derive the momentum effect from a representative investor's outcome-dependent (over-)confidence. Hong and Stein (2007) adopt "a fundamentally different approach" and derive the momentum effect from the interaction between heterogeneous agents. I find evidence consistent with Daniel, Hirshleifer, and Subrahmanyam (1998) and inconsistent with Hong and Stein (2007).

First Essay: It Pays to Have Friends

1. Introduction

Amid corporate scandals and conflicts of interest, increased board independence is an oft prescribed remedy. Many academic studies examine the monitory benefits of independent boards (e.g., Weisbach, 1988; Byrd and Hickman, 1992; Brickley, Coles, and Terry, 1994; Cotter, Shivdasani, and Zenner, 1997; Mayers, Shivdasani, and Smith, 1997; and Paul, 2007), and mutual fund investors are calling for more independent directors to oversee fund managers. Moreover, recent corporate-governance reforms issued by the NYSE, Amex, and Nasdaq require that listed firms (with some exceptions) have independent boards. But are these "independent" boards really independent?

Currently, a director is classified as independent if he has neither financial nor familial ties to the chief executive officer (CEO) or to the firm. Absent from these conventional criteria are social ties; that is, the nonfamilial, informal connections. However, given that agents are not driven solely by economic gains (e.g., Mills and Clark, 1982; Silver, 1990; and Uzzi, 1996), social ties are a potentially rich source of a director's dependence to the CEO. Board consultants in the popular press broach this issue, saying that when directors debate whether or how to fire a CEO, "they [the directors] typically need the most help in dealing with their attachment to the CEO" (Business Week, 2007). Our purpose is to incorporate these heretofore omitted ties into the definition of board independence and to examine their relevance to the monitory and disciplinary effectiveness of the board.

Drawing from the economics and sociology literatures, we propose mutual alma mater, military service, regional origin, academic discipline, and industry as indications of an informal tie between a director and the CEO. These mutual qualities and experiences, through homophily (i.e., an affinity for similar others), facilitate interactions and thereby foster personal connections. Whether it is conscious or not, actors enjoy an easier mutual understanding and are more comfortable with others who share similar characteristics and experiences (Marsden, 1987; and McPherson, Smith-Lovin, and Cook, 2001), and "contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin, and Cook, 2001, p. 416).

Using hand-collected data, we focus on the Fortune 100 firms from 1996 to 2005. We find that, under the conventional measure of independence, 87% of the boards in our sample are classified as independent; that is, these boards have a majority composition of conventionally independent directors. Under our new measure, which augments the conventional definition with the proposed social restrictions, this percentage drops to 62%. Moreover, the incidence of socially linked directors increases as a new CEO's tenure at the firm progresses, suggesting that CEOs select directors along these social dimensions.

To illustrate a conventionally independent board that is not conventionally and socially independent, we consider the board of Cardinal Health. In the year 2000, this board had 13 directors, ten of whom were conventionally independent of the CEO. However, one conventionally independent director was not only from the same hometown, but also graduated from the same university as the CEO (incidentally, this director provided a job, at his own firm, for the CEO's son). Another conventionally independent director graduated from the same university and specialized in the same academic discipline as the CEO. Similarly, three others shared informal ties with the CEO, and ultimately, only five of the 13 directors were conventionally and socially independent of the CEO.

To test the monitory relevance of these social ties, we examine the differential association between board independence and the level of CEO compensation when we replace the conventional measure of board independence (which does not consider social ties) with our new measure. If these social ties do not affect the disciplinary or monitory capacity of directors, then a director who is conventionally independent but socially linked to the CEO is an equally effective monitor as a director who is both conventionally and socially independent. As such, we would expect no differential association between board independence and the level of compensation attributed to this distinction.

We find no significant difference in the CEO's total annual compensation when a conventionally independent board is present. However, when a conventionally and socially independent board is present, the CEO's total compensation decreases, on average, by $3.3 million. This magnitude is not only statistically significant, but also economically meaningful (average annual compensation is $12.8 million), and we make similar observations with respect to the CEO's annual salary plus bonus. In addition, we find a compensation differential within the subsample of firms with conventionally independent boards; those firms with boards that are conventionally independent but not conventionally and socially independent award a significantly higher level of compensation to their CEOs. These results further signify that it is not only the conventional ties but also the social ties that matter. Moreover, the excess compensation attributed to this type of board extends to a negative association with subsequent operating performance. This evidence punctuates the monitory relevance of these social ties because alternative interpretations of this excess component of compensation (e.g., the CEO of a more complex firm could require a higher level of compensation and a friendlier board) cannot explain its negative association with the firm's subsequent performance.

We also examine the role of social ties in other supervisory and disciplinary actions of the board, such as CEO turnover and pay-performance elasticity. We find that, within the subsample of firms with conventionally independent boards, those CEOs whose boards are not conventionally and socially independent exhibit a lower sensitivity of turnover and compensation to performance. We also find that CEOs whose audit committees are conventionally independent but socially linked (to the CEO) receive larger bonuses than otherwise equivalent CEOs whose audit committees are both conventionally and socially independent, suggesting that social ties affect the audit committee's oversight of financial statements.

Overall, our results suggest that social ties affect how directors monitor and discipline the CEO and that, consequently, a considerable percentage of the boards currently classified as independent are substantively not.

This paper is organized as follows. In Section 2, we discuss the significance of social ties, we develop our hypotheses, and we discuss our measures for social ties. In Section 3, we describe our data sources, variables, and summary statistics. In addition, we examine what determines the incidence of socially dependent directors. In Section 4, we examine the monitory relevance of social ties in the level of compensation, pay-performance elasticity, and CEO turnover. Moreover, we explore alternative interpretations of the excess compensation attributed to social ties. In Section 5, we discuss our contribution to the corporate governance literature, and in Section 6, we conclude.

2. Motivation, hypotheses, and identification of social ties

Given that actors are not driven solely by financial motives, social ties have a potentially large impact on a director's monitory and disciplinary capacity. In particular, when two actors share a social bond, there is a shift in normative expectations, whereby their actions are governed by communal norms, which promote mutual caring and trust, as opposed to exchange-based norms, which promote dispassionate reciprocation (Mills and Clark, 1982; and Silver, 1990). Furthermore, a social relationship "disposes one to interpret favorably another's intentions and actions" (Uzzi, 1996, p. 678). Thus, when a CEO enjoys a personal tie with a director, the director's resulting concern for the CEO clouds objective monitoring and disciplining of the CEO.[2]

There is considerable evidence that social ties influence economic outcomes. Uzzi (1996) studies the apparel industry and observes that social ties promote cooperation and "voluntary, non-obligating exchanges of assets and services between actors" (p. 678). For example, a buyer will find alternate uses for fabric mistakes rather than refuse the material at the manufacturer's cost. Uzzi (1999) studies middle-market banking and finds that social ties between firms and their lenders affect firms' access to and cost of capital. Ingram and Roberts (2000) find a substantial increase in hotel yields (i.e., revenue per

[2] His disutility from violating the normative expectations imposed by social ties is also a factor. This disutility can be self-imposed (e.g., guilt) or imposed by others (e.g., disapproval) (Elster, 1989).

room) when competing hotel managers share a social tie. This increased yield is not achieved through explicit collusion or price-fixing, but through collaboration, information exchange, and the mitigation of aggressive competitive behavior. Westphal, Boivie, and Chng (2006) find that managers form social ties with the managers of firms to which they are vertically dependent in order to mitigate opportunism, and Cohen, Frazzini, and Malloy (2008; 2009) find that mutual fund managers and sell-side equity analysts enjoy an informational advantage via their education networks.

2.1. Measuring and identifying social ties

Unlike family or business ties, social ties are neither legally defined nor straightforward to identify. Studies on social embeddedness generally rely on surveys and interviews to identify the explicit social ties between actors (e.g., Uzzi, 1996, 1999; Westphal, 1999; Ingram and Roberts, 2000; McDonald and Westphal, 2003; and Westphal, Boivie, and Chng, 2006); that is, individuals are asked to report whether and with whom they share social ties.[3] In contrast, our approach is to operationalize social ties through mutual qualities and experiences, which, through homophily (i.e., an affinity for similar others), facilitate interactions and thereby foster personal connections. Whether it is conscious or subconscious, "contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin, and Cook, 2001, p. 416), and actors enjoy an easier mutual understanding and are more comfortable with others who share similar

[3] For instance, survey participants are asked to "indicate whether each person is (i) among your closest friends, (ii) a friend, but not among your closest friends, (iii) less than a friend but more than an acquaintance, (iv) an acquaintance" (Westphal, Boivie, and Chng, 2006, p. 433). Answers (i) and (ii) are coded "friendship ties," whereas answers (iii) and (iv) are not.

characteristics and experiences (Marsden, 1987; and McPherson, Smith-Lovin, and Cook, 2001). Cohen, Frazzini, and Malloy (2008; 2009) use a similar approach, linking mutual-fund managers and sell-side equity analysts to corporate officers and directors via shared education networks (i.e., mutual alma mater).

This approach has several advantages. For one, unlike survey-based measures, the measures we propose are broadly observable and (relatively) easy to identify. The systematic availability of characteristics such as educational institution, regional origin, and military service makes such measures attractive for use in future studies. Furthermore, surveys are designed to capture conscious "friendship ties" (e.g., see sample survey question in the footnote from the previous paragraph), whereas many homophilous ties are likely built subconsciously, making them difficult to pinpoint in survey responses.

Drawing from the economics and sociology literature, we propose mutual alma mater, military service, regional origin, discipline, and industry as indications of an informal tie between a director and the CEO. Because the probability of a social connection increases with similarity (McPherson, Smith-Lovin, and Cook, 2001), we require that a director and CEO (directly) share at least two of these ties to constitute social dependence. Alternatively, a director and CEO can share one direct tie and one third-party connection (to whom each is directly dependent), which enhances an existing tie by strengthening shared normative expectations (Granovetter, 2005) as well as facilitating further contact. Defining director dependence in dichotomous terms (a director is either independent or not) allows us to define whether a majority of board members are independent, which in turn allows us to examine whether the boards currently classified as independent are still classified as such once social ties are considered. Later, we explore various other specifications, such as the extent of a director's dependence (i.e., the number of ties shared).

Regional Origin. There are unique regional qualities that vary within the United States. For instance, there is a marked regional distinction in the choice of leisurely activities that is unexplained by demographic and socioeconomic differences (Marsden, Reed, Kennedy, and Stinson, 1982), and "[Americans] think of themselves as linked geographically by certain traits, such as New England self-reliance, southern hospitality, midwestern wholesomeness, western mellowness" (US Department of State, 2003). This regional clustering of dialect, beliefs, culture, and lifestyle contributes to an affinity for others from the same locale. For example, regional homophily appears in the social choices of college students, exceeding what is expected if social circles are formed randomly with respect to regional origin (Reed, 2003). We define regional origin as the non-US country or US region of birth, because birthplace is a readily available and easily defined measure, as opposed to the more difficult concept of being from somewhere. Moreover, birthplace is highly correlated with this vaguer notion of home. From 1995 to 2000, 8.7% of nationals changed their state of residence, and only 4.6% changed regions (US Census Bureau, 2003).[4] In accordance with the US Census Bureau, we cluster US states and territories into the following regions: South, Northeast, Midwest, Mountain, Pacific, and Territories.[5] We focus on these broader regional categories to keep with the

---

[4] One possible concern is that the childhood mobility patterns of CEOs and directors are much higher, because they likely come from more educated and therefore more mobile families. However, of the educated, married population of young adults (ages 25 to 39), only 18.6% changed their state of residence from 1995 to 2000 (US Census Bureau, 2003), and we project that even fewer changed regions.

[5] Details are available at http://www.census.gov/geo/www/us_regdiv.pdf.

theoretical and empirical groundwork on regional homophily. However, we also consider a finer classification of regional origin using individual states.

Mutual alma mater, military service, discipline, and industry. Connections forged through a mutual alma mater enjoy enhanced interaction via in-jokes, shared traditions, and a sense of group belonging, as evidenced by alumni networks, newsletters, donations, and college sports events. Similarly, veterans share a bond through their common experiences (Crosse and Hocking, 2004; and Friedman, 2005). Crosse and Hocking (2004) argue that veterans are in an environment that "depends on a highly structured, organized force… [with] a demand not paralleled in any other work environment," suggesting that this unique shared experience contributes to a steadfast bond among veterans. Mutual industry and academic discipline signify additional similarities through shared interests and common experiences, providing further points of contact. Moreover, these shared characteristics denote similarities beyond the common experiences they provide, because they are endogenously determined.

In our classification scheme, we classify the university ties in tandem with the director's and the CEO's age class(es), because an overlapping period of attendance starkly increases similarities in experiences. Moreover, university cohorts are more likely to have known each other prior to an appointment. To determine mutual industry and discipline, we partition industries of primary employment using the Fama-French (1997) 49-industry classification, and we partition academic majors into 26 categories from the *US News and World Report*. A full list of academic disciplines is provided in Appendix A.

2.2. Hypothesis development

In terms of agency theory, the board's primary role is to enforce shareholders' interests and to mitigate the CEO's self-serving behavior. With respect to executive compensation, this framework specifies that the board's role is to lower the level of total compensation. In reality, however, many directors themselves are not perfect agents and likewise suffer the agency problems they were designed to address. Thus, agency theory prescribes that boards be primarily composed of independent directors because they are more likely to objectively monitor and discipline the CEO (Fama and Jensen, 1983). This is not to say that an independent board is an unconditionally more effective one. Studies focusing on the advisory role of the board argue the merits of a friendlier board (Adams and Ferreira, 2007; Coles, Daniel, and Naveen, 2008; and Linck, Netter, and Yang, 2008), but insofar as its disciplinary or supervisory role is concerned, the board is more effective as an independent unit. Because compensation is a monitory issue, the possible advisory benefits of a dependent board do not extend to (shareholder) benefits in terms of CEO compensation.

We expect that it is not only the conventional (i.e., financial and familial) ties that affect a board's monitory effectiveness, but also the social ties that matter. To test the relevance of these social ties, we examine the differential association between board independence and the level of executive compensation when we augment the conventional definition of board independence with our proposed social restrictions. If social ties are irrelevant, then we should observe no differential relation between board independence and the level of compensation when we replace the conventional board-independence measure with our new measure. Moreover, we examine the variation in compensation within the subset of firms whose boards are conventionally independent. There are two types of conventionally independent boards: those that are conventionally and socially independent, and those that are not. If social ties do not matter, then there should be no compensation differential attributed to this distinction.

3. Data description

This section discusses our data sources and regression variables. We also explore the determinants of a board's social composition, in particular the hypothesis that CEOs desire socially dependent directors.

3.1. Sources

We focus on the Fortune 100 firms (as declared in 2005) and obtain a list of these Fortune 100 directors and CEOs from the Investor Responsibility Research Center (IRRC) and Compustat Executive Compensation databases. Our sample period runs from 1996 to 2005 and was determined by the availability of the IRRC Directors database. We hand-collect data for each CEO and director's educational institution, military service, regional origin, and academic discipline from the Marquis Who's Who database. To determine each director's industry of employment, we first exploit the Primary Employment field provided by the IRRC Directors database, and for the remaining director-years with a blank Primary Employment field, we collect this information from the Marquis Who's Who and Notable Names databases. Next, we match each of these firms to an SIC code (we create a separate category for retired directors), and we use the Fama-French (1997) 49-industry classification to define industry ties. For publicly traded firms, we obtain the corresponding SIC code through the Center for Research in Security Prices (CRSP), and for the remaining firms, we determine SIC codes using a combination of the Manta, Websters Online, Goliath, Alacra Store, American Hospital Directory, Law Firm Directory, Martindale-Hubbell, and HG.org databases. Furthermore, we collect CEO-award information from the *Business Week* archives, and we collect information on family-run firms by cross-examining the information provided in *Family Business* with proxy disclosures, the Compustat Executive Compensation database, the IRRC Directors database, and the Blockholders database. We obtain executive compensation, financial statement, and stock price data from the Compustat Executive Compensation, Compustat, and CRSP databases, respectively.

Of the Fortune 100 firms, four are not publicly traded, and of the 96 publicly traded firms, three are not covered by the IRRC Directors database. In regressions using past performance as a measure of the incumbent CEO's quality, we further exclude those firm-years in which there are new arrivals because past firm performance cannot be attributed to an incoming CEO. Our final sample consists of 704 firm-years (1,568 directors and CEOs).

3.2. Regression variables

3.2.1. Executive compensation

We use two different measures of the level of compensation, our dependent variable: *Salary + Bonus* and *Total Compensation*. *Salary + Bonus* consists of only the base salary plus bonus. *Total Compensation* is calculated as the sum of base salary, bonus, long-term incentive payouts, the value of restricted stock grants, and the Black-Scholes value of option grants converted into their stock equivalents using the options' median delta.[6]

3.2.2. Board independence

Following regulatory convention, the board-independence dummy is an indicator variable that equals one if a majority of the directors are classified as independent, and zero otherwise.[7] We compare and contrast two classifications of director independence, which we refer to as the c*onventional measure* and the *new measure*.

Under the *conventional measure* (as specified by the IRRC), a director is classified as independent if he or she is not a current or former employee of the firm (or of a subsidiary of the firm), a relative of an executive officer, a customer of or a supplier to the company, a provider of professional services, a recipient of charitable funds, a designee under a documented agreement by a significant shareholder or group, or interlocked with an executive of the firm.[8] An interlocking directorate, also known as board cooptation, is a situation in which an executive of firm X is a director at firm Y at the same time that an executive of firm Y is a director at firm X. The list of independence criteria also includes a catchall phrase for any other type of affiliation that poses a potential conflict of interest, because there are a myriad of possibilities that cannot be

---

[6] Following Baker and Hall (2004), we use a delta of 0.7, which approximates the median delta in the Hall and Liebman (1998) data.

[7] Other studies using an independence dummy or piece-wise linear approach include Weisbach (1988), Hermalin and Weisbach (1991), Byrd and Hickman (1992), Cotter, Shivdasani, and Zenner (1997), and Masulis, Wang, and Xie (2007).

[8] Details are available at http://wrds.wharton.upenn.edu/support/docs/irrc/directors_terms.doc.

definitively specified. However, the scope of this catchall is limited to proxy disclosures, and firms are not inclined to report beyond what is explicitly required.

Under the *new measure*, a director is classified as independent if he or she is both conventionally and socially independent, whereby a director is classified as socially dependent if the director and CEO have two or more of the following in common: 1) served in the military, 2) graduated from the same university (and were born no more than three years apart), 3) were born in the same US region or the same non-US country, 4) have the same academic discipline, 5) have the same industry of primary employment, or 6) share a third-party connection through another director to whom each is directly dependent. For example, suppose that the CEO is a 55-year-old, Stanford-educated, business major who served in the military and was born in the Northeast, and director A is a 55-year-old, Stanford-educated, electrical engineering major born in the South. Although the director and CEO share only one direct tie (i.e., through mutual alma mater), if there is third-party director B who is a 57-year-old Stanford graduate who studied electrical engineering and served in the military, then we consider director A socially dependent to the CEO (because in addition to their mutual alma mater connection, the two are socially connected to a mutual third party with whom each shares two direct ties).

3.2.3. Other regression variables

In addition to the board-independence dummy, we include the following control variables: *ln(Total Assets)*, *ln(MB)*, *ROA*, *RET*, σ^2, *CEO Equity Holdings*, *CEO Award*, *CEO=Chairman*, *CEO Tenure*, *ln(Board Size)*, *Old Directors*, *Busy Board*, *Directors’*

Equity Holdings, *CEO from Other Company*, *Classified Board*, *Democracy Firm*, *Dictatorship Firm*, and *Family Firm* (Appendix B has a description of each variable and its expected relation with the level of CEO compensation). We also include year dummies as well as industry dummies using the Fama-French (1997) five-industry classification.[9] We use the five-industry classification because finer industry classifications result in much sparser partitions, with many industry categories having only one or two firms. Thus, using such fine classifications to define our industry dummies would amount to including firm-specific dummies, which we do not include due to the high persistence of many of the governance variables (e.g., board independence, classified-board provision).

3.3. Breakdown of social ties

In Table 1, we present summary statistics on the average proportions of directors with various ties to the CEO or to the firm. We determine average proportions by first calculating, for each firm-year, the proportion of directors with the relation in question, and then taking the pooled mean of these proportions. For instance, the average proportion of directors with a social tie is obtained by calculating for each firm-year the proportion of directors with a social tie and then taking the pooled average across all firm-years.

In our sample, we find that social ties between CEOs and directors are about as common as conventional ties. The average proportion of conventionally dependent directors is 0.296, and the average proportion of socially dependent directors is 0.276.

[9] Obtained from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The average proportion of directors who are either conventionally or socially dependent (or both) is 0.416, indicating a substantial presence of social ties among the directors who have a conventional tie to the CEO.

We also examine what proportion of the socially dependent directors share each of the following specific ties with the CEO: military service, alma mater, regional origin, academic discipline, industry, and third-party ties. We find that, of all socially dependent directors, 8.9% share a military connection with, 49.6% graduated from the same university as, 68.0% share regional origin with, 60.2% have the same academic discipline as, 65.2% have the same industry of primary employment as, and 66.0% share a third-party connection with the CEO. Moreover, we observe a substantial presence of these specific ties among the directors who have a conventional tie to the CEO. Of the conventionally dependent directors, 6.6% share a military connection with, 39.0% graduated from the same university as, 44.9% share regional origin with, 42.6% have the same academic discipline as, 66.0% have the same industry of primary employment as, and 43.7% share a third-party connection with the CEO.

3.4. Board characteristics and the determinants of the incidence of socially linked directors

In Table 2, we present summary statistics on various CEO and board characteristics. In Column 1, which presents statistics for the entire sample, we observe that 87.4% of the boards are conventionally independent. However, when we augment the conventional definition of director independence with the additional social restrictions, the percentage of independent boards drops to 62.4%. Thus, if social ties matter, then a substantial proportion of conventionally independent boards are not truly independent.

We now explore the determinants of a board's social dependence. A CEO's clout in the board-selection process "comes from his perceived ability relative to a replacement" (Hermalin and Weisbach, 1998, p. 97). Thus, if CEOs desire socially dependent directors, we expect that the incidence of such directors increases with quality or power signals, such as tenure and board chairmanship. Consistent with this hypothesis, we observe in Table 2 that, on average, the CEOs of firms whose boards are conventionally independent but not conventionally and socially independent (Column 4) have greater tenure and more often have busy boards; these CEOs are also more likely to have received a "Business Week Best Manager" award than the CEOs of firms whose boards are both conventionally and socially independent (Column 3).

In Table 3, we present the results from a pooled regression of the board's social-dependence fraction on various CEO, board, and firm characteristics. We use lagged values of the economic variables, such as past performance and firm size, because selection power and selection decisions based on economic determinants must be based on past values of such variables. To ensure that past performance is matched to the appropriate CEO, we exclude those firm-years in which there are new arrivals because past firm performance cannot be attributed to an incoming CEO. On the other hand, we use contemporaneous values of the board-composition variables, because directors can be selected mid-year, and the CEO's current power in the selection process is based on the current governance structure. To address potential timing concerns, we also estimate our regression using lagged values of the governance variables, and we obtain similar results (untabulated). We include year dummies and industry dummies using the Fama-French (1997) five-industry classification, and all *t*-statistics are calculated using White standard errors adjusted for clustering (by firm), which account for heteroskedasticity and serial correlation (Petersen, 2009).

We find that *CEO Tenure* has a significantly positive relation with the incidence of socially dependent directors. On average, a CEO with six more years of tenure has a board with a social-dependence fraction that is 0.042 greater (*t*-statistic = 2.11). Moreover, when the CEO has received a "Business Week Best Manager" award, the social-dependence fraction increases by 0.077 (*t*-statistic = 2.12). This positive association lends further support to the hypothesis that CEOs desire socially dependent directors, because a "Best Manager" distinction alludes to the CEO's power and thereby to his clout in the selection process. The social-dependence fraction is also significantly higher, both economically and statistically, when the board is busy (coefficient estimate = 0.052, *t*-statistic = 2.30) as well as when there is a greater proportion of old directors on the board (coefficient estimate = 0.263, *t*-statistic = 3.12); presumably, these variables indicate a lack of director oversight, which also empowers the CEO. Finally, the coefficient estimates on the industry dummies (untabulated) indicate that, all else equal, the *Health* industry has the highest incidence of socially dependent directors, followed by the *High-Tech* and *Other* industries, respectively. The *Consumer* and *Manufacturing* industries have the lowest incidence of socially dependent directors.

The positive association between the degree of social dependence and indicators of CEO quality or power is consistent with the idea that CEOs select directors with whom they share social ties. To further explore this interpretation, in Fig. 1, we examine the changes in a board's social dependence when a new CEO is appointed. If CEOs do not seek socially linked directors, then, on average, we expect to see no time-series increase in the social-dependence fraction as the new CEO advances in tenure. Using an unbalanced panel of 81 CEO appointments, we plot the evolution of the board's social dependence, in event time, from the year prior to the new CEO's arrival (t = 0) to the third year of the new CEO's tenure (t = 3).[10] In Panel A, we plot the average fraction of directors who are socially dependent with respect to the incumbent CEO, and in Panel B, we plot the percentage change in the average fraction of socially dependent directors relative to time t = 0. Upon arrival of the new CEO, we observe an 8.1% decrease from 0.272 to 0.250 in the average proportion of directors who are socially dependent to the incumbent CEO. Then, as the new CEO's time with the firm progresses, he seems to rebuild the board's social dependence. By his third year, the average social-dependence fraction is back up to 0.284, suggesting that CEOs select directors along these social dimensions.

Given that other indicators of quality or power are associated with greater clout in the director selection process, we expect the rate at which a board's social dependence increases with tenure to be higher for those CEOs who exhibit these quality or power signals. Consistent with this hypothesis, we find that, when we interact CEO tenure with the various indicators of CEO quality or power (untabulated), ten of the 14 interactions

[10] One possible concern with the use of an unbalanced panel is that our figure could reflect cross-sectional variation in social ties as opposed to time-series variation. In particular, the positive association between CEO tenure and the board's social dependence could come solely from a socially dependent board's unwillingness to replace a CEO to whom it is socially linked. This interpretation signifies the disciplinary importance of social ties, but it is likewise interesting to know whether CEOs actively select such directors. Thus, we also investigate a balanced panel of CEO appointments, and we observe a similar pattern depicting an overall increase in the incidence of social ties over time (untabulated).

terms have the predicted sign and an *F*-test indicates significance at the 0.01 level, suggesting that such measures contribute to a faster increase in the incidence of socially dependent directors.

4. Empirical results

We now proceed to examining the effect of social ties on executive compensation. In Table 4, we present summary statistics on CEO compensation and various firm characteristics (Appendix C contains a correlation matrix of variables, including the governance variables from Table 2 and our dependent variable, CEO compensation). The overall average salary plus bonus and total compensation are \$3.8 million and \$12.8 million, respectively (Column 1). In a cross-panel comparison, we observe that CEO salary plus bonus and total compensation are lower at firms whose boards are both conventionally and socially independent (Column 3) than at firms whose boards are conventionally independent but not conventionally and socially independent (Column 4). This observation is consistent with our conjecture that conventionally-and-socially independent boards are more effective at controlling agency issues than boards that are only conventionally independent. However, there are many other determinants of executive compensation for which we need to control.

4.1. Level of CEO compensation

To test the relevance of social ties, we estimate the following regression:

$$C_{i,t} = \alpha + \beta_1 BoardIndependence_{i,t} + X\beta_{2\text{-}19} + Year\ \beta_{20\text{-}28} + Industry\ \beta_{29\text{-}32} + \varepsilon_{i,t}. \qquad (1)$$

$C_{i,t}$, the dependent variable, is the level of compensation in millions for the CEO of firm *i* in year *t*. We use two different measures of compensation: *Base Salary + Bonus*, and *Total Compensation*, calculated as the sum of base salary, bonus, long-term incentive payouts, the value of restricted stock grants, and the Black-Scholes value of option grants converted into their stock equivalents using the options' median delta. $BOARD\ INDEPENDENCE_{i,t}$ is a dummy that equals one if the board of firm i is classified as independent (under the criteria in question), and zero otherwise. *X* is a set of the following control variables: *ln(Total Assets)*, *ln(MB)*, *ROA*, *RET*, σ^2, *CEO Equity Holdings*, *CEO Award*, *CEO=Chairman*, *CEO Tenure*, *ln(Board Size)*, *Old Directors*, *Busy Board*, *Directors' Equity Holdings*, *CEO from Other Company*, *Classified Board*, *Democracy Firm*, *Dictatorship Firm*, and *Family Firm*. Following Core, Holthausen, and Larcker (1999), we use lagged values of the economic determinants and contemporaneous values of the governance variables. However, to address potential timing concerns, we also estimate our regressions using lagged values of the governance variables and we obtain similar results (untabulated). To ensure that past performance is matched to the appropriate CEO, we exclude those firm-years in which there are new arrivals because past firm performance cannot be attributed to an incoming CEO. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$, and *Industry* denotes the industry dummies, $Industry_2$ through $Industry_5$, using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

The results, presented in Table 5, show a substantially stronger coefficient estimate when we replace the conventional measure of board independence (which does not incorporate social ties) with our new measure. When we regress the CEO's salary plus bonus on the conventional board-independence dummy (Column 1), we obtain a coefficient estimate of -0.755 (*t*-statistic = -1.16). However, when we replace the conventional dummy with the new board-independence dummy (Column 2), we obtain a coefficient estimate of -0.780 (*t*-statistic = -2.31). This magnitude is also economically meaningful; the CEO's salary plus bonus decreases by roughly \$0.8 million when a conventionally-and-socially independent board is present (average salary plus bonus is \$3.8 million).

In Columns 3 and 4, we extend our analysis to the CEO's total compensation. When we regress total compensation on the conventional board-independence dummy (Column 3), we obtain a coefficient estimate of 0.572 (*t*-statistic = 0.24). However, when we replace the conventional dummy with the new board-independence dummy (Column 4), the coefficient estimate sharply increases in magnitude to -3.347 (*t*-statistic = -2.50). This translates to a total compensation decrease of roughly \$3.3 million when the board is both conventionally and socially independent of the CEO (average total compensation is \$12.8 million)

The new board-independence measure's greater association with compensation suggests that our proposed social ties are an important source of a director-CEO connection that affects the board's monitory capacity. Moreover, consistent with prior literature, the regression results indicate that the level of compensation is higher for CEOs of large firms, for CEOs of growth firms, for CEOs who have strong prior performance, when the CEO is also the chairman of the board, for CEOs whose boards include a higher proportion of old directors, and when at least one of the directors is the

CEO at another firm. Also consistent with prior literature, *CEO Equity Holdings* has a statistically significant (but economically insubstantial), negative relation with the level of compensation. Due to clustering, which oftentimes more than doubles OLS standard errors, many variables that otherwise would be (and may have been found to be) significant determinants of CEO compensation are no longer so once this adjustment is applied to account for time-series persistence.

As an additional test of the relevance of social ties, we examine the variation in compensation within the subset of firms with conventionally independent boards, which allows us to determine whether social ties have a significant contribution beyond that of conventional ties. Focusing on this subsample, we estimate the same regression as in Eq. (1), but, in place of the board-independence dummy, we use a $NOT\ INDEPENDENT_{i,t}$ dummy that equals one if the board (despite being conventionally independent) is not conventionally and socially independent, and zero otherwise. If social ties are irrelevant, then we expect no compensation differential attributed to this distinction. By focusing on firms with conventionally independent boards, we ensure that any compensation differential we observe is due to the extent of the directors' social ties to the CEO.

The results, presented in Table 6, show a significant difference in CEO compensation between the conventionally independent boards that are conventionally and socially independent, and those that are not. In Column 1, we observe that the CEO of a firm with a conventionally-but-not-conventionally-and-socially independent board receives a salary plus bonus that is \$0.6 million greater (t-statistic = 1.71) than that of his conventionally-and-socially independent counterpart, despite each board's conventionally independent status. In Column 2, we observe that this compensation differential extends to the CEO's total compensation package; the CEO of a firm with a conventionally-but-not-conventionally-and-socially independent board receives a total compensation that is \$4.1 million greater (*t*-statistic = 2.69) than that of his conventionally-and-socially independent counterpart. These results further signify the monitory importance of these social ties, because within the subsample of firms with conventionally independent boards, a compensation premium is awarded by firms whose boards' degree of social dependence rules out conventional-and-social independence.

4.2. Subsequent operating performance

The results thus far suggest that social ties affect the board's monitory effectiveness. However, there are alternative explanations for the higher level of compensation associated with having a board that is conventionally independent but not conventionally and socially independent. One possibility is that, when a CEO's job is more difficult or complex, he requires not only a higher level of compensation but also a board with a greater advisory role (i.e., perhaps a friendlier board). Thus, the compensation premium associated with social ties could reflect the firm's complexity as opposed to the board's decreased monitory capacity. A similar argument applies to a high-quality CEO, who has more freedom and bargaining power in the board selection process (Hermalin and Weisbach, 1998). Such a CEO could benignly desire more socially dependent directors, and receive a higher level of compensation due to his high quality.[11] Whether through facilitated expropriation, increased counsel, or CEOs' benign preferences for socially

[11] For example, a CEO from University X could view his alma mater as a signal of quality and may desire directors who hold degrees from University X with the intent to form a higher quality board (as opposed to a less independent one).

dependent directors, all of these possibilities highlight the relevance of these social ties. Our purpose now is to disentangle these competing interpretations.

Following Core, Holthausen, and Larcker (1999), we examine the relation between subsequent operating performance and the excess component of compensation attributed to having a board that is not conventionally and socially independent. If greater social dependence reflects either a high-quality CEO's preferences (other than to entrench himself) or a complex firm's advisory needs, then we expect to see no relation or perhaps a positive relation between subsequent performance and this excess component of compensation. To ensure that any relation we observe is due to the extent of the directors' social ties to the CEO, we focus our analysis on the subsample of firms with conventionally independent boards. Then, we estimate the following regression:

$$\overline{Performance}_{i,t+1,t+3} = \alpha + PredictedExcessCompensation_{i,t}\beta_{1-2} + X\beta_{3-5} + Year\beta_{6-14} + Industry\beta_{15-18} + \varepsilon_{i,t} \quad (2)$$

$\overline{Performance}_{i,t+1,t+3}$, the dependent variable, is the operating performance averaged over the subsequent one-, two-, or three-year period. We use three different measures of operating performance: return on assets (*ROA*), return on sales (*ROS*), and return on equity (*ROE*). *Predicted Excess Compensation*$_{i,t}$ consists of two variables: *Excess(NOT INDEPENDENT*$_{i,t}$*)*, the predicted excess compensation attributed to having a board that is not conventionally and socially independent (despite being conventionally independent); and *Excess(Other Governance Variables*$_{i,t}$*)*, the predicted excess compensation from the remaining governance variables: *CEO Equity Holdings*, *CEO=Chairman*, *ln(Board Size)*, *Old Directors*, *Busy Board*, *Directors' Equity Holdings*, *CEO from Other Company*, *Classified Board*, *Democracy Firm*, *Dictatorship Firm*, and *Family Firm*. Predicted excess components of total compensation are calculated using the coefficient estimates reported in Table 6 and are scaled by total compensation. *X* is a set of the following control variables: *ln(Total Assets)*, *ln(MB)*, and σ^2. We use time-*t* values of *ln(Total Assets)* and σ^2, and we use time-(*t-1*) values of *ln(MB)* to avoid unduly capturing market expectations of upcoming earnings as opposed to expectations of growth opportunities. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$, and *Industry* denotes the industry dummies, $Industry_2$ through $Industry_5$, using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

The results, presented in Table 7, show a significantly negative relation between subsequent operating performance and the excess compensation attributed to having a board that is not conventionally and socially independent. To gauge the economic importance, consider a one standard deviation increase (0.418) in *Excess(NOT* $INDEPENDENT_{i,t}$*)*. For the one-year performance measures, such an increase is associated with a 0.4% decrease in *ROA* (*t*-statistic = -1.89), a 0.5% decrease in *ROS* (t-statistic = -1.72), and a 0.8% decrease in *ROE* (*t*-statistic = -2.61). For the two-year measures, such an increase is associated with average, annual decreases of 0.5% in *ROA* (*t*-statistic = -2.10), 0.5% in *ROS* (*t*-statistic = -1.86), and 0.8% in *ROE* (*t*-statistic = -2.54). For the three-year measures, such an increase is associated with average, annual decreases of 0.4% in *ROA* (*t*-statistic = -2.46), 0.5% in *ROS* (t-statistic = -2.24), and 0.7% in *ROE* (*t*-statistic = -2.08).

Because all of these firms have conventionally independent boards, the negative associations that we find are explicitly due to the extent of social ties to the CEO. These results further punctuate the monitory and disciplinary importance of social ties, because neither the advisory needs of a complex firm nor the innocent social preferences of a high-quality CEO can explain this negative association between subsequent operating performance and the excess compensation attributed to having a board that is not conventionally and socially independent.

4.3. Other channels of monitoring

We now examine the role of social ties in other supervisory and disciplinary duties of the board. In particular, we study the effect of social ties on pay-performance elasticity, CEO turnover, and earnings management. To ensure that any relation we observe is due to the extent of the directors' social ties to the CEO, we focus our analyses on the subsample of firms with conventionally independent boards.

4.3.1. Board independence and pay-performance elasticity

Here, we examine the role of social ties in the CEO's pay-performance relation. Jensen and Murphy (1990) and Murphy (1999) argue that the relation between CEO pay and performance (i.e., the change in shareholder wealth) is weak. One explanation is that lack of oversight leads to compensation plans in which interests are not adequately aligned between shareholders and risk-averse, self-interested CEOs. If social ties do not exacerbate this conflict, then we expect no difference in the pay-performance relation attributed to the extent of the board's social ties to the CEO.

Within the subsample of firms with conventionally independent boards, we regress the percentage change in CEO compensation on $RET_{i,t}$, $RET_{i,t}$ x $NOT\ INDEPENDENT_{i,t}$, and *INTERACT*, which consists of various other interaction terms.

NOT INDEPENDENT$_{i,t}$ is a dummy that equals one if the board (despite being conventionally independent) is not conventionally and socially independent, and zero otherwise. *INTERACT* is a set of interaction terms in which *RET*$_{i,t}$ is interacted with each of the following variables: *CEO Award*, *CEO=Chairman*, *CEO Tenure*, *ln(Board Size)*, *Old Directors*, *Busy Board*, *Directors Equity Holdings*, *CEO from Other Company*, *Classified Board*, *Democracy Firm*, *Dictatorship Firm*, *Family Firm*, and σ^2. In accordance with previous studies, we use contemporaneous values of all independent variables. We include year and industry dummies, and all *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

We interact *RET*$_{i,t}$ with σ^2 because, consistent with the predictions of the principal-agent model, Aggarwal and Samwick (1999) find that pay-performance sensitivity decreases in stock return volatility. The remaining interactions are with variables that proxy a CEO's clout with his board or lack of director oversight, which we expect to lessen the relation between pay and performance. Finally, in regressing the percentage change in pay on the percentage change in shareholder wealth, we estimate pay-performance elasticity as opposed to pay-performance sensitivity, which examines the dollar change in pay with respect to the dollar change in shareholder wealth (Murphy, 1999). We opt to estimate pay-performance elasticity because, in doing so, we obtain greater explanatory power of our dependent variable. However, we obtain similar results when we estimate pay-performance sensitivity (untabulated).

The results, presented in Table 8, show a significant difference in pay-performance elasticity within the subsample of firms with conventionally independent boards. Consistent with prior literature, we observe a significantly positive relation between the percentage change in compensation and the percentage change in shareholder wealth (Columns 1 and 3). However, the CEO of a firm with a conventionally-but-not-conventionally-and-socially independent board receives a total compensation package that is 0.510 less elastic with respect to performance (*t*-statistic = -1.91) than that of his conventionally-and-socially independent counterpart (Column 4). In other words, for a 20% decrease in stock returns, the CEO of a firm with a conventionally-but-not-conventionally-and-socially independent board has a total compensation package that decreases by 10.2% less than that of an otherwise equivalent CEO of a firm with a conventionally-and-socially independent board. Ultimately, firms with conventionally-and-socially independent boards exhibit, on average, an 18% decrease in the CEO's total compensation for a 20% decrease in shareholder wealth (untabulated).

4.3.2. Board independence and CEO turnover

Here, we examine the role of social ties in the CEO's turnover-performance sensitivity. CEO turnover is another area in which social ties potentially hinder the board from acting in shareholders' best interests. Board consultants in the popular press broach this issue, saying that when directors debate whether or how to fire a CEO, "they [the directors] typically need the most help in dealing with their attachment to the CEO" (Business Week, 2007), and academic studies find weaker sensitivity of turnover to performance with the presence of factors indicating that the board is beholden to the CEO (e.g., Weisbach, 1988; Yermack, 1996; and Faleye, 2007). If social ties do not cloud objective disciplining, then we expect no difference in turnover-performance sensitivity attributed to the extent of the board's social ties to the CEO.

Within the subsample of firms with conventionally independent boards, we use the logistic function to estimate a binary response model of the $Turnover_{i,t}$ indicator on $RET_{i,t-1}$, $RET_{i,t-1}$ x $NOT\ INDEPENDENT_{i,t-1}$, and $NOT\ INDEPENDENT_{i,t-1}$, as well as *INTERACT*, which consists of various other interaction terms, and *X*, which consists of various controls. $Turnover_{i,t}$ is a dummy that equals one if a CEO turnover occurs at firm *i* in year *t*, and zero otherwise. $NOT\ INDEPENDENT_{i,t-1}$ is a dummy that equals one if in year *t-1* the board (despite being conventionally independent) is not conventionally and socially independent, and zero otherwise. The set *X* consists of the following variables: *CEO Award*, *CEO=Chairman*, *CEO Tenure*, *ln(Board Size)*, *Old Directors*, *Busy Board*, *Directors Equity Holdings*, *CEO from Other Company*, *Classified Board*, *Democracy Firm*, *Dictatorship Firm*, and *Family Firm*, which proxy a CEO's clout with his board or lack of director oversight, as well as *CEO Age*, which serves to distinguish voluntary retirements from involuntary departures (as does *CEO Tenure*). Departures of mature CEOs with long tenure are more likely to be voluntary (Murphy, 1999). *INTERACT* is a set of interaction terms in which $RET_{i,t-1}$ is interacted with each of the variables in *X*, except for *CEO Age*. In accordance with previous studies, we use lagged values of all independent variables. Because this regression involves lagged board-structure variables, which are unavailable in 1995, we begin our analysis in 1997. We include year and industry dummies, and all *p*-values account for clustering (by firm).

The results, presented in Table 9, show a significant difference in the probability of a CEO turnover within the subsample of firms with conventionally independent boards; all else equal, the probability of turnover decreases, on average, by 3.7% for firms with boards that are conventionally independent but not conventionally and socially independent (p-value = 0.09). Moreover, we observe a suggestive difference in turnover-performance sensitivity attributed to this distinction. The CEO of a firm with a conventionally-but-not-conventionally-and-socially independent board is less likely to be terminated based on poor performance (p-value = 0.18) than his conventionally-and-socially independent counterpart. For a one standard-deviation decrease (from the mean) in returns, the probability of turnover increases by roughly 3.2% less when the board is not conventionally and socially independent.

4.3.3. Audit-committee independence and CEO bonus

Here, we examine the role of social ties in the audit committee's oversight responsibilities. The audit committee's function is to oversee the integrity of the firm's financial statements, of which accounting earnings are the primary determinant of the CEO's bonus (Murphy, 1999). There is evidence that managers attempt to manipulate earnings to maximize their bonuses (Healy, 1985), and related studies suggest that the level of earnings manipulation is a function of the firm's governance and ownership structure (e.g., Dechow, Sloan, and Sweeney, 1996; and Warfield, Wild, and Wild, 1995). In particular, Klein (2002) argues that firms with independent audit committees engage in less earnings management. If social ties do not cloud objective monitoring, then we expect no bonus differential (and thus no difference in earnings manipulation) attributed to the presence of social ties between the CEO and members of the audit committee.

Within the subsample of firms whose audit committees consist entirely of conventionally independent directors, we regress the CEO's bonus (in millions) on a *NOT INDEPENDENT*$_{i,t}$ dummy, the CEO's total compensation minus his bonus, and the same set of controls, *X*, as in regression Eq. (1). *NOT INDEPENDENT*$_{i,t}$ is a dummy that equals one if the audit committee (despite consisting entirely of conventionally independent directors) has one or more directors who are socially dependent to the CEO, and zero otherwise. Because this regression involves audit committee data (which are not available until after 1997), we begin our analysis in 1998. We control for the CEO's total compensation (minus bonus), because the CEO's bonus is positively associated with his overall level of compensation and audit committee independence is positively associated with board independence. We include year and industry dummies, and all *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

The results, presented in Table 10, show a significant bonus differential within the subsample of firms with conventionally independent audit committees. On average, the CEO of a firm with a conventionally-but-not-conventionally-and-socially independent audit committee receives a bonus that is \$0.734 million greater (*t*-statistic = 1.75) than that of his conventionally-and-socially independent counterpart (average CEO bonus is \$2.6 million), thereby lending support to the monitory relevance of social ties in the audit committee's supervision of the firm's financial statements. This bonus premium is not a by-product of our earlier compensation results, because we control for the CEO's overall compensation. We obtain similar results when we control for base salary in place of total compensation (untabulated), with a coefficient estimate of 0.813 (*t*-statistic = 1.95).

4.4. Additional analyses

To ensure that our results are not sensitive to alternative specifications, we now examine various board-independence classifications and alternative regression specifications. All untabulated analyses are available upon request.

4.4.1. Alternative classifications of conventionally-and-socially independent boards

In Table 11, we present the results from a range of sensitivity tests of alternative, independence classifications. As in Table 5, we estimate regression Eq. (1) using two different measures of compensation: *Salary* + *Bonus* (Panel A) and *Total Compensation* (Panel B), and all *t*-statistics are calculated using White standard errors adjusted for clustering (by firm). In Columns 1 through 3, we present the results from using a board-independence dummy, whereby, in Column 1, we require that a 50% majority of directors be independent; in Column 2, we require that a 60% majority of directors be independent; and in Column 3, we require that all members of the compensation committee be independent. In regressions using the 60% cutoff, we also include a mixed-board dummy that equals one if the percentage of independent directors is between 40% and 60%, and zero otherwise. Moreover, for regressions involving compensation committee information, our analyses begin in 1998 in accordance with data availability. In Column 4, we present the results from using the fraction of independent directors (as opposed to an independence dummy). Finally, in Column 5, we present the results from using the board's average number of ties per director, which we calculate by dividing the total number of director-CEO ties (with a maximum of seven per director) by the number of directors for that firm-year. In contrast to the other measures (including the independence fraction), which categorize directors in dichotomous terms, this last measure allows us a finer metric to define the extent of a director's dependence to the CEO. For each of these measures of board independence, we present the results from using two different specifications of director independence. In the first row, we consider only the conventional ties, and in the second row, we augment the conventional criteria with our social criteria.

We find that our earlier results are robust to different board-independence cutoffs, to the use of an independence fraction instead of a dummy, and to the use of an average-ties measure. Across our various specifications of board independence, the coefficient estimates on the conventional-and-social independence measures (Row 2) are both economically meaningful and statistically significant. Moreover, we observe similarly significant results when we redefine regional ties by a finer state-wise classification (untabulated). In comparison, the coefficient estimates on the conventional-independence measures (Row 1) are substantially smaller in economic and statistical significance.

Using these alternative specifications, we also replicate Table 6 (which provides a clearer picture of the monitory relevance of social ties beyond that of conventional ties because we examine the variation in compensation within the subsample of firms with conventionally independence boards), and we obtain even stronger results (untabulated).

4.4.2. Additional sensitivity tests

In additional tests (untabulated), we include an outside blockholder dummy as a control variable, because an outside blockholder has increased supervisory incentives due to his large stake in the firm. An outside blockholder is a shareholder who has at least 5%

ownership in the firm and is not an officer, a director, an affiliated entity, or otherwise employed by the firm. The board-independence coefficient estimates are equal in magnitude to those obtained in our original regressions, but, because the blockholder database ends in 2001, our sample size sharply decreases to 350 observations with the inclusion of this variable, thereby increasing the standard errors of the board-independence coefficient estimates (resulting in *t*-statistics of -1.86 and -1.65, respectively, when using the *Salary + Bonus* and *Total Compensation* measures). As always, we use White standard errors adjusted for clustering by firm. Whether the outside blockholder dummy is included or not, compensation regressions within this reduced sample (of 350 observations) yield very similar board-independence coefficient estimates and standard errors.

Furthermore, our results continue to hold under the following alternative specifications of our empirical tests (untabulated): calculating total compensation using the Black-Scholes value of options instead of converting them into their stock equivalents; estimating quantile regressions to reduce the influence of potential outliers; including the CEO's first-year level of compensation as an additional control for CEO quality; adding squared values of our independent variables to capture possible nonlinearities; adjusting variables by the industry median (as opposed to adjusting by the mean); including an *Other Provisions* index in place of the *Democracy* and *Dictatorship* dummies (the *Other Provisions* index is equal to the GIM index minus one if the firm has a classified-board provision, and minus zero otherwise); and including the Bebchuk, Cohen, and Ferrell (2004) index in place of the *Classified-Board*, *Democracy*, and *Dictatorship* dummies (the BCF index accrues one point for each of the following provisions: classified board, poison pill, golden parachute, limits to bylaw amendments, supermajority requirements for charter amendments, and supermajority requirements for mergers).

4.4.3. Missing data

Social ties are indeterminate for some directors due to missing data points. We have 81.2% coverage in terms of educational institution, 66.8% coverage in terms of regional origin, 57.8% coverage in terms of discipline, and 96.1% coverage in terms of industry. Because military service is a noteworthy career point, we assume that a blank military service field indicates that the director or CEO in question simply did not serve in the military. Overall, we have at least one social ties data point for 98.4% of directors, we have at least two data points for 82.3% of directors, and we have at least three data points for 76.2% of directors.

Directors who are missing data along our social criteria, by default, are not linked socially to the CEO. One possible concern, then, is that the missing data share a systematic component, resulting in a spurious correlation between social ties and CEO compensation. To the contrary, we find that our coverage rates are not significantly related to firm size, market-to-book, or the various governance variables (nor do they vary significantly across industries), suggesting that the missing social ties data are missing at random.

To further ensure that our results are not driven by the missing data, we re-estimate regression Eq. (1) (untabulated), this time separating the (conventionally and socially) independent directors into two categories: those who have low coverage (less than two data points) in terms of social ties data, and those who have high coverage (at least three data points). Unless the missing data share a systematic component associated with lower CEO compensation, we expect a weaker relation between compensation and low-coverage independent directors than between compensation and high-coverage independent directors (because independent directors with lower data coverage are less certain to be truly independent than those with higher data coverage). Consistent with this notion, we find that in a regression of *Salary + Bonus* on the low- and high-coverage independence fractions, the high-coverage coefficient estimate is stronger, both in magnitude and statistical significance, than the low-coverage coefficient estimate. We make similar observations when we regress *Total Compensation* on the low- and high-coverage independence fractions, and in both cases, only the high-coverage coefficient estimates are reliably different from zero. Moreover, we make similar observations under different cutoffs of high versus low data coverage. The stronger association between CEO compensation and the high-coverage independent directors substantiates that our results are not driven by the missing social ties data, and provides further evidence that our proposed measures contribute to a decline in monitory and disciplinary effectiveness.

5. Contribution and discussion

Our paper contributes to the governance literature in the following ways. First, we propose a measure of social ties between directors and their CEOs, and we provide evidence of its practical applicability. In contrast to the survey-based measures generally employed by studies pertaining to social embeddedness (e.g., Uzzi, 1996, 1999; Westphal, 1999; Ingram and Roberts, 2000; McDonald and Westphal, 2003; and

Westphal, Boivie, and Chng, 2006), our measure is based on several broadly available characteristics. In this respect, our measure is similar to that of Cohen, Frazzini, and Malloy (2008), who study the effects of social ties between mutual fund managers and corporate officers or directors via mutual alma mater.[12] We add to their measure by suggesting that it is not only a shared educational institution that contributes to a mutual affinity, but also shared military service, regional origin, discipline, and industry.

Moreover, we are the first to examine whether social ties affect a director's monitory and disciplinary effectiveness (above and beyond any effect that the conventional ties may have) and whether boards that are currently (i.e., conventionally) classified as independent are essentially so. Thus, the evidence presented in this paper is relevant to the many academic studies examining the monitory benefits of independent boards (e.g., Weisbach, 1988; Byrd and Hickman, 1992; Brickley, Coles, and Terry, 1994; Cotter, Shivdasani, and Zenner 1997; Mayers, Shivdasani, and Smith, 1997; and Paul, 2007), because our findings suggest that a board's independent mindedness depends not only on conventional ties to the CEO, but also on our proposed social ties. We specifically contribute to the executive compensation, CEO turnover, and earnings management literatures as follows:

Executive Compensation. Studies examining the relation between board composition and executive compensation include Mehran (1995); Westphal and Zajac

[12] In a digressive (but related) vein, some studies use various demographics, such as age, insider versus outsider status (i.e., whether the director is an employee of the firm), and level of formal education to capture similarities in strategic decision making (e.g., Wally and Baum, 1994; Westphal and Zajac, 1995; Papadakis, Lioukas, and Chambers, 1998). For instance, they argue that risk tolerance decreases with age, that cognitive ability increases with the level of formal education, and that outsiders could be "more likely to recognize opportunities for change" whereas insiders "tend to favor the status quo" (p. 64).

(1995), Yermack (1996), Hallock (1997), Core, Holthausen, and Larcker (1999), Larcker, Richardson, Seary, and Tuna (2005), and Faleye (2007), who find that executive compensation is higher and is less sensitive to performance in the presence of certain structural measures indicating weaker governance, as well as when directors and CEOs have similar perspectives on corporate strategy. We add to this literature by providing evidence that social ties contribute, beyond any impact that conventional ties may have, to both the level and composition of compensation. We find that conventionally independent boards have a substantially weaker, negative relation with executive compensation than boards that are both conventionally and socially independent. Moreover, we find that pay-performance elasticity is substantially weaker when boards are not both conventionally and socially independent of the CEO, further suggesting that conventional measures of independence do not fully capture a board's monitory effectiveness.

CEO Turnover. We also contribute to the literature examining the sensitivity of turnover to performance in the presence of factors indicating that the board is beholden to the CEO (e.g., Weisbach, 1988; Yermack, 1996; and Faleye, 2007) by providing suggestive evidence that social ties contribute to weaker turnover-performance sensitivity. Within the subsample of firms with conventionally independent boards, the probability of a CEO turnover is less sensitive to performance at firms with boards with that are not conventionally and socially independent (though not at a statistically significant level).

Earnings Management. Finally, we contribute to the literature examining the association between governance and earnings management (e.g., Dechow, Sloan, and

Sweeney, 1996; and Klein, 2002). We contend that it is not only managerial stock holdings (Warfield, Wild, and Wild, 1995) or conventionally independent audit committees (Klein, 2002) that contribute to less earnings manipulation, but also the absence of social ties. Focusing on the subsample of firms whose audit committees consist entirely of conventionally independent directors, we find a significantly higher level of bonus associated with the presence of audit committee social ties to the CEO, providing suggestive evidence that even if audit committees are wholly conventionally independent, social ties allow CEOs to influence earnings in order to increase their bonuses.

6. Conclusion

Directors are not dispassionate. It is not only financial and familial ties that interfere with their disciplinary and monitory roles; social ties also matter. Here, we propose several observable characteristics that likely connect a director (socially) to the CEO: mutual alma mater, military service, regional origin, discipline, and industry. We augment the conventional definition of board independence with these additional social restrictions and find that the percentage of independent boards in our sample drops from 87% to 62%. Moreover, we provide evidence that CEOs select directors along these social dimensions and that these social ties have a significant impact on directors' monitory and disciplinary effectiveness. Thus, we conclude that social ties compromise arms-length contracting and, as such, are relevant to the classification of independent directors.

Second Essay: Country-Specific Sentiment and Security Prices

1. Introduction

A growing body of both theoretical and empirical research reveals that sentiment, while irrelevant to decisions at hand, may still have an important influence on investor behavior and financial markets (e.g., De Long, Shleifer, Summers, and Waldman 1990; Lee, Shleifer, and Thaler 1991; Shleifer and Vishny 1997; Shleifer 2005; and Baker and Wurgler 2006, 2007). This literature generally takes the origin of investor sentiment as exogenous; that is, studies remain silent on what causes investors to be overly optimistic or pessimistic about a firm's economic prospects. Only recently have economists begun to explore the foundations of sentiment and tied stock returns to "mood variables," such as the level of sunshine (Hirshleifer and Shumway 2003), the amount of daylight (Kamstra, Kramer, and Levi 2003), the event of an aviation disaster (Kaplanski and Levy 2009), and whether a country's soccer team is eliminated from an important tournament (Edmans, Garcia, and Norli 2007). The argument is that these variables affect mood, which, in turn, causes subjects to view economic prospects overly favorably or unfavorably.

My purpose in this paper is to provide evidence on a new dimension of sentiment-driven demand. Specifically, I study whether a country's popularity affects demand for securities from that country and causes prices to deviate from their fundamental values. Single country closed-end funds (CCEFs) provide an attractive setting to explore this question. CCEFs are corporations holding a portfolio of securities in a single (non-US) country. Both the CCEF and the shares held by the CCEF are traded on stock exchanges.

While the CCEF's market value is determined in the US, the value of the fund's underlying assets is determined (primarily) by "foreign" investors in the security's "home market." To the extent that foreign investors are sheltered from American sentiments toward their respective countries, the value of the CCEF's underlying assets provides an adequate benchmark against which the fund's market value can be compared (Bodurtha, Kim, and Lee 1995). If country-sentiment does not influence investors' demand and market outcomes, then I expect no association between country popularity and the discount between the fund's market value and the market value of the fund's underlying assets.

The findings presented in this study are largely supportive of country popularity affecting decision-making and market outcomes. I measure a country's popularity among Americans using the Gallup Poll on Americans' attitudes toward other countries. Survey participants are asked how they view country X, choosing from four answers: very favorably, mostly favorably, mostly unfavorably, and very unfavorably. Looking at 23 CCEFs from 14 countries over the 1993 to 2006 period, I find that funds from less-popular countries trade at a higher discount than funds from popular countries. The estimated effect is both statistically and economically meaningful. The results hold under different regression specifications and are robust to alternative survey-response aggregation methodologies. The association between country popularity and discount is not limited to CCEFs, but extends to a sample of 309 American Depository Receipts (ADRs) from 19 countries over the 1992 to 2006 period.[13] Furthermore, consistent with the hypothesis that country sentiment affects investors' investment decisions, I observe

[13] ADRs are claims to shares of foreign securities that are traded in the US.

that mutual funds investing in popular countries enjoy significantly higher fund inflows than mutual funds investing in less-popular countries.

Low country popularity is associated not only with high discounts for securities from these countries, but also with high institutional holdings. One explanation is that while low country popularity causes retail investors to unload their holdings of these low popularity securities (increasing the discount), institutional investors – less affected by investor sentiment – take the other side of the unsophisticated demand (increasing institutional holdings). This interpretation conforms nicely with the general notion that retail investors are more susceptible to sentiment than institutional investors (Baker and Wurgler 2007).

The paper is organized as follows: Section 2 describes the data. Sections 3 and 4 report results from an event study and regressions of CCEF discounts on country popularity and various control variables. Section 5 conducts additional analyses. Section 6 concludes.

2. Data

2.1. Country closed-end fund discount

This analysis focuses on country closed-end funds that are identified with a single country (CCEF) and possess the necessary data to construct the closed-end fund discount, the *Country Popularity Score*, *Inverse Security Price*, *Dividend Yield, Turnover Ratio, Home Market Index Returns, US Market Index Returns*, and *Institutional Holdings* (all defined below or in Appendix D). The sample includes 23 CCEFs from 14 countries over the period 1993:12 to 2006:06 (listed in Appendix E). The countries are: Brazil, France, Germany, India, Indonesia, Israel, Japan, Korea, Mexico, Philippines, Russia, Spain, Taiwan, and the UK. Following Chan, Jain, and Xia (2008), I exclude data for the first six months after the fund's IPO and for the month preceding the announcement of a liquidation/open-ending to "avoid distortions associated with the flotation and winding up of closed-end funds" (p. 383).

Monthly closed-end fund premia/(discounts) are calculated using closing prices and net asset values reported in COMPUSTAT:

$$\frac{Price_{i,t} - NAV_{i,t}}{NAV_{i,t}}. \tag{1}$$

Any positive (or negative) association between some variable x and equation (1) could either be described as x being positively (or negatively) associated with the closed-end fund *premium* or as x being negatively (or positively) associated with the closed-end fund *discount*. In this study, results are described in terms of discounts. The average closed-end fund discount in my sample is 10.48%; the standard deviation is 14.92%.[14] The mean and standard deviation of the CCEF discount in this study are similar to those reported in related studies (e.g., Bodurtha, Kim, and Lee 1995; and Chan, Jain, and Xia 2008).

2.2. Country popularity

To measure each country's popularity among Americans, I use Gallup surveys. The surveys are based on telephone interviews with a national representative adult sample of 1,007. In the survey, respondents are asked the following question on 42 countries: [15]

[14] Unless otherwise noted, the mean and the standard deviation are always pooled across all observations.

[15] No other questions are asked in the survey.

(I'd like your overall opinion of some foreign countries.) Is your overall opinion of ... very favorable, mostly favorable, mostly unfavorable, or very unfavorable?

Based on the survey participants' responses, I construct a *Country Popularity Score* by multiplying the percentage of survey participants who respond (1) very favorably by four, (2) mostly favorably by three, (3) mostly unfavorably by two, and (4) very unfavorably by one and adding these four numbers into one cumulative score.[16]

The mean *Country Popularity Score* of all countries covered in my analysis is 3.48; the standard deviation is 1.03. The mean *Country Popularity Score* suggests that, on average, Americans think mostly favorably of countries in my sample. However, stark differences in popularity can be seen both across countries and over time. For an example of a cross-sectional difference in country popularity, the UK was seen very favorably by 46% of Americans in February 2006. But at the same time, only 5% held the same view of Russia. For an example of an intertemporal change to a country's popularity, in February 2003, before the Iraq invasion, 3% viewed France very unfavorably. That percentage increased sharply to 39% by March 2003 after the country objected strenuously to the US-led war.

The survey frequency is reported in Appendix H. The median number of months passed between two surveys is 12 months. The 25th percentile and 75th percentile are 11 months and 17 months, respectively. In my analysis, I use data from the most recent survey. One concern is whether a country's past popularity is representative of a

[16] Participants who feel that they do not have sufficient information to form an overall opinion of a country can opt for "no opinion." On average, 7.97% of respondents had no opinion towards a country. The percentages in constructing the country popularity score are all with respect to survey participants who had some opinion towards a country. A snapshot of these fractions as of December 2006 (the last month in my sample) is reported in Appendix I.

country's present popularity. The average absolute change in the *Country Popularity Score* between surveys conducted more than one year apart is equal to 0.28. In comparison, the average absolute change in the *Country Popularity Score* between surveys conducted one month (less than one year) apart equals 0.58 (0.41). These results imply that when warranted by a large change in a country's perception, surveys are conducted more frequently; moreover, it appears that not much information is lost when surveys are conducted on a less frequent basis because a country's popularity does not change substantially in these cases. However, I do note that my results become slightly stronger when restricting myself to observations for which the most recent survey was taken less than six (twelve) months ago.

2.3. Other variables

In addition to the *Country Popularity Score*, I include the following variables in my regression analysis: *Inverse Security Price*, *Dividend Yield, Turnover Ratio, Home Market Index Returns,* and *US Market Index Returns*. Please refer to Appendix D for a description of each variable and its expected relation with the discount. The data sources are: CRSP, COMPUSTAT, and COMPUSTAT GLOBAL ISSUE.

3. Iraq war

The beginning of the Iraq War was associated with a dramatic change in Americans' perceptions of various countries, in particular, France and Germany. As such, it presents an interesting setting for an initial exploration of the relevance of country popularity to security prices.

In March 2003, France and Germany made clear they would not support an invasion of Iraq. As a result, US government officials and part of the American media offered harsh criticism. Some Americans even boycotted French and German products, with the stated goal of "punishing France and Germany" for their lack of support. Chavis and Leslie (2008) suggest that the unofficial US boycott of French wine alone cost France $112 million.

The change in sentiment toward France and Germany is captured by the Gallup Poll on Americans' attitudes towards other countries and the *Country Popularity Score* constructed from it, providing some indication that the *Country Popularity Score* generally succeeds in measuring Americans' sentiment towards other countries: The beginning of the Iraq War was accompanied by a sharp drop in the average *Country Popularity Score* of France and Germany from 2.66 to 1.61.[17] There are two CCEFs from France and Germany around the beginning of the Iraq War. Consistent with country-specific sentiment having a non-negligible impact on security prices, the average discount of the two French and German CCEFs increases substantially from 20.3% in February 2003 to 32.7% in March 2003. Next, a multivariate analysis will test whether the observation made for the special case of the beginning of the Iraq War extends to the full panel.

4. Main analysis

I estimate the partial effect of a country's popularity on security prices using both fixed-effects and first-differencing estimators. Estimates under the fixed-effects specification

[17] France's score decreased from 2.49 in February 2003 to 1.29 in March 2003; Germany's score decreased from 2.84 to 1.92 during the same period.

are obtained by adding fund dummies and estimating OLS regressions; estimates under the first-differencing specification are obtained by estimating OLS regressions for the first difference of my dependent and independent variables. The dependent variable is $Discount_{i,t}$ (Eq. 1). The independent variable of most interest in the context of this study is the $Country\ Popularity\ Score_{i,t}$. Other independent variables include: $Inverse\ Security\ Price_{i,t-1}$, $Dividend\ Yield_{i,t-1}$, $Turnover\ Ratio_{i,t}$, $Home\ Market\ Index\ Returns_{i,t}$, and $US\ Market\ Index\ Returns_{i,t}$.[18] I calculate *t*-statistics using White standard errors adjusted for clustering (by year-month and fund).[19]

As reported in Table 12, the coefficient estimate on the *Country Popularity Score* under the fixed-effects regression specification equals 0.052 (*t*-statistic 1.97), implying that a one-unit drop in the *Country Popularity Score* leads to a 5.2% increase in the discount. Such a drop in popularity would move the median firm (in terms of discount) to the 82nd percentile. The first-differencing estimator produces a similarly economically meaningful coefficient estimate on the *Country Popularity Score*. Here, the estimate equals 0.039 (*t*-statistic 2.58), implying that a one-unit drop in the *Country Popularity Score* leads to a 3.9% increase in the discount.

Both fixed-effects and first-differencing estimators solely exploit time-series variation in the dependent and independent variables to obtain estimates of the partial effect of country popularity on security prices. To explore the relation between country popularity and security prices in the cross-section, I also run Fama-MacBeth (1973)

---

[18] Again, please refer to Appendix D for a description of each variable and its expected relation with the discount. Appendix D also discusses the timing of my independent variables.

[19] Throughout the paper, whenever I calculate standard errors adjusted for clustering along multiple dimensions, I use the estimator devised by Cameron, Gelbach and Miller (2007).

regressions: Every month, I regress *Discount* on the *Country Popularity Score* and, except for the *US Market Index Returns*, the same set of control variables as before. The reason I drop *US Market Index Returns* is that *US Market Index Returns* are the same for all funds at a given point in time. I then take the time-series mean of the coefficient estimates from the cross-sectional regressions. I adjust the standard errors for serial correlation and heteroskedasticity using Newey-West (1987) with twelve lags. As reported in Column 3 of Table 12, I find that country popularity and CCEF discounts are associated in the cross-section: The time-series mean is 0.030 and has a *t*-statistic of 3.69.

Both fixed-effects and first-differencing estimators allow unobserved, time-constant effects (such as managerial ability) to be correlated with the explanatory variables.[20] There remains the concern that the regression error terms, $\varepsilon_{i,t}$, and the explanatory variables, $X_{i,s}$, might be correlated for $s \neq t$, thus violating the strict exogeneity assumption. Future values of the *Country Popularity Score* might be correlated with $\varepsilon_{i,t}$ if sentiment has price impact and changes in sentiment are reflected in the *Country Popularity Score* with a lag due to the low survey frequency. In addition, $\varepsilon_{i,t}$ might be correlated with past values of the *Country Popularity Score* if sentiment has price impact but only slowly gets factored into the price. These feedback effects do not appear to be very important in my data: Specifically, I find that including both past and future *Country Popularity Scores* as additional explanatory variables in the fixed-effects specification does not materially alter my findings. For instance, when including *Country Popularity* $Score_{t-1}$ and *Country Popularity* $Score_{t+1}$ as additional independent variables, neither the coefficient on *Country Popularity* $Score_{t-1}$ nor the one on *Country Popularity*

[20] The first-differencing estimator can continue to produce "reasonable" estimates if the unobserved effect rarely changes over time.

Score$_{t+1}$ is reliably different from zero; the coefficient on *Country Popularity Score*$_t$ turns to 0.030 (*t*-statistic 1.60).[21]

In Table 13, I explore alternative aggregations of survey responses from the Gallup Poll on Americans' attitudes towards other countries. In particular, I replace the *Country Popularity Score* with the fraction of survey participants thinking very or mostly favorably of a country (Panel A) and the fraction of survey participants thinking very or mostly unfavorably of a country (Panel B).

Consistent with earlier results, the discount of CCEFs is negatively associated with the fraction of survey participants thinking very or mostly favorably of a country: The coefficient estimate on the fraction of survey participants is equal to 0.343 (*t*-statistic 2.23) under the fixed-effects specification, 0.218 (*t*-statistic 2.60) under the first-differencing specification, and 0.160 (*t*-statistic 4.20) under the Fama-MacBeth (1973) specification. The coefficient estimate of 0.343 suggests that a 10% drop in the fraction of survey participants thinking very or mostly favorably of a country leads to a 3.43% increase in the discount.

Also consistent with earlier results, the discount of CCEFs is positively associated with the fraction of survey participants thinking very or mostly unfavorably of a country: The coefficient estimate on the fraction of survey participants is equal to -0.210 (*t*-statistic -1.49) under the fixed-effects specification, -0.170 (*t*-statistic -2.07) under the first-differencing specification, and -0.220 (*t*-statistic -4.33) under the Fama-MacBeth

[21] Similarly, including Δ*Country Popularity Score*$_{t-1}$ and Δ*Country Popularity Score*$_{t+1}$ as additional independent variables in my first-differencing specification produces a coefficient estimate of 0.044 (*t*-statistic 2.26) on Δ*Country Popularity Score*$_t$. This estimate is very similar to the one obtained without including Δ*Country Popularity Score*$_{t-1}$ and Δ*Country Popularity Score*$_{t+1}$.

(1973) specification. The coefficient estimate of -0.170 suggests that a 10% increase in the fraction of survey participants thinking very or mostly unfavorably of a country increases the discount by 1.70%.

Recent closed-end fund studies detect only a weak association between the discount of domestic closed-end funds and measures of investor sentiment, such as the US Consumer Confidence Index (Lemmon and Portniaguina 2006) and the UBS/Gallup Sentiment Survey (Qiu and Welch 2006). My finding that discounts of CCEFs decrease in sentiment while, at the same time, related studies find no such association for domestic closed-end funds then seems confusing.

However, the contradiction is more apparent than real. Generally, if some sentiment were to have price impact, but to affect both the value of the security and the value of the security's underlying assets, then changes in sentiment would not be fully reflected in the discount leading to an understatement of the sentiment's economic significance. In some cases, this understatement will lead to the (incorrect) inference that sentiment has no meaningful impact on security prices. Finding a sentiment that could potentially affect the market value of the fund – but not the value of the fund's underlying assets – is challenging in the case of domestic closed-end funds.[22]

But this challenge lessens significantly with CCEFs, because the investor base determining the security's market value remains disconnected from the investor base determining the value of its underlying assets. The value of the security's underlying assets is determined (primarily) by "foreign" investors in the security's "home market," whereas the security's market value is determined in the US. To the extent that foreign

[22] As Lemmon and Portniaguina (2006) and Qiu and Welch (2006) point out, this feature of domestic closed-end funds makes the domestic closed-end fund discount a very noisy measure of investor sentiment.

investors are sheltered from American sentiments toward their respective countries, the value of a CCEF's underlying assets provides an adequate benchmark against which the fund's market value may be examined (Bodurtha, Kim, and Lee 1995).

Overall, studying the effect of a country-specific sentiment on CCEF discounts provides a more powerful analysis of how sentiment-driven demand affects security prices, which likely explains why there is a strong association between CCEF discounts and country popularity, on one hand, but none between domestic closed-end fund discounts and various measures of investor sentiment, on the other.

5. Additional analysis

To further explore the role of country popularity on decision making and security prices, I examine whether the association found between CCEF discount and country popularity extends to American Depository Receipts (ADRs). Moreover, I test whether single-country mutual funds investing in popular countries, on average, enjoy higher inflows than mutual funds investing in less-popular countries. I also explore which types of investors are most affected by country sentiment and whether managers take a country's popularity into account when either starting or liquidating a CCEF.

5.1. ADRs

ADRs provide another interesting setting to explore the effect of country popularity on security prices. ADRs are claims to shares of foreign securities that are traded in the US. Similar to CCEFs, the price of the foreign securities is determined by "foreign investors" in their respective "home markets," whereas the price of the claim is determined in the

US. As with CCEFs, the market price of the ADR usually differs from the price of the ADR's underlying asset, although the magnitude of this disparity is generally much smaller for ADRs than for CCEFs (Karolyi 1998; Lamont and Thaler 2003). Given the similarity in security structure between CCEFs and ADRs, a natural question that arises is whether the association found between country popularity and CCEF discounts extends to ADRs.

The data necessary to conduct my analysis are found in 309 ADRs from 19 countries over the period 1992:11 to 2006:06.[23] The countries are: Australia, Brazil, China, France, Germany, India, Indonesia, Israel, Italy, Japan, Korea, Mexico, Philippines, Russia, South Africa, Spain, Taiwan, Turkey, and the UK.

Monthly ADR premia/(discounts) are calculated using ADR trading prices and trading prices of the ADR's underlying assets in local currency adjusted for ADR ratios and exchange rates:

$$\frac{PriceADR_{i,t} \text{ - } Adj.PriceUnderlyingAsset_{i,t}}{Adj.PriceUnderlyingAsset_{i,t}}, \qquad (2)$$

where ADR trading prices are from CRSP, ADR ratios are from COMPUSTAT, trading prices of the ADR's underlying assets in local currency are from COMPUSTAT GLOBAL ISSUE, and exchange rates are from COMPUSTAT GLOBAL CURRENCY. The average discount of ADRs in my sample is 0.30%; the standard deviation is 3.99%. The mean and standard deviation of the ADR discount in this study are similar to those reported in related studies (e.g., Chan, Hong, and Subrahmanyam 2008).

[23] ADRs are identified as such in COMPUSTAT if the company name includes either "ADR" or "ADS" and does not contain "REDH," "PRE FASB," or "PRO FORMA." ADRs are identified as such in CRSP if the share code is between 30 and 31.

Analogously to the CCEF analysis, I estimate the partial effect of a country's popularity on security prices using both fixed-effects and first-differencing estimators. I also report estimates from Fama-MacBeth (1973) regressions. The dependent variable is *Discount*$_{i,t}$ (Eq. 2). Independent variables include: *Country Popularity Score*$_{i,t}$, *Inverse Security Price*$_{i,t-1}$, *Dividend Yield*$_{i,t-1}$, *Turnover Ratio*$_{i,t}$, *Home Market Index Returns*$_{i,t}$, and *US Market Index Returns*$_{i,t}$ (dropped when estimating Fama-MacBeth (1973) regressions). For both the fixed-effects and the first-differencing regression specification, I calculate *t*-statistics using White standard errors adjusted for clustering (by year-month and fund). For the Fama-MacBeth (1973) regression specification, standard errors are adjusted for serial correlation and heteroskedasticity using Newey-West (1987) with twelve lags.

Results are reported in Table 14: The coefficient estimate on the *Country Popularity Score* equals 0.002 (*t*-statistic 1.74) under the fixed-effects specification, 0.004 (*t*-statistic 1.55) under the first-differencing specification, and 0.001 (*t*-statistic 0.80) under the Fama-MacBeth (1973) specification. The coefficient estimate of 0.002 suggests that a one-unit drop in the *Country Popularity Score* increases discounts by 0.20%. Such an increase would move the median firm (in terms of discount) to the 56th percentile.

While, generally, the association between country popularity and discounts found for CCEFs extends to ADRs, the effect is substantially weaker for ADRs than for CCEFs. This should not surprise, given that deviations between price of the claim and price of the underlying asset can be much more easily arbitraged away for ADRs than for CCEFs

(Lamont and Thaler 2003). Moreover, many investors may not know an ADR's country of origin.[24]

In additional (untabulated) tests, I examine whether the association between ADR discount and country popularity becomes stronger if the ADR's country of origin appears in the company name and investors are more likely to be aware that they are holding or not holding ADRs from a popular or less-popular country. For the sample of 23 ADRs from 10 countries over the 1992 to 2006 period for which the country of origin appears in the company name, the fixed-effects estimator produces an estimate of 0.004 (*t*-statistic 2.15), twice as large as the coefficient estimate for the full sample (see Table 14). Despite the sharp reduction in sample size, the statistical significance of the coefficient estimate increases.[25] First-differencing and Fama-MacBeth (1973) estimators also produce larger coefficient estimates. However, estimates are still not reliably different from zero.

5.2. Fund flows

The analysis so far has consisted of a joint test of country popularity affecting (uninformed) investors' investment decisions and the market impact of those investment decisions. In this subsection, I test the hypothesis that country popularity affects

[24] For instance, in a tangential yet related vein, Andersonanalytics (2006), in a recent survey, finds that more than 95% of US college students are unaware of Nokia's country of origin, despite Nokia being the world's largest manufacturer of mobile phones and the high relevance of mobile phones in US college students' lives (Aoki and Downes 2003).

[25] The stronger association between country popularity and ADR discount for this subsample is not driven by the fewer countries in the subsample (from 19 countries in the full sample to 10 in the subsample). The coefficient estimate on the Country Popularity Score for ADRs that do not have their country of origin in their name but are from the same 10 countries as the ADRs used in this subsample is only 0.001 and not reliably different from zero.

(uninformed) demand itself by examining mutual fund flows which "provide a transparent measure of decisions made by a large set of investors who are, on average, less sophisticated and more likely to display sentiment" (Baker and Wurgler 2007, p. 142).

The analysis focuses on mutual funds that are identified with a single country (using the S&P Area Codes in the CRSP Mutual Fund Database) and can produce the data necessary to construct normalized fund flows, the *Country Popularity Score* and various control variables (defined below). Overall, my sample consists of 29 mutual funds from 5 countries over the period 1992 to 2006. The countries are: China, Israel, Japan, Korea, and the UK.[26]

The normalized net cash flow to fund *i* during month *t* is measured as follows:

$$\frac{TNA_{i,t} - TNA_{i,t-1} \times \left(1 + r_{i,t}\right) - MGTNA_{i,t}}{TNA_{i,t-1}}, \tag{3}$$

where $TNA_{i,t}$ refers to the TNA at the end of month t, $r_{i,t}$ is the fund's return for month t, and $MGTNA_{i,t}$ is the increase in TNA due to mergers during month t. The data come from the CRSP Survivor-Bias Free U.S. Mutual Fund Database. The normalized net cash-flow measure in equation (3) implicitly assumes that the new money is invested at the end of each month. Measuring normalized net cash flow under the alternative assumption that the new money is invested at the beginning of each month produces results very similar to those using equation (3). For brevity and for consistency with prior studies (Zheng 1999; Sapp and Tiwari 2004; Keswani and Stolin 2008), only results for normalized net

[26] The mutual funds used in this study are listed in Appendix G. The analysis is conducted on a fund level basis (FUNDNO; obtained from MFLINKS).

cash flow as measured in equation (3) will be reported.[27] Following Gruber (1996), I assume that investors in merged funds place their money in the surviving fund and continue to earn the return on the surviving fund. This assumption mitigates survivorship bias because defunct funds are not excluded from the sample before they disappear.

To analyze determinants of fund flows, I estimate a pooled regression with a fund's monthly normalized net cash flow (Eq. 3) as the dependent variable:

$$Flow_{i,t}=\alpha_{2\text{-}29}+\beta_1 CountryPopularityScore_{i,t}+\beta_2 Ret_{i,t-12,t-1}+\beta_3 ln(TNA_{i,t-1})$$
$$+\ \beta_4 Av.Flow_t + \varepsilon_{i,t}. \tag{4}$$

The right-hand-side variable of most interest in the context of this study is the *Country Popularity Score*. Other right-hand-side variables include: (1) $Ret_{i,t-12,t-1}$, the fund's past-one-year holding period return, to capture the tendency for flows to chase past returns (Ippolito 1992; Sirri and Tufano 1998); (2) $ln(TNA_{i,t-1})$, the logarithm of TNA at the beginning of the month, as small funds may grow faster than larger funds; and (3) $Av.Flow_t$, the average monthly flow of all funds in the CRSP Mutual Fund Database universe to capture a general demand effect. Mutual fund dummies control for unobservable mutual fund-specific fixed effects. I calculate *t*-statistics using White standard errors adjusted for clustering (by year-month and mutual fund).

As reported in Table 15, country popularity and fund flows are positively correlated. The coefficient on the *Country Popularity Score* of 0.047 (*t*-statistic of 2.06) suggests that a one-unit increase in the *Country Popularity Score* leads to a 4.70%

---

[27] Gruber (1996) reports results under both assumptions.

increase in fund flows.[28] All other associations are as predicted and significant: Fund flows are positively related to past returns, negatively related to TNA, and positively related to the average flow across all funds in the CRSP Mutual Fund Database universe.

In summary, I find that low country popularity is generally associated with high CCEF discounts. The association partially extends to ADRs. Moreover, I detect a positive correlation between country popularity and fund flows. Taken together, these observations provide fairly compelling evidence that investors care about a country's popularity and that this sentiment affects their buying/selling decisions, which ultimately affect security prices.

5.3. Institutional holdings

In order to gain a better understanding of which types of investors are most affected by country sentiment, I estimate the following pooled regression for my sample of CCEFs and ADRs:

$$Inst.Holdings_{i,t}=\alpha+\beta_1 CountryPopularityScore_{i,t}+\beta_2 Inv.Price_{i,t}$$
$$+\beta_3 Div.Yield_{i,t-1}+Year\beta_{4\text{-}9}+\varepsilon_{i,t}. \qquad (5)$$

$Inst.Holdings_{i,t}$, the dependent variable, is the institutional holdings of CCEF *i* (ADR *i*) at time *t*. As institutional holdings are only released quarterly, all observations in this regression are quarterly as well. Data to calculate *Institutional Holdings* come from the THOMPSON Institutional Holdings database (S34). *Country Popularity Score*$_{i,t}$ is as explained above. $Inv.Price_{i,t-1}$ is the inverse of fund *i*'s (ADR *i*'s) lagged price level and is

[28] The Country Popularity Score in the mutual fund sample has a mean of 3.03 and a standard deviation of 0.60.

included to capture institutional investors' preference for high liquidity (Gompers and Metrick 2001). *Div.Yield*$_{i,t-1}$ is dividends paid by CCEF *i* (ADR *i*) over the previous 12 months, scaled by the fund's lagged net asset value, and is included to capture fiduciary motives (Del Guercio 1996). Year dummies are included to capture time effects (Gompers and Metrick 2001). I calculate *t*-statistics using White standard errors adjusted for clustering (by year-quarter and fund).

As reported in Table 16, country popularity and institutional holdings associate negatively. For CCEFs, the coefficient estimate on the *Country Popularity Score* is -0.054 (*t*-statistic -2.34), which suggests that a one-unit increase in the *Country Popularity Score* leads to a 0.054 decrease in institutional holdings. For reference, the average institutional holdings in the CCEF sample are 0.239; the standard deviation is 0.070. For ADRs, the coefficient estimate of -0.010 (*t*-statistic -1.37) on the *Country Popularity Score* implies that a one-unit increase in the *Country Popularity Score* leads to a 0.010 decrease in institutional holdings. Again, for reference, the average institutional holdings in the ADR sample are 0.111; the standard deviation is 0.050.

That country popularity negatively associates with both discount and institutional holdings suggests that country popularity primarily affects investment decisions of retail investors: Retail investors driven by positive sentiment toward a country acquire (more) securities from that particular country by buying from institutional investors and therefore simultaneously decrease their discount and institutional holdings. An analogous argument can be made for negative sentiment increasing both discount and institutional holdings. This interpretation agrees nicely with the general notion that retail investors are more susceptible to sentiment than institutional investors (Baker and Wurgler 2007).

Such an interpretation of the results also implies that while institutional investors take the other side of unsophisticated demand, they are not able to eliminate its price effect. If they did so, no significant association between country popularity and discount should be detected in the regression analysis.

5.4. IPO and liquidation/open-ending

If a country's popularity does influence investors' investment decisions and affects prices, one wonders if managers are aware of the effect of country popularity and cater to investors' country preferences. This question can be examined by comparing the average country popularity around a CCEF's IPO with the average country popularity around a CCEF's announcement of liquidation/open-ending. Unfortunately, only 5 funds had an IPO and announced a liquidation/open-ending while being covered in the Gallup Poll on Americans' opinion towards other countries.[29]

The average *Country Popularity Score* around a CCEF's IPO is 2.89. In comparison, the average *Country Popularity Score* around a CCEF's announcement of liquidation/open-ending is 2.74. The finding that country popularity is higher around the IPO than around the announcement of liquidation/open-ending provides some support to the hypothesis that managers take a country's popularity into consideration when either starting or ending a CCEF. Put bluntly, the beginning of the Iraq invasion was a bad time to start a French CCEF. However, both the economic and statistical significance of this 0.15 (*t*-statistic 1.76) difference are modest (all untabulated).

[29] A list of all five CCEFs is reported in Appendix F.

6. Conclusion

In this study, I find that high levels of country popularity are associated with low CCEF discounts (and to some extent low ADR discounts). Moreover, high country popularity is associated with high mutual fund inflows and low institutional holdings. The interpretation most consistent with my findings is that country popularity, a country-specific sentiment, shifts (uninformed) demand and affects security prices. As such, the evidence presented in this paper pertains to the ongoing discussion on the foundations of investor sentiment and its effect on market outcomes (Hirshleifer and Shumway 2003; Kamstra, Kramer, Levi 2003; Edmans, Garcia, and Norli 2007; and Kaplanski and Levy 2009).[30]

My paper also contributes to the literature on social norms and their economic impact (e.g., Becker 1957; Arrow 1972; Akerlof 1980; Levitt 2004). Negative sentiment toward a country may approximate societal norms against a country's political decisions (such as the French opposition to the Iraq war), or more broadly, a country's political, legal, and economic system. Investors not wanting themselves to be associated with these countries may, therefore, shun investing in securities from these countries. The finding that low country popularity correlates with high discounts, then, corroborates Hong and Kacperczyk's (2009) finding that societal norms appear to affect market outcomes.

[30] My paper is also related to the work of Morse and Shive (2008), who find that more patriotic countries have greater home bias in their equity selection. This study corroborates and extends their finding by suggesting that it is not only country sentiment with respect to one's own country that affects decision making, but also country sentiment with respect to foreign countries.

Third Essay: Distinguishing Behavioral Models of Momentum

1. Introduction

Over the past several years, a body of empirical work has uncovered patterns in average stock returns that are difficult to explain with traditional asset-pricing models, such as the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965).[31] As a result, "behavioral" models, which depart from the traditional assumption of strict investor rationality, have become an oft proposed alternative (Hirshleifer 2001; Barberis and Thaler 2005). While united by their departure from the perfect investor rationality assumption, these behavioral models generally rely on different irrational behavior patterns and provide competing explanations for the exact economic mechanisms underlying return "anomalies" (Barberis and Thaler). Given these differences, it is natural to try to determine which of the alternative behavioral models (and their various underlying behavioral biases) best explains some of the anomalous evidence observed in financial markets. The goal of this paper is to explore this question by testing the implications of two prominent behavioral models – those of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (2007) – to see which offers a better explanation of momentum, the most prominent of all anomalies (Fama and French 2008).[32]

Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (2007) adopt fundamentally different approaches to explain the momentum effect: Daniel, Hirshleifer,

[31] See, for instance, Jegadeesh and Titman (2001) and Jegadeesh and Titman (2002).

[32] As explained in Section A.2., the analysis conducted in this paper also provides a comparison of Daniel, Hirshleifer, and Subrahmanyam's (1998) model with that of Hong and Stein (1999).

and Subrahmanyam assume that investors, overconfident about their ability to generate value-relevant news, underestimate the extent to which their privately gathered information is clouded by noise. As a result, investors overweigh their private signals and push prices too far relative to fundamentals. If overreaction develops gradually and corrects itself slowly, stock prices display momentum.[33] In contrast, Hong and Stein assume that due to bounded rationality and investor segmentation, value relevant information arrives in the hands of some investors before others and becomes only partially reflected in the price. Over time, as the remaining investors absorb the news, the price adjusts fully to the information, resulting in momentum.

In this paper, I show that both models can be compared by examining how the momentum effect relates to the average correlation of investors' forecast errors, ρ_{FE}. Intuitively, the momentum effect in the model of Daniel, Hirshleifer, and Subrahmanyam (1998) increases in the extent to which investors' beliefs are correlated and prices are pushed in the same direction. If investors' beliefs are correlated, investors' mistakes, at a given point in time, will be correlated as well. Consequently, the model of Daniel, Hirshleifer, and Subrahmanyam predicts that momentum should *increase* in ρ_{FE}. The model of Hong and Stein (2007) makes the exact opposite prediction, namely that momentum should *decrease* in ρ_{FE}. The reason is that information arriving in the hands of some investors before others not only causes momentum in stock returns; it also causes investors' beliefs and mistakes, at a given point in time, to differ (and to be less correlated).

[33] This and the previous statement hold if investors' signal noise terms are positively correlated and if the transition from the delayed overreaction-phase to the gradual correction-phase is sufficiently smooth.

To estimate ρ_{FE}, I make the assumption that financial analysts' beliefs are representative of those of the investor population and I use analyst forecasts from the Institutional Brokers Estimate System (IBES) to calculate the average sample correlation in analysts' forecast errors. If analysts use the same information sources and interpret them similarly, their mistakes will be correlated (Daniel, Hirshleifer, and Subrahmanyam 1998). On the other hand, if some analysts enjoy exclusive access to information sources, such as a firm's top-management, or, if boundedly rational analysts ignore different pieces of value-relevant news, their mistakes will differ.[34] Both scenarios are likely to be important in the data, as implied by the wide cross-sectional dispersion in $\hat{\rho}_{FE}$. What remains to be seen is whether momentum profits are larger among high $\hat{\rho}_{FE}$ stocks, or larger among low $\hat{\rho}_{FE}$ stocks.

In my analysis, I focus on ordinary shares listed on the NYSE, AMEX, or NASDAQ over the period of 1984 to 2005. I rank stocks independently on the basis of six-month lagged returns and estimates of ρ_{FE} and form nine (three by three) equally-weighted portfolios. The breakpoints are the 30th and the 70th percentiles. The portfolios are held for six months. I find that momentum profits are larger among high $\hat{\rho}_{FE}$ stocks than among low $\hat{\rho}_{FE}$ stocks: For stocks whose $\hat{\rho}_{FE}$ is above the 70th percentile, the difference between winners and losers is 0.68% a month. In contrast, for stocks whose $\hat{\rho}_{FE}$ is below the 30th percentile, the difference between winners and losers is only 0.26% a month. I make similar observations when extending the analysis to earnings momentum

[34] For instance, some analysts may have access to top-management, but, at the same time, ignore important information from an independent industry research report; others may not have access to top-management, but, at the same time, incorporate information from the independent industry research report into their forecasts.

and when controlling for other variables which previous studies show are drivers of momentum. The finding that momentum increases in $\hat{\rho}_{FE}$ is consistent with the prediction of the model of Daniel, Hirshleifer, and Subrahmanyam (1998) but inconsistent with the prediction of the model of Hong and Stein (2007).

The model of Hong and Stein (2007), whose momentum prediction this paper rejects, has received some empirical support by Lee and Swaminathan (2000). Lee and Swaminathan find that momentum trading strategies (buying past-winner stocks and selling past-loser stocks) work significantly better for stocks with high recent turnover. Because, in the framework of Hong and Stein, trading volume increases in investor heterogeneity, the finding that momentum increases with turnover seems to support Hong and Stein's momentum prediction. However, I show that the stronger, subsequent return continuation of high turnover stocks can be explained by the fact that high turnover stocks have more extreme past returns to begin with. When controlling for past returns within a Fama-MacBeth regression framework, the results reverse and momentum strategies perform significantly better for low turnover stocks than for high turnover stocks.

There is one important caveat: One mechanism through which value-relevant information arrives in the hands of some investors before others is limited attention (Hong and Stein 2007; DellaVigna and Pollet 2008). Because I require firms to be covered by at least two analysts to calculate the average sample correlation in analysts' forecast errors, my sample is biased towards large firms with high institutional holdings. Limited attention likely plays a larger role among small firms with low visibility and high retail investor holdings (Barber and Odean 2008). So while the results presented in this paper are inconsistent with the momentum prediction of Hong and Stein, it is not clear to what extent this finding would extend to the full cross-section of securities.[35]

The paper proceeds as follows. Section 2 details how ρ_{FE} relates to investor heterogeneity and correlation in investors' signal noise terms and introduces an estimator for ρ_{FE}. Section 3 presents the results using $\hat{\rho}_{FE}$. Sections 4 and 5 conduct additional tests and extend the analysis to earnings momentum. Section 6 concludes.

2. Relative investor group size and correlation in signal noise terms

In this section, I introduce the model of Hong and Stein (2007) and the model of Daniel, Hirshleifer, and Subrahmanyam (1998) and explain why we can compare the two models by examining the relation between the momentum effect and the average correlation in investors' forecast errors, ρ_{FE}. Moreover, I discuss how the analysis conducted in this paper relates to the earlier model of Hong and Stein (1999) as well as recent findings that the momentum effect increases in analyst dispersion (Zhang 2006, Verardo 2007). I then introduce my estimator for ρ_{FE}.

2.1. New prediction

2.1.1. Heterogeneous-agent model of Hong and Stein (2007)

In Hong and Stein's (2007) heterogeneous-agent model (in this subsection referred to as HS), there is a stock with payoff $Y = A+B$, where A and B are two independent mean-zero normal random variables. At time 1, a fraction f of all investors (Type A investors) observes the realization of A, denoted a, and the remaining fraction $(1-f)$ (Type B

[35] My sample covers 24.15% of all firms in the CRSP universe (75.38% by market capitalization).

investors) observes the realization of *B,* denoted *b*. Even though both *A* and *B* are value-relevant, investors' forecast (belief) of *Y* is equal to their observed realization only. Investors do not learn from prices. At time 2, *b* becomes observable to Type A investors and *a* becomes observable to Type B investors.

The level of heterogeneity in this model is characterized by $f(1\text{-}f)$, which represents the relative group size of Type A investors to Type B investors. Heterogeneity is minimized when f either equals one or zero (i.e. when $f(1\text{-}f)= 1*0= 0*1=0)$ and investors, at any point in time, observe the same signals and do not differ in their beliefs. As soon as $f > 0$, differences in beliefs are introduced (at time 1) between investors observing *a* and investors observing *b*. Heterogeneity increases as the two groups become more similar in size (i.e. as $f(1\text{-}f)$ increases). It is maximized when the two investor groups are exactly equal in size (i.e. when $f(1\text{-}f)= (0.5)*(0.5)=0.25$).

In HS, momentum increases in $f(1\text{-}f)$. In other words, momentum increases in the level of investor heterogeneity (see Appendix J.A.2.). The intuition is best conveyed in an example: Consider the case where most investors are of Type A (i.e., $f(1\text{-}f)$ low, low heterogeneity). Then price changes will largely reflect the news observed by Type A investors, which, at time t=1, is the realization of *A*, and at time t=2, is the realization of *B*.[36] Because *A* and *B* are orthogonal to each other, price changes will only be weakly auto-correlated. Contrast this to the case where Type A and Type B investors both represent 50% of the investor population (i.e., $f(1\text{-}f)$ maximized, maximum heterogeneity). In such a scenario, half of *A* and *B*'s information will get factored into the

[36] Prices are weighted averages of investors' beliefs (proportional to relative investor mass).

price at time=1, with the remaining half becoming priced at time=2 and price changes will be strongly auto-correlated.

Empirical assessments of the HS model face the challenge that the fractions f and *(1-f)* are not directly observable. The model can, nevertheless, be tested by examining how the momentum effect relates to the average correlation in investors' forecast errors, denoted by ρ_{FE}:

$$\rho_{FE} \equiv \frac{\sum_{1}^{{}_N W_2} \rho_{i,FE}}{{}_N W_2}, \tag{1}$$

where $\rho_{i,FE}$ is the correlation in forecast errors for investor pair i and ρ_{FE} is the average correlation in forecast errors across all ${}_N W_2$ investor pairs. N is the number of investors.

Under the assumptions imposed in HS, ρ_{FE} (at t=1) can be rewritten as (see Appendix J.A.3.):

$$\begin{aligned} \rho_{FE} &= \frac{\binom{fN}{2} + \binom{(1-f)N}{2}}{\binom{N}{2}} = \frac{[fN-1]f + [(1-f)N-1](1-f)}{N-1} \\ &= 1 - f(1-f)\frac{2N}{N-1}, \end{aligned} \tag{2}$$

where f is the fraction of Type A investors, *(1-f)* is the fraction of Type B investors and N is the number of investors. The reason is that, in the special case of two investor groups, the correlation in forecast errors between two investors of same type equals one, whereas the correlation in forecast errors between two investors of different types equals zero (A and B are orthogonal).[37] The average correlation in forecast errors is, therefore, simply the number of investor pairs where both investors are of same type divided by the number

[37] Because the payoff $Y = A + B$, forecast errors (at time 1) for Type A (Type B) investors equal B (A).

of all investor pairs: The number of investor pairs where both investors are of Type A is $\binom{fN}{2}$; the number of investor pairs where both investors are of Type B is $\binom{(1-f)N}{2}$; the number of all investor pairs is $\binom{N}{2}$.

Equation (2) shows that ρ_{FE} decreases in *f(1-f)*. The negative association between ρ_{FE} and *f(1-f)* makes sense intuitively: If all investors are of same type (i.e. *f(1-f)*=0) and, as a result, all base their forecasts on the same information, they will always err on the same side and on the same order of magnitude. That is, forecast errors will be perfectly correlated. As soon as investors start conditioning on different signals (i.e. *f(1-f)*>0), their mistakes will differ. That is, forecast errors will be less than perfectly correlated.

Applying the observation that ρ_{FE} decreases in *f(1-f)* to the prediction that momentum increases in *f(1-f)*, yields the new prediction that momentum decreases in ρ_{FE} (see Appendix J.A.3.). No assumptions other than the ones made in HS were used to derive this new prediction.

2.1.2. Model of Hong and Stein (1999)

The analysis of how momentum relates to ρ_{FE} can also be considered a test of Hong and Stein (1999). That model features two classes of traders: newswatchers and momentum traders. The model when only newswatchers are present (Section II.A., p. 2148), which can be thought of as "only speaking to the unconditional evidence on underreaction," is analogous to the model of Hong and Stein (2007): The investor population is divided into investor groups. (There can be more than two investor groups.) At a given point in time, each investor group observes an independent signal, upon which investors condition their demand. Investors do not condition on prices. Signals travel across investor groups until they have been observed by all groups. Given the analogy between these two models, it may not surprise that in the "newswatcher-model" of Hong and Stein (1999), the momentum effect also increases in investor heterogeneity, which, in turn, is negatively related to ρ_{FE} (see Appendix J.A.4).

2.1.3. Analyst dispersion

The model of Hong and Stein (2007) predicts not only that momentum increases in investor heterogeneity (hereafter h), but also that momentum increases in the volatility of the firm's underlying fundamentals (hereafter v) (see Appendix J.A.2). Because analyst dispersion increases in both h and v (Barron, Kim, Lim, and Stevens 1998), examining the effect of analyst dispersion on cross-sectional differences in the momentum effect provides another way of testing Hong and Stein. Consistent with Hong and Stein, Zhang (2006) and Verardo (2007) find that momentum trading strategies work significantly better for stocks with high analyst dispersion.[38]

However, studying the joint impact of h and v on the momentum effect produces only indirect evidence on the partial effects of h and v. For instance, the positive association between momentum and analyst dispersion could be entirely explained by the (positive) effect of v on both momentum effect and analyst dispersion. Studying the partial effect of h (through ρ_{FE}) on momentum, as opposed to the joint impact of h and v

[38] The finding that momentum increases in analyst dispersion is also consistent with the model of Daniel, Hirshleifer, and Subrahmanyam (1998) (see Section II.D; also see Zhang 2006).

(through analyst dispersion), therefore, allows for a more refined and potentially more powerful test of the Hong and Stein (2007) model (also see Appendix J.A.6).[39]

2.1.4. Model of Daniel, Hirshleifer, and Subrahmanyam (1998)

In the model of Daniel, Hirshleifer, and Subrahmanyam (1998) investors are assumed to be overconfident about information that they privately gather. Therefore, when investors receive a private signal, they overweigh the signal (compared to what would be justified given the signal's true precision) and push prices too far relative to fundamentals. If investors' private signals happen to be confirmed by some subsequent *public* signal, then investors attribute this "confirmation" to their own skill (self-attribution bias) and further overreact. In contrast, disconfirming public news only marginally reduces investors' confidence. These features, on average, create positive return autocorrelation in the overreaction phase. Returns are also positively autocorrelated in the correction phase, as the initial overreaction becomes only partially corrected over time. The only negative contribution to autocorrelation comes from returns straddling the turning point from the overreaction phase to the correction phase. However, "if overreaction or correction is sufficiently gradual, then stock price changes exhibit unconditional short-lag positive autocorrelation 'momentum'" (p. 1858).

[39] Consistent with the interpretation in Zhang (2006), the fact that momentum increases in analyst dispersion and five alternative measures of v (Zhang 2006), combined with the finding presented in this paper that momentum strongly decreases in $\hat{\rho}_{FE}$ (where ρ_{FE} is my proposed measure for h) suggests that the positive association between momentum and analyst dispersion is due to a) momentum increasing in v and b) analyst dispersion primarily measuring v.

In the model of Daniel, Hirshleifer, and Subrahmanyam (1998), the momentum effect increases with the correlation of investors' signal noise terms and the extent to which behavioral forces push in the same direction, rather than being diversified away.[40]

Similar to investor heterogeneity, the correlation of investors' signal noise terms is not directly observable. However, interestingly, the model of Daniel, Hirshleifer, and Subrahmanyam (1998) can be tested by examining exactly the same relation as in the test of the Hong and Stein model (2007), namely the relation between the momentum effect and the average correlation in investors' forecast errors. The reason is straightforward: In the framework of Daniel, Hirshleifer, and Subrahmanyam, an investor's forecast error is equal to the investor's signal noise term weighted by the signal's perceived precision. Hence, as investors' signal noise terms become more correlated, so do their forecasts errors (see Appendix J.B.3.).

In sum, ρ_{FE} can be used to test both the prediction that momentum increases in investor heterogeneity (Hong and Stein 2007) as well as the prediction that momentum increases in the correlation of investors' signal noise terms (Daniel, Hirshleifer, and Subrahmanyam 1998). While the model of Hong and Stein predicts that momentum decreases in ρ_{FE}, the model of Daniel, Hirshleifer, and Subrahmanyam predicts that momentum increases in ρ_{FE}. The two models, thus, make opposite predictions of how momentum should relate to ρ_{FE}.

[40] See footnote 6 on page 1845: "For simplicity, we assume this correlation [the correlation in signal noise terms] is unity; however, similar results would obtain under imperfect (but nonzero) correlation."

2.2. Estimation of ρ_{FE}

Given that investors' forecasts are unobservable, I make the assumption that financial analysts' forecasts are representative of those of the investor population. This allows me to use financial analysts' observable forecasts to calculate estimates of ρ_{FE}. I will discuss potential violations of this assumption in Section 3.4. One approach to estimating ρ_{FE} would be to calculate the sample correlation in forecast errors for each analyst pair in the time-series and then to calculate the cross-sectional mean. However, for a given analyst, there is not much time-series variation in forecast errors (forecasts are not continuously updated) and the long estimation period required to obtain accurate estimates would severely restrict my sample. Moreover, the correlation in forecast errors is likely to vary over time. I, therefore, choose to employ a cross-sectional estimator for ρ_{FE}:

$$\hat{\rho}_{FE} = \frac{\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j\neq 1}^{N}(y-x_i)(y-x_j)}{\frac{1}{N}\sum_{i=1}^{N}(y-x_i)^2}, \tag{3}$$

where y is *EPS*, and x_i is the most recent *EPS* forecast of analyst i. This estimator has, among others, been used by Doukas, Kim, and Pantzalis (2006). However, its explanatory power as a determinant of momentum has not yet been examined.

In order to avoid the use of forward looking information, I use the most recently reported quarterly earnings (and forecasts thereof) to calculate $\hat{\rho}_{FE}$.[41] To clarify by example: Let's assume that quarterly earnings are announced in January2000 and April2000. To calculate $\hat{\rho}_{FE}$ for the months of January2000, February2000, and March2000, I use (a) $EPS_{January2000}$ and b) analyst forecasts (for $EPS_{January2000}$) as of

[41] I require earnings to be reported within the past six months.

January2000. Were I to use analyst forecasts (for $EPS_{April2000}$) as of February2000 and March2000 to calculate $\hat{\rho}_{FE,February2000}$ and $\hat{\rho}_{FE,March2000}$, for consistency, I would also have to use $EPS_{April2000}$. However, $EPS_{April2000}$ is not observable to investors in February2000 and March2000.

Note that using the January-based measure in February and March implicitly assumes that the cross-sectional correlation measure displays some persistence. Conceptually, there is reason to believe that ρ_{FE} is persistent: The two independent sources of information, A and B, in the model of Hong and Stein (2007), can be envisioned as theoretical models used to simplify the forecasting problem (Hong, Stein, and Yu 2007). As Hong, Stein, and Yu highlight, an important element in the usage of theoretical models is that "people tend to resist changing their models even in the face of evidence that…would appear to strongly contradict these models" (p. 1212). If people are so stubborn, it seems unlikely that the fraction *f* of people using model A and the fraction (*1-f*) of people using model B would radically change from one month to another. Similarly, there is no reason to believe that the correlation in signal noise terms would change significantly over a short period of time. I now discuss the empirical evidence on the time-series properties of $\hat{\rho}_{FE}$.

For consistency with later analyses, every month, I rank stocks independently in ascending order on the basis of six-month lagged returns and $\hat{\rho}_{FE}$. I then form nine (three by three) equally weighted portfolios. The breakpoints are the 30th and 70th percentiles. The portfolios are held for either six or twelve months. Table 17 reports the average of the subsequent *re-calculated* realizations of $\hat{\rho}_{FE}$ for each of the nine portfolios.[42] We observe that $\hat{\rho}_{FE}$ is remarkably persistent: When portfolios are held for six months (Panel A), the average correlation in forecast errors across the three high correlation portfolios is 0.515; the average correlation in forecast errors across the three low correlation portfolios is 0.420. The difference in the average of subsequent realizations of $\hat{\rho}_{FE}$ between the low and high correlation portfolios remains stark after twelve months (Panel B). The observed persistence implies that the ex post measure in (3) conveys information about ex ante expectations at that point in time. Moreover, the positive association between ranking-$\hat{\rho}_{FE}$ and post-ranking-$\hat{\rho}_{FE}$ suggests that, despite measurement error, a non-negligible fraction of the variation in $\hat{\rho}_{FE}$ can be explained by variation in ρ_{FE}.

In the model of Hong and Stein (2007), the 0.515 average $\hat{\rho}_{FE}$ of the high correlation securities corresponds to relative investor group sizes of 26% and 74%.[43] In other words, the 0.515 average implies that 26% of all investors are of Type A and the remaining 74% are of Type B (or vice versa). In comparison, the 0.420 average $\hat{\rho}_{FE}$ of the low correlation securities corresponds to relative investor group sizes of 37% and 63%. I now set out to assess whether the momentum effect is stronger for securities with low ρ_{FE} and more equal-sized investor groups (as predicted by Hong and Stein), or whether momentum is stronger for securities with high ρ_{FE} and high correlation in signal noise terms (as predicted by Daniel, Hirshleifer, and Subrahmanyam 1998).

---

[42] If, for instance, earnings are reported in January2000 and April2000 and a stock is assigned to a portfolio based on $\hat{\rho}_{FE}$ calculated from earnings$_{\text{January2000}}$, only $\hat{\rho}_{FE}$ calculated from earnings reported in April2000 and thereafter are considered when computing the average of the subsequent realizations of $\hat{\rho}_{FE}$ for each of the nine portfolios (in order to avoid any spurious correlation between ranking- and post-formation-$\hat{\rho}_{FE}$).

[43] These fractions were obtained using equation (A.13), where *N* is 4.98, the mean analyst coverage. On a related note, the 5th analyst coverage (*N*) percentile is 2, the median *N* is 4, and the 95th *N* percentile is 12.

3. Evidence using the average correlation in analysts' forecast errors

3.1. Data

I use financial analyst forecast information and quarterly earnings data from the Institutional Brokers Estimate System (IBES) unadjusted U.S. Detail History dataset to construct $\hat{\rho}_{FE}$ and analyst coverage.[44] I use financial-statement and financial-market data from Compustat and the Center for Research in Security Prices (CRSP), respectively, to develop the following variables: 1) *Market capitalization*; 2) *Monthly volatility*, which is calculated as in French, Schwert and Stambaugh (1987): $\sigma_t^2 = \sum_{d=1}^{D_t} r_d^2 + 2\sum_{d=2}^{D_t} r_d r_{d-1}$, where D_t is the number of days in month t and r_d is the return on day d. The second term adjusts for serial correlation in daily returns[45]; 3) *Turnover*, which is share volume divided by shares outstanding; 4) *Book-to-market ratio*; 5) *Cash flow volatility*, which is the standard deviation of cash flow from operations in the past five years with a minimum of three years (Zhang 2006); and 6) *Standardized unexpected earnings* (SUE).[46] I use the Thomson Reuters database (CDA/Spectrum Institutional (13f) Holdings) to calculate *institutional holdings*. I restrict myself to ordinary shares that are listed on the NYSE, AMEX or NASDAQ. Each stock must be covered by at least two analysts. The sample

---

[44] Diether, Malloy, and Scherbina (2002); Doukas, Kim, and Pantzalis (2006); and Zhang (2006) provide a detailed discussion of the advantages of using the raw detail forecast data unadjusted for stock splits. However, the results are robust to the standard-issue IBES dataset.

[45] In rare cases, the autocorrelation in returns is less than -0.5 and the variance estimate is negative. For these stocks, the variance estimator is the sum of squared daily returns only.

[46] Please see Zhang (2006) for a detailed description of how cash flow from operations is calculated. SUE is described in Section IV.

period spans from 1984 to 2005 and is determined by the availability of quarterly earnings-per-share data (and estimates thereof) in the IBES dataset.[47]

3.2. Momentum effect

In Table 18, I replicate Jegadeesh and Titman (1993) to analyze whether my sample differs in terms of the momentum effect from related studies. I form equally-weighted decile portfolios based on six-month lagged returns. Following Jegadeesh and Titman, I skip a week after the portfolio formation date. The portfolios are held for six months. The difference in monthly returns between P10, the portfolio of stocks in the best-performing 10%, and P1, the portfolio of stocks in the worst-performing 10%, is 0.99% (*t*-statistic of 2.55). The magnitude of this difference is comparable to what previous literature has found.

3.3. Independent sorts on past returns and $\hat{\rho}_{FE}$

In Table 19, I examine the effect of the average correlation in forecast errors, ρ_{FE}, on the strength of the momentum effect. I rank stocks independently in ascending order on the basis of six-month lagged returns and $\hat{\rho}_{FE}$. I then form nine (three by three) equally weighted portfolios. The breakpoints are the 30th and 70th percentiles. I skip one week after the portfolio formation date. The portfolios are held for six months.[48]

---

[47] Annual earnings-per-share and estimates thereof in the IBES dataset start in 1980 but data coverage is very sparse until 1982. My results are robust to using annual data and extending the sample period by two years.

[48] The results are robust to sorting sequentially rather than independently.

In Panel A of Table 19, I report average monthly returns for each of the nine portfolios and the three long-short portfolios. For high correlation stocks ($\hat{\rho}_{FE}$ above the 70th percentile), the difference between winner stocks and loser stocks is 0.68% a month (t-statistic of 2.81). For low correlation stocks ($\hat{\rho}_{FE}$ below the 30th percentile), the difference between winners and losers is only 0.26% a month (t-statistic of 1.00). The difference in the momentum effect between high- and low correlation stocks is 0.42% a month (t-statistic of 4.38).

In Panel B of Table 19, I report the alphas obtained from regressing the nine excess monthly portfolio returns and the three monthly long-short portfolio returns on the Fama-French (1993) factors. The alpha of the long-short portfolio for high correlation stocks is 0.84% (t-statistic of 3.52). In contrast, the alpha of the long-short portfolio for low correlation stocks is only 0.44% (t-statistic of 1.78). The difference between these two alphas is 0.39% a month, with a t-statistic of 4.12. To summarize my results up to this point, I find that the momentum effect is stronger for high correlation stocks. The results are the opposite of what is implied by the model of Hong and Stein (2007) but in line with the prediction of Daniel, Hirshleifer, and Subrahmanyam (1998).

3.4. Independent sorts on past returns, $\hat{\rho}_{FE}$, and firm characteristics

Next, I disaggregate the analysis of Table 19 by various firm characteristics: market capitalization, book-to-market ratio, analyst coverage, stock return volatility, cash flow volatility, institutional holdings, and turnover.[49] The methodology is the same except that portfolios are formed based on independent *triple*-sorts (rather than double-sorts).

The results, which are reported in Table 20, show the following: First and foremost, I find that except for the group of medium turnover NASDAQ securities, the positive association between momentum and $\hat{\rho}_{FE}$ observed in the full sample carries over to each firm characteristic category (albeit in some categories, the association is no longer statistically and economically significant). Second, while the momentum effect is generally smaller among high analyst coverage stocks, I find that the *spread* in the momentum effect between high and low correlation securities is stronger for high analyst coverage stocks than for low analyst coverage stocks. Because ρ_{FE} is estimated more accurately for stocks with high analyst coverage, the greater difference in the momentum effect between high and low correlation securities for high analyst coverage stocks suggests that measurement error in $\hat{\rho}_{FE}$ probably only weakens my results.

An important assumption underlying my empirical analysis is that analyst beliefs are similar to those of the general investor population. However, one may contend that while analysts' beliefs are representative of informed investors' beliefs, they only are a poor proxy for retail investors' beliefs. In particular, one may argue that informed investors only make up a fraction of the investor population, so that even if informed investors' beliefs are highly correlated (high $\hat{\rho}_{FE}$), information only partially gets into prices and does not fully become incorporated until it reaches the "slower" retail investor population. The fact that there is more momentum among high $\hat{\rho}_{FE}$ stocks, then, no longer seems so inconsistent with the slow information diffusion framework of Hong and

[49] The turnover analysis is conducted separately for NYSE/AMEX stocks and NASDAQ stocks because turnover is measured differently for the two types of stocks.

Stein (2007). To further explore this interpretation, I disaggregate my analysis by institutional holdings. If this alternative interpretation were true, then the difference in momentum profits between high and low $\hat{\rho}_{FE}$ stocks should be weaker among stocks predominantly held by (informed) institutional investors. To the contrary, I find that this is where the difference in momentum profits is the greatest (Table 21): For the subset of securities whose institutional holdings is above the 80^{th} percentile (mean institutional holdings = 81.11%) and for which the assumption that analysts' beliefs are representative of those of the investor population appears to be the most reasonable, the difference in momentum profits between high and low $\hat{\rho}_{FE}$ stocks is 0.55% a month. In comparison, for stocks whose institutional holdings is below the 80^{th} percentile, the difference in momentum profits is (only) 0.37% a month.

Even if analysts' *true* beliefs offered a reasonably fair representation of investors' beliefs, one may still contend that analysts' *observable* forecasts are not. In particular, one concern is that value-relevant negative news may not fully be reflected in analysts' observable forecasts, which would cause (a) the sample correlation in analysts' forecast errors to be upward biased and (b) prices to react more sluggishly to bad news.[50] The larger momentum profits among high correlation stocks may, therefore, be entirely consistent with the momentum implication of the Hong and Stein (2007) model. To some extent, this concern is mitigated by the fact that past winners and losers contribute

[50] Note that *ex ante* it is not clear whether the sample correlation is systematically upward biased. If all analysts' true beliefs were negative, and a few analysts decided to report upward biased forecasts, then the sample correlation would be downward biased. Please see Daniel, Hirshleifer, and Teoh (2002; p. 147-148) for a brief review of why analysts' observable forecasts may be biased.

roughly equally to the larger magnitude of momentum profits among high correlation stocks (Table 19).

To further explore the role of analysts' forecast bias, I again compare the spread in the momentum effect between high and low correlation securities across stocks with varying degrees of institutional holdings. Ljungqvist, Marston, Starks, Wei, and Yan (2007) argue that because the cost of publishing biased and misleading research should be larger in stocks that are highly visible to institutional investors, forecasts should be less biased among securities with high institutional holdings. Ljungqvist, Marston, Starks, Wei, and Yan provide empirical evidence supporting their argument. As reported in Table 20, the spread in the momentum effect between high and low correlation securities is stronger for stocks with high institutional holdings than for stocks with low institutional holdings. In other words, the positive association between momentum and $\hat{\rho}_{FE}$ is stronger for the subset of securities for which analysts' *observable* forecasts are probably more representative of analysts' *true* beliefs and, hence, for which ρ_{FE} is likely estimated with more precision. Similar to analyst coverage, the results, therefore, suggest that analyst forecast bias can be a problem, but probably causes me to underestimate the positive association between momentum and ρ_{FE}.

Table 20 also reports differences in momentum across firm characteristic categories. The model of Daniel, Hirshleifer, and Subrahmanyam (1998) provides a second momentum implication, namely that momentum increases in the level of overconfidence. Behavioral biases, such as overconfidence, strengthen with information uncertainty (Einhorn 1980). Because many firm characteristics, on which I sort, can be construed as measures for information uncertainty (market capitalization, book-to-market ratio, analyst coverage, stock return and cash flow volatility), the analysis of Table 20 can be interpreted as an additional test of the Daniel, Hirshleifer, and Subrahmanyam model. Consistent with the prediction in Daniel, Hirshleifer, and Subrahmanyam that momentum increases in overconfidence (but also consistent with the prediction in Hong and Stein (2007) that momentum increases in the volatility of the firm's fundamentals (see Appendix J.A.2)), I find that momentum is stronger for firms with small market capitalization, low book-to-market ratio, low analyst coverage, high stock return volatility, and high cash flow volatility.

Along with the observation that momentum increases with turnover (also reported in Table 20), these findings are all in line with prior literature: Asness (1997) and Daniel and Titman (1999) find that momentum is stronger among growth firms. Jegadeesh and Titman (1993), Grinblatt and Moskowitz (2004) and Zhang (2006) find that momentum is stronger among small firms. Hong, Lim, and Stein (2000) and Zhang find that momentum decreases with analyst coverage.[51] Zhang also finds that momentum increases with stock return volatility and cash flow volatility. Lee and Swaminathan (2000) find that momentum increases in turnover.[52] The similarity in findings is reassuring, as it suggests that with respect to the momentum effect, my sample does not differ significantly from samples used in related studies.

While reassuring on one hand, in the special case of turnover, the similar results are also unsettling. In the model of Hong and Stein (2007), momentum and turnover are

---

[51] Hong, Lim, and Stein (2000) look at *residual* analyst coverage.

[52] In unreported results, I also conduct independent triple-sorts on the basis of past returns, $\hat{\rho}_{FE}$, and the following firm characteristics: price, analyst forecast dispersion, firm age, analyst experience and the fraction of All-Star-Analysts. The conclusions carry over. Results are available upon request.

positively correlated because greater investor heterogeneity (lower ρ_{FE}) not only leads to more momentum, but also to more trading. Lee and Swaminathan's (2000) finding that the momentum effect is stronger for stocks with high recent turnover has, therefore, been taken as supportive evidence for the Hong and Stein model (Hong and Stein 2007, Hong, Stein and Yu 2007). My finding that momentum does not decrease in $\hat{\rho}_{FE}$ but, at the same time, does increase in turnover then seems confusing. I will discuss this apparent contradiction in the next section.

4. Additional analysis

4.1. Evidence with turnover

In Table 22, Panel A, I replicate Lee and Swaminathan's (2000) finding for the full CRSP sample. I follow Lee and Swaminathan and focus on NYSE/AMEX ordinary shares with a stock price of greater than or equal to \$1. The sample period is 1926 to 2005. I no longer require stocks to be covered by at least two analysts. Each month, I rank stocks independently in ascending order on the basis of six-month lagged returns and on turnover averaged over the six months before the portfolio formation date. I then form nine (three by three) equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentiles. I skip a week after the portfolio formation date. The portfolios are held for six months. As in Lee and Swaminathan (2000), the difference in monthly returns between winners and losers is significantly greater both economically and statistically for high turnover stocks. The difference for high turnover stocks is 0.65% a month, whereas the difference for low turnover stocks is only 0.05% a month.

In Table 22, Panel B, I report the average past six-month returns for each of the nine (three by three) portfolios. The difference in past returns between winner- and loser-portfolio for low turnover stocks is 45.87%. For high turnover stocks, that difference is much larger at 66.20%. Given that Jegadeesh and Titman (1993) show that more extreme past returns lead to stronger return continuation, it seems possible that the stronger return continuation for high turnover stocks is driven by more extreme past returns of those high turnover stocks rather than by turnover per se.

To examine this possibility, I control for past returns within a Fama-MacBeth regression framework. I follow Brennan, Chordia, and Subrahmanyam (1998), and run a Fama-MacBeth regression with risk-adjusted returns on market capitalization, book-to-market ratio, six-month lagged returns, and six-month lagged returns interacted with a turnover dummy. I risk-adjust returns using the Fama-French (1993) factors.[53] The turnover dummy equals one if turnover is below the 30th percentile, two if turnover is between the 30th and 70th percentile, and three if turnover is above the 70th percentile. The breakpoints are the same as in Table 22, where I sort stocks independently based on past returns and turnover. This is done to facilitate comparison. Following Brennan, Chordia, and Subrahmanyam, I lag all variables by two months. All coefficients are multiplied by 100.

The results for the Fama-MacBeth regressions are reported in Table 23. The first regression is the baseline regression with book-to-market ratio, market capitalization, and past returns as independent variables. Consistent with Brennan, Chordia, and Subrahmanyam (1998), I find that returns, on average, increase in book-to-market ratio,

---

[53] The factors are obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

decrease in firm size, and increase in past returns, even after adjusting for factor loadings on the Fama-French (1993) factors. In regression (2), I interact past returns with the turnover dummy, but do not control for past returns. The results are comparable to those presented in Table 22. The coefficient on the interaction term is positive, suggesting that the effect of past returns is stronger for stocks with high turnover. But when I control for past returns in regression (3), the coefficient on the interaction term turns negative and is statistically significant.

The fact that momentum no longer increases in turnover once past returns are controlled for has two potential explanations: On the one hand, it could be that contrary to the prediction of Hong and Stein (2007), momentum does not increase in investor heterogeneity. On the other, the explanation could be transaction costs: Stocks with high turnover probably have lower transaction costs. Lower transaction costs should attract arbitrageurs and reduce momentum profits. So while the results presented in Table 23, at first, seem inconsistent with Hong and Stein, the positive association between trading and momentum (through greater heterogeneity) may simply be overshadowed by the negative association between trading and momentum (through reduced transaction costs). The validity of the latter explanation is limited by the fact that I (partially) account for differences in transaction costs by including market capitalization as an independent variable. To further explore whether transaction costs are driving my results, in regression (4), I include the inverse of the stock price as an additional control for transaction costs.[54] I find that including the inverse of price does not alter the observation that momentum no longer increases in trading volume (once past returns are controlled

[54] Pontiff (1996) uses both the market capitalization and the inverse of price as measures of transaction costs.

for). The momentum effect continues to no longer increase in trading volume when including quadratic and cubic terms of the independent variables to account for potential nonlinearities.[55]

It is not always appropriate to orthogonalize a determinant of momentum with past returns. If the model predicts that a variable determines the strength of momentum because it leads to more extreme past returns, then past returns should not be controlled for within a Fama-MacBeth regression framework. In Hong and Stein (2007), however, investor heterogeneity does not determine the strength of momentum through more extreme past returns; holding the level of past returns constant, stocks with more investor heterogeneity should have a stronger return continuation (see Appendix J.A.5).

4.2. Additional sensitivity

Before turning to my last set of tests, I address one more (somewhat subtle) concern. $\hat{\rho}_{FE}$ can be rewritten as:

$$\hat{\rho}_{FE} = \frac{se - \dfrac{d}{N}}{\left(1 - \dfrac{1}{N}\right)d + se}, \tag{4}$$

where $se = (EPS - mean\ EPS\ forecast)^2$ is the squared error in the mean forecast, d is the sample variance in analysts' EPS forecasts, and N is the number of analysts (see Appendix J.C; also see Barron, Kim, Lim, and Stevens 1998). The *intuition* for equation (4) is as follows: Similar signals cause forecasts to be less dispersed. Low values

[55] This result should *not* be construed as criticism of Lee and Swaminathan (2000). It merely suggests that Lee and Swaminathan's findings are not necessarily at odds with my observation that momentum increases in $\hat{\rho}_{FE}$.

obtained from *d*, therefore, indicate high similarity of signals (and high ρ_{FE}). Moreover, similar signals reduce the extent to which forecast errors are diversified away when calculating the mean forecast. High values obtained from *se*, therefore, indicate high similarity of signals (and high ρ_{FE}).

However, *se* and *d* (considered by themselves) are not clean estimators for the similarity in signals as part of the variation in their realizations is explained by the volatility of the signals. To see this, reconsider the model of Hong and Stein (2007): Holding the fraction of investors observing the realization of *A* and *B* constant (and assuming that the fractions are greater than zero), an increase in the variance of *A* and *B* will cause the realizations of these two random variables and the forecasts based upon them to be more dispersed. Thus, *d* not only depends on the relative size of investor groups observing *A* and *B* at different points in time; it also depends on the volatility of the signals. *se* increases in the volatility of the signals as well. Because both *se* and *d* increase in the volatility of signals, by subtracting *d* from *se*, we "control" for the volatility of signals-component in the realizations of *se* and *d* and we "are left" with the similarity of signals-component.

All else being equal, stocks with large positive shocks to earnings surprises are more likely to be assigned to the high correlation portfolios (see equation (4)). The concern then is that the assignment of stocks to high- and low correlation portfolios is largely based on the magnitude of shocks to earnings surprises (as opposed to the stocks' underlying ρ_{FE}), and that differences in shocks to recent earnings surprises explain the stronger return continuation of the high correlation portfolios. To the contrary, however, when requiring post portfolio formation date and report date of (quarterly) earnings used to construct $\hat{\rho}_{FE}$ to be at least six months apart, the high correlation stocks continue to exhibit more momentum than low correlation stocks: The difference in the momentum effect between high and low correlation stocks under the "six-months-minimum restriction" is equal to 0.33% (*t*-statistic of 2.74). I make a similar observation when using annual earnings (and forecasts thereof): Here, the difference in the momentum effect between high and low correlation stocks under the six-months-minimum restriction equals 0.29% (*t*-statistic of 2.64). Without the six-months-minimum restriction, the difference in the momentum effect between high and low correlation stocks equals 0.27% (*t*-statistic of 2.51). Because shocks to earnings surprises announced more than six months ago are unlikely to affect (current) returns in an economically meaningful way, the difference in momentum between high and low correlation stocks does not seem to be fully explained by shocks to recent earnings surprises.[56]

Estimates of ρ_{FE} obtained from earlier earnings announcements (and forecasts thereof) are not necessarily preferable to estimates obtained from the most recent earnings announcement. When sorting stocks on estimates of ρ_{FE} and past returns, and calculating the average of the subsequent "*re-estimated*" realizations of $\hat{\rho}_{FE}$ for each of the nine portfolios (analogous to Table 17), I observe that the spread in the average of the subsequent realizations of $\hat{\rho}_{FE}$ between high- and low correlation portfolios is highest when ranking on estimates of ρ_{FE} from the most recent earnings announcement (compared to ranking on estimates of ρ_{FE} from prior earnings announcement;

[56] For instance, Ball and Brown (1968) find that stock returns are predictable up to two months after annual earnings announcements. Similarly, Chan, Jegadeesh, and Lakonishok (1996) find that returns of the "arbitrage portfolio" (positive unexpected earnings minus negative unexpected earnings) earned over one year are only marginally higher than returns earned over six months.

untabulated). In other words, while recent estimates are potentially more vulnerable to the concern that part of the difference in the momentum effect between high- and low correlation portfolios is due to the differential magnitude of shocks to recent earnings surprises, they also convey more information about ex ante expectations at that point in time.

4.3. Long-run reversal

The model of Daniel, Hirshleifer, and Subrahmanyam (1998) not only predicts momentum, but also that the momentum effect reverses over long horizons, and that this reversal is stronger among high correlation securities.[57] Figure 2 provides empirical evidence on the reversal prediction. Every month, I rank stocks independently in ascending order on the basis of six-month lagged returns and $\hat{\rho}_{FE}$. I then form nine (three by three) equally weighted portfolios. The breakpoints are the 30th and 70th percentiles. I skip one week after the portfolio formation date. The portfolios are held for 18 months. Figure 2 plots event-time monthly excess returns of both the winner- and loser portfolio for high correlation securities and low correlation securities. To obtain excess returns, I subtract average monthly returns across all securities in my sample from the portfolio returns.

Consistent with the model of Daniel, Hirshleifer, and Subrahmanyam (1998), the results show that high correlation securities not only have larger momentum profits, but

[57] The model of Hong and Stein (2007) does not predict long-run reversal. The model of Hong and Stein (1999) shows that long-run reversal can be obtained by introducing momentum traders which condition their demand solely on past price movements.

also stronger reversals. However in untabulated analysis, I find that the difference in reversals between high- and low correlation securities is not reliably different from zero.

5. Earnings momentum

So far, all tests have been on price momentum. An extensive body of literature also examines return predictability based on momentum in past earnings (e.g., Jones and Litzenberger 1970; Bernard and Thomas 1989; and Chan, Jegadeesh, and Lakonishok 1996). Chan, Jegadeesh and Lakonishok suggest that earnings momentum strategies may exploit underreaction to information about companies' short-term prospects, whereas price momentum strategies may exploit a slow reaction to a broader set of value-relevant information, including companies' long-term prospects. In my last set of tests, I examine the explanatory power of ρ_{FE} on earnings momentum.[58]

Following Chan, Jegadeesh and Lakonishok (1996), I rank stocks independently in ascending order on the basis of SUE and $\hat{\rho}_{FE}$. SUE is defined as:

$$SUE_{i,t} = \frac{QuarterlyEarnings_{i,t} - QuarterlyEarnings_{i,t-4}}{\sigma_{i,t}}, \qquad (5)$$

where $QuarterlyEarnings_{i,t}$ is quarterly earnings-per-share most recently announced as of month t for stock i; $QuarterlyEarnings_{i,t-4}$ is earnings-per-share four quarters ago; and $\sigma_{i,t}$ is the standard deviation of unexpected earnings, $QuarterlyEarnings_{i,t}$ - $QuarterlyEarnings_{i,t-4}$, over the preceding eight quarters. I form nine (three by three) equally-weighted portfolios. The breakpoints are the 30th and 70th percentiles. I skip a week after the portfolio formation date. The portfolios are held for six months.

[58] Earnings momentum in Daniel, Hirshleifer, and Subrahmanyam (1998) is discussed in Section B.4, p. 1863. Hong and Stein (2007) have no prediction on earnings momentum.

Panel A of Table 24 shows average monthly returns for each of the nine portfolios as well as various long-short portfolios. The difference in returns between the high and low SUE-portfolio for high correlation stocks is 0.43% (*t*-statistic 4.13). In contrast, the difference between the high and low SUE-portfolio for low correlation stocks is only 0.05% (*t*-statistic of 0.58). The difference in earnings momentum between high and low correlation stocks is 0.38% a month (*t*-statistic of 4.54). The magnitude of earnings momentum reported in this study is smaller than the ones found in related papers. This is because, contrary to related papers, I require firms to be covered by at least two analysts to construct $\hat{\rho}_{FE}$.

I also run time-series regressions of the nine (three by three) excess portfolio returns and the three long-short-portfolio returns on the Fama-French (1993) factors. I report the alphas in Panel B of Table 24. The main results prevail. The alpha of the long-short portfolio for high correlation stocks is 0.51% and significant at the 1% level. In contrast, the alpha of the long-short portfolio for low correlation stocks is 0.14% (*t*-statistic of 1.71). Taken together, the results suggest that earnings momentum increases in ρ_{FE}.

6. Conclusion

In this paper, I compare the momentum implications of two prominent behavioral models – those of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (2007). While united by their departure from the perfect rationality assumption, these two behavioral models adopt fundamentally different approaches to explain the momentum effect. The results presented in this paper are inconsistent with the momentum prediction of Hong and Stein.[59] However, the question is far from being settled. Further subjecting the models of Daniel, Hirshleifer, and Subrahmanyam and Hong and Stein (and other behavioral models) to attempts at falsification should prove to be an interesting area for future research.

[59] Note that my results are merely *consistent* with the momentum prediction of Daniel, Hirshleifer, and Subrahmanyam (1998). There may well be some other behavioral or rational force explaining the positive association between momentum and sample correlation in analysts' forecast errors.

Conclusion

The results presented in this dissertation add to the growing evidence that certain phenomena observed in financial markets are better understood when relaxing some of the assumptions underlying the traditional finance paradigm. Further, I provide evidence on which departure from the "classical assumptions" seems the most promising.

In future research, I hope to further explore the effect of social ties and continue developing new (heretofore not yet empirically assessed) predictions which can be used to compare competing behavioral models.

Appendix A
Academic disciplines

This is a list of the academic discipline categories. We begin with the basic partition from the *US News and World Report*, which we augment with several disciplines that are not available in this guide (denoted by *). Our final list ensures that every reported major is assigned to one of these categories.

Areas of concentration

1	Business
2	Law
3	Medicine
4	Engineering
5	Education
6	Biological sciences
7	Chemistry
8	Computer science
9	Earth sciences
10	Mathematics
11	Physics
12	Library and information studies
13	Criminology
14	Economics
15	English
16	History
17	Political science
18	Psychology
19	Sociology
20	Health
21	Public affairs
22	Fine arts
23	Theology*
24	Agriculture*
25	Foreign languages*
26	Journalism*

Appendix B
Description of variables

This is a discussion of our control variables and their expected relations with the level of CEO compensation.

Firm Size (Total Assets): To measure firm size, we use the book value of total assets in millions (in our regressions, we use the log of this variable). Previous studies find a positive relation between size and the level of compensation (Murphy, 1999; Baker, Jensen, and Murphy, 1988), and there are various alternative explanations regarding the reasons. Some argue that larger firms employ superior managers (Rosen, 1982). Others argue that managers exploit size to justify higher compensation (Bebchuk and Fried, 2003).

Growth Opportunities (MB): To measure growth opportunities, we take the ratio of the market value of equity to the book value of equity plus deferred taxes (in our regressions, we use the log of this variable). Growth firms likely need better managers, implying that the level of compensation increases with the market-to-book ratio (Smith and Watts, 1992; and Gaver and Gaver, 1993).

Prior Firm Performance (ROA)/Past Returns (RET): To measure prior firm performance, we calculate the cumulative stock return and the return on assets (i.e., the ratio of net income to total assets) from the previous fiscal year. From an agency standpoint, compensation should be an increasing function of performance. Moreover, firms with poor prior performance might be forced to decrease the level of compensation to reduce expenses or public outrage, and excellent prior performance can justify higher compensation. To ensure that firm performance is matched to the appropriate CEO, we exclude new arrivals from our regressions because past firm performance cannot be attributed to the incoming CEO. We use one-year measures of performance to minimize the number of observations we lose.

Variance of Residuals (σ^2): To proxy for firm-specific risk, we calculate the variance of the residuals from the market-model regression over the past five-year period. Theoretically, firm risk could be positively or negatively associated with the level of compensation (Banker and Datar, 1989).

CEO Equity Holdings: We also control for the percentage of the company's shares that are owned by the CEO. Some hypothesize that (from a managerial-power point of view) executive compensation increases with CEO ownership, but they allow for a possible inverted U-shaped association (Finkelstein and Hambrick, 1989). Others argue that the association between the level of compensation and the CEO's equity holdings is "theoretically ambiguous" (Cyert, Kang, and Kumar, 2002, p. 454).

Quality (CEO Award): This is a dummy that equals one if the CEO has ever won the "Business Week Best Manager Award", and zero otherwise. We hand-collect this information from the *Business Week* archives. The idea is that recipients of this award might be of higher quality and that higher quality deserves higher total compensation. Alternatively, this award might signify greater power over the board.

CEO=Chairman of the Board (CEO=Chairman): This is a dummy that equals one if the CEO also serves as the chairman of the board, and zero otherwise. If the CEO is also the chairman of the board, the board could be easier for the CEO to control, a hypothesis that is empirically supported by Yermack (1996) and Core, Holthausen, and Larcker (1999), among others. Thus, we expect chairman CEOs to receive a higher level of compensation than their non chairman counterparts.

CEO Tenure: This is the number of years the CEO has been in office. Higher tenure alludes to the CEO's quality (because he is worth keeping) and his worth as a "rare commodity" (Hermalin and Weisbach, 1998, p. 97). Thus, we expect compensation to increase with tenure.

Board Size: Board size is the number of directors on the board (in our regressions, we use the log of this variable). Lipton and Lorsch (1992) argue that larger boards are more susceptible to managerial control and have increased coordination and free-rider problems, and Yermack (1996) finds that firm value is decreasing in board size. To the contrary, Coles, Daniel, and Naveen (2008) find that firms with greater advisory needs exhibit a positive association between board size and firm value. However, because executive compensation is a monitory, not an advisory, issue, we expect a positive relation between board size and compensation.

Old Directors: Following the mandatory age requirements of many firms, we define a director as old if he or she is 70 years or older, and we calculate the *Old Directors* variable as the fraction of directors over the age of 69. Older directors are possibly less effective monitors (NACD, 1996; and Core, Holthausen, and Larcker 1999). Thus, we expect this fraction to have a positive impact on the level of compensation.

Busy Board: This is a dummy that equals one if the board is busy, and zero otherwise. Following Fich and Shivdasani (2006), we designate a board as busy if a majority of the independent directors concurrently serve on three or more boards. Some argue that directors who serve on too many boards do not have sufficient time to provide adequate monitoring (NACD, 1996). Core, Holthausen, and Larcker (1999) and Fich and Shivdasani (2006) present evidence that busy boards indicate weak corporate governance. If busy directors are less effective monitors, then busy boards should be positively associated with the level of compensation.

Directors' Equity Holdings: We also control for the average percentage of the company's shares that are owned by the directors. Greater equity ownership suggests that the directors' interests are more aligned with those of the shareholders. As such, the directors are incensed to be better monitors and, accordingly, we expect the level of CEO compensation to be lower.

CEO from Other Company: This is a dummy that equals one if at least one of the directors is the CEO of another firm, and zero otherwise. We expect that CEOs award their fellow CEOs a higher level of compensation, regardless of whether or not they are interlocked**.**

Classified Board: This is a dummy that equals one if the firm has a classified-board provision (i.e., the directors have a staggered election-term structure), and zero otherwise. Bebchuk and Cohen (2005) argue that classified boards entrench management and find that they are negatively associated with firm value. Faleye (2007) further argues that classified boards reduce director effectiveness and finds that CEO turnover and compensation are less sensitive to performance at firms with classified boards. If board-staggering empowers managers, then we expect these managers to receive a higher level of compensation.

Democracy/Dictatorship Firm: Following Gompers, Ishii, and Metrick (2003), *Democracy Firm* is a dummy that equals one if the firm's GIM index is less than or equal to five, and zero otherwise. *Dictatorship Firm* is a dummy that equals one if the firm's GIM index is greater than or equal to 14, and zero otherwise. A firm's GIM index takes on a value between 0 and 24, accruing one point for each provision that increases managerial power or depresses shareholder activism. We expect that firms with higher indices award higher levels of compensation.

Family Firm: This is a dummy that equals one if at least one relative of the founder is an officer, a director, or a 5% minimum blockholder (either individually or as a group) of the firm, and zero otherwise (we do not consider family firms in which the founder is still a chairman or CEO of the firm). Descendent-run firms have significantly lower firm value, and minority shareholders in these firms are "worse off than they would be in nonfamily firms" (Villalonga and Amit, 2006, p. 388). Thus, we expect a positive association between *Family Firm* and the level of compensation.

Appendix C
Correlation matrix

This table presents a correlation matrix of the independent variables used in our main analysis.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	*Board Ind. Dummy*$_{new}$	**1.00**										
(2)	*Board Ind. Dummy*$_{conv}$	0.49	**1.00**									
(3)	*Board Ind. Fraction*$_{new}$	**0.81**	0.48	**1.00**								
(4)	*Board Ind. Fraction*$_{conv}$	**0.51**	**0.75**	**0.67**	**1.00**							
(5)	*ln(Total Assets)*	-0.05	0.05	-0.03	0.08	**1.00**						
(6)	*ln(MB)*	-0.05	-0.02	-0.10	-0.08	-0.24	**1.00**					
(7)	*ROA*	0.09	0.02	0.05	0.00	-0.33	**0.64**	**1.00**				
(8)	*RET*	-0.08	-0.07	-0.11	-0.12	-0.08	0.23	0.11	**1.00**			
(9)	*Variance*	0.05	-0.01	0.09	0.06	-0.14	-0.06	-0.02	0.08	**1.00**		
(10)	*CEO Equity Hldgs*	-0.11	-0.22	-0.18	-0.24	-0.06	0.01	0.09	0.11	0.10	**1.00**	
(11)	*CEO Award*	0.01	0.08	-0.01	0.08	0.15	0.18	0.19	-0.01	-0.06	-0.09	**1.00**
(12)	*CEO=Chairman*	0.07	0.17	0.09	0.19	0.08	-0.09	-0.08	-0.06	-0.15	0.02	-0.13
(13)	*CEO Tenure*	-0.23	-0.25	-0.30	-0.29	0.00	0.04	-0.02	0.07	-0.05	0.43	-0.20
(14)	*ln(Board Size)*	0.00	0.05	0.02	-0.06	0.21	0.13	-0.03	-0.01	-0.31	-0.32	0.07
(15)	*Old Directors*	-0.15	-0.09	-0.12	-0.02	0.19	-0.23	-0.17	-0.06	-0.02	0.03	-0.07
(16)	*Busy Board*	0.00	0.15	0.00	0.13	0.10	-0.02	-0.03	0.00	-0.13	-0.10	0.06
(17)	*Directors Equity Hldgs*	-0.20	-0.35	-0.20	-0.36	-0.05	-0.03	0.06	0.06	0.04	0.43	-0.01
(18)	*CEO Other Company*	0.10	0.14	0.14	0.19	0.16	0.06	0.01	-0.12	0.06	-0.15	0.11
(19)	*Classified Board*	0.02	0.04	0.05	0.10	-0.33	0.03	-0.03	0.04	0.18	-0.06	-0.16
(20)	*Democracy Firm*	-0.08	-0.12	-0.13	-0.16	0.08	0.09	0.05	-0.03	-0.06	-0.04	0.09
(21)	*Dictatorship Firm*	0.01	0.02	0.00	-0.02	-0.08	-0.07	-0.04	0.05	-0.01	-0.03	-0.07
(22)	*Family Firm*	-0.09	-0.17	-0.12	-0.18	-0.01	-0.19	-0.15	-0.03	0.02	0.01	-0.06

		(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1)	*Board Ind. Dummy*$_{new}$											
(2)	*Board Ind. Dummy*$_{conv}$											
(3)	*Board Ind. Fraction*$_{new}$											
(4)	*Board Ind. Fraction*$_{conv}$											
(5)	*ln(Total Assets)*											
(6)	*ln(MB)*											
(7)	*ROA*											
(8)	*RET*											
(9)	*Variance*											
(10)	*CEO Equity Hldgs*											
(11)	*CEO Award*											
(12)	*CEO=Chairman*	**1.00**										
(13)	*CEO Tenure*	0.16	**1.00**									
(14)	*ln(Board Size)*	0.16	0.07	**1.00**								
(15)	*Old Directors*	0.05	0.12	0.00	**1.00**							
(16)	*Busy Board*	0.08	-0.18	-0.03	-0.15	**1.00**						
(17)	*Directors Equity Hldgs*	-0.08	0.13	-0.09	-0.01	-0.10	**1.00**					
(18)	*CEO Other Company*	0.10	-0.05	0.15	-0.03	-0.01	-0.04	**1.00**				
(19)	*Classified Board*	0.10	0.05	-0.03	0.02	-0.06	-0.16	-0.09	**1.00**			
(20)	*Democracy Firm*	-0.22	0.06	0.09	0.03	-0.06	0.13	0.01	-0.32	**1.00**		
(21)	*Dictatorship Firm*	0.06	0.03	0.02	0.09	-0.08	-0.03	0.02	0.13	-0.04	**1.00**	
(22)	*Family Firm*	-0.17	-0.10	-0.14	0.00	-0.08	0.40	-0.10	-0.18	0.15	-0.04	**1.00**

Appendix D
Description of Control Variables

- *Inverse Security Price*: Assets with higher stock prices might be easier to arbitrage because of lower transaction costs (Pontiff 1996). For country closed-end funds (CCEFs), *Inverse Security Price* is the inverse of the fund's price level as reported in COMPUSTAT. For American Depository Receipts (ADRs), *Inverse Security Price* is the inverse of the ADR's price level in the US as reported in CRSP.
- *Dividend Yield*: Part of the closed-end fund discount arises from management fees (Ross 2005). Because dividends lower the value of management fees, discounts should narrow with dividends. Moreover, Pontiff (1996) argues that dividends reduce holdings costs for the arbitrageur pointing to another channel through which dividends could decrease the discount. *Dividend Yield* is dividends-per-share paid by the CCEF (the ADR) over the previous 12 months scaled by the fund's (the ADR's) lagged net asset value (lagged price).

When the CCEF or ADR trades at a discount, *(Price-NAV)/NAV*, the dependent variable, should be less negative for securities with low costs of arbitrage. In other words, when the CCEF or ADR trades at a discount, *(Price-NAV)/NAV* should be <u>high</u> (or less negative) for securities with low *Inverse Security Price* and high *Dividend Yield*.

Similarly, when the CCEF or ADR trades at a premium, *(Price-NAV)/NAV*, the dependent variable, should be less positive for securities with low costs of arbitrage. In other words, when the CCEF or ADR trades at a premium, *(Price-NAV)/NAV* should be <u>low</u> (or less positive) for securities with low *Inverse Security Price* and high *Dividend Yield*.

- *Turnover Ratio*: For CCEFs, this variable is the ratio of the median turnover of US stocks over the median turnover of stocks in the CCEF's respective home market.[60] For ADRs, this variable is the ratio of the ADR's turnover in the US over the ADR's underlying asset's turnover in the home market. The datasources are COMPUSTAT GLOBAL ISSUE and CRSP. I include the *Turnover Ratio* to control for differences in liquidity between the CCEF (the ADR) and the underlying asset in the home market
- *Home Market Index Returns/US Market Index Returns*: *Home Market Index Returns* are monthly value-weighted index returns of the CCEF's (the ADR's) respective home market (in local currency). The returns are calculated using the COMPUSTAT GLOBAL ISSUE dataset. *US Market Index Returns* are the CRSP value-weighted index returns. I include Home Market Index Returns and US Market Index Returns to control for general demand (sentiment) changes in the home market and the US market respectively (Bodurtha, Kim, and Lee 1995).

Except for *Inverse Security Price*$_{i,t-1}$ and *Dividend Yield*$_{i,t-1}$, values of my independent variables are contemporaneous. The reason I lag *Inverse Security Price*$_{i,t-1}$ and *Dividend Yield*$_{i,t-1}$ by one period is that *Discount*$_{i,t}$, *Inverse Security Price*$_{i,t}$ and *Dividend Yield*$_{i,t}$, are (all three) functions of *Price*$_t$. As a result, should country sentiment have price impact, sentiment changes would not only become reflected in *Discount*$_{i,t}$, but also in *Inverse Security Price*$_{i,t}$ and *Dividend Yield*$_{i,t}$. Because the coefficient on *Country Popularity Score*$_{i,t}$ estimates the correlation between *Discount*$_{i,t}$ and the part of *Country*

[60] I take the median rather than the mean to reduce the effect of outliers.

Popularity Score$_{i,t}$, which is unrelated to the other independent variables (including the impact of country popularity on security prices as reflected in *Inverse Security Price*$_{i,t}$ and *Dividend Yield*$_{i,t}$), using contemporaneous values of *Inverse Security Price* and *Dividend Yield* would unduly reduce the power of my empirical analysis.

Appendix E
Country Closed-End Funds Used in This Study

Country Closed-End Funds (Ticker)	Country
Brazil Fund (BZF)	Brazil
Brazilian Equity Fund (BZL)	Brazil
France Growth Fund (FRF)	France
New Germany Fund (GF)	Germany
India Fund (IFN)	India
India Growth Fund (IGF)	India
Morgan Stanley India Fund (IIF)	India
Indonesia Fund (IF)	Indonesia
First Israel Fund (ISL)	Israel
Japan Equity Fund (JEQ)	Japan
Japan Smaller Cap Fund (JOF)	Japan
Fidelity Advisor Korea Fund (FAK)	Korea
Korea Equity Fund (KEF)	Korea
Korea Fund (KF)	Korea
Korean Investment Fund (KIF)	Korea
Emerging Mexico Fund (MEF)	Mexico
Mexico Equity and Income Fund (MXE)	Mexico
Mexico Fund (MXF)	Mexico
First Philippines Fund (FPF)	Philippines
Templeton Russia Fund (TRF)	Russia
Spain Fund (SNF)	Spain
Taiwan Fund (TWN)	Taiwan
United Kingdom Fund (UKM)	UK

Appendix F
Country Closed-End Funds with IPO and Liquidation/Open-Ending Announcement Date

Country Closed-End Funds (Ticker)	Country
Emerging Germany Fund (FRG)	Germany
Fidelity Advisor Korea Fund (FAK)	Korea
Korean Investment Fund (KIF)	Korea
Emerging Mexico Fund (MEF)	Mexico
United Kingdom Fund (UKM)	UK

Appendix G
Mutual Funds Used in This Study

Mutual Fund Name
AMIDEX 35 Mutual Fund –ISRAEL
Blue and White –ISRAEL
Colonial Newport Japan Fund
Credit Suisse Japan Growth
DFA Japanese Small Company
DFA United Kingdom Small Company
Deutsche Japanese Equity
Dreyfus Premier Japan Fund
Fidelity Advisor Japan
Fidelity Advisor Korea
Fidelity Japan Fund
Fidelity Japan Small Companies Fund
Flag Investors Japanese Equity
GAM Japan Capital Fund
Gartmore China Opportunities
Goldman Sachs Tr:Japanese Equity Fund
Japan Fund
Japan Smaller Companies Fund
Matthews Japan Fund
Matthews Korea Fund
Morgan Stanley Dean Witter Japan Fund
Nikko Japan Tilt Fund
PIMCO:JapaneseStock+TotalReturnStrategy
ProFunds:Ultra Japan
Rydex Srs Tr:Large Cap Japan Fund
Scudder Japanese Equity Fund
T. Rowe Price Japan Fund
Vista Mutual Fd:Japan Fund
Warburg Pincus Japan Growth Fund

Appendix H
Survey Frequency

This table presents the dates the country popularity surveys used in this paper were conducted.

Country	Year	Month	Country	Year	Month	Country	Year	Month
Australia	1987	1	India	2001	2	Russia	2002	2
Australia	2001	2	India	2002	2	Russia	2003	2
Australia	2004	2	India	2004	2	Russia	2003	3
Brazil	1999	2	India	2005	2	Russia	2004	2
Brazil	2001	2	India	2006	2	Russia	2005	2
Brazil	2004	2	Indonesia	2002	3	Russia	2006	2
China	1994	2	Indonesia	2005	2	S. Africa	1991	3
China	1996	1	Israel	2002	2	S. Africa	2001	2
China	1996	3	Israel	2003	2	Spain	2003	2
China	1997	6	Israel	2004	2	Spain	2003	3
China	1998	6	Israel	2005	2	Taiwan	1996	3
China	1998	7	Israel	2006	2	Taiwan	2000	3
China	1999	3	Italy	2001	2	Taiwan	2001	2
China	1999	5	Italy	2003	2	Taiwan	2002	2
China	2000	1	Japan	1992	2	Taiwan	2006	2
China	2000	3	Japan	1993	6	Turkey	2003	3
China	2000	11	Japan	1994	2	UK	1991	3
China	2001	2	Japan	1994	6	UK	1996	3
China	2002	2	Japan	1995	11	UK	1999	2
China	2003	2	Japan	1996	3	UK	1999	5
China	2004	2	Japan	1999	2	UK	2000	11
China	2005	2	Japan	1999	5	UK	2001	2
China	2006	2	Japan	2000	11	UK	2002	2
France	1991	3	Japan	2001	2	UK	2003	2
France	1996	3	Japan	2002	2	UK	2003	3
France	1999	2	Japan	2003	2	UK	2004	2
France	2001	2	Japan	2004	2	UK	2005	2
France	2002	2	Japan	2005	2	UK	2006	2
France	2003	2	Japan	2006	2			
France	2003	3	Korea	1991	3			
France	2004	2	Korea	2000	11			
France	2005	2	Korea	2002	2			
France	2006	2	Korea	2003	2			
Germany	1996	3	Mexico	1996	3			
Germany	1999	2	Mexico	1999	2			
Germany	1999	11	Mexico	2001	2			
Germany	2000	11	Mexico	2002	2			
Germany	2001	2	Mexico	2003	2			
Germany	2002	2	Mexico	2004	2			
Germany	2003	2	Mexico	2005	2			
Germany	2003	3	Mexico	2006	2			
Germany	2004	2	Philippines	2001	2			
Germany	2005	2	Philippines	2002	2			
Germany	2006	2	Philippines	2006	2			

Appendix I
Survey Participants with "No Opinion"

This table presents a snapshot (Dec 2006) of the fraction of survey participants (from the country popularity survey used in this study) who have not formed an opinion towards a country.

Country	Fraction
Australia	0.050
Brazil	0.130
China	0.068
France	0.060
Germany	0.058
India	0.105
Indonesia	0.150
Israel	0.084
Italy	0.110
Japan	0.058
Korea	0.110
Mexico	0.042
Philippines	0.116
Russia	0.070
S. Africa	0.100
Spain	0.160
Taiwan	0.144
Turkey	0.150

Appendix J

A. Momentum in Hong and Stein (2007)

A.1. Setup (for A.2. to A.3. and A.5.)

In the model of Hong and Stein (2007), there is a stock with payoff $Y = A+B$ (paid at time 2) where A and B are two independent mean-zero normal random variables. Assume for simplicity that $\sigma_A^2 = \sigma_B^2 = \sigma^2$. At time 0, investors' forecast of Y is equal to zero. There is neither a risk nor a time premium for holding the stock and $P_0 = 0$.

At time 1, a fraction f of all investors observes the realization of A and the remaining fraction $(1\text{-}f)$ observes the realization of B. Even though both A and B are value-relevant, investors' forecast of Y equals their observed realization only (investors do not learn from prices). That is for the fraction f of investors observing the realization of A (Type A investors), forecasts, X_A , are given by

$$X_A = A; \tag{A.1}$$

for the remaining fraction $(1\text{-}f)$ of investors observing the realization of B (Type B investors), forecasts, X_B, are given by

$$X_B = B. \tag{A.2}$$

Given that $Y=A+B$, forecast errors for Type A investors are equal to

$$FE_A = B, \tag{A.3}$$

and forecast errors for Type B investors are equal to

$$FE_B = A. \tag{A.4}$$

Investors can frictionlessly take either long or short positions. Under these assumptions, $P_1 = fA+(1\text{-}f)B$, i.e. the price at time 1 is a weighted average of investors' beliefs. At time 2, the price equals the payoff, $P_2 = A+B$.

A.2. Momentum

The (dollar) returns in each period are given by

$$ret_{0\to1} = fA + (1-f)B\,, \tag{A.5}$$

$$ret_{1\to2} = (1-f)A + fB\,. \tag{A.6}$$

The covariance between $ret_{0\to1}$ and $ret_{1\to2}$ equals

$$\sigma_{ret_{0\to1},ret_{1\to2}} = f(1-f)(2\sigma^2)\,. \tag{A.7}$$

Momentum described by the return covariance is increasing on f(1-f).

Now, consider the expectation of $ret_{1\to2}$ conditional on $ret_{0\to1}$.

$$\begin{aligned} E(ret_{1\to2} \mid ret_{0\to1}) &= \alpha + \beta ret_{0\to1} = \alpha + \frac{\sigma_{ret_{1\to2},ret_{0\to1}}}{\sigma^2_{ret_{0\to1}}} ret_{0\to1} \\ &= \alpha + \frac{f(1-f)(2\sigma^2)}{\left(f^2+(1-f)^2\right)\sigma^2} ret_{0\to1} \\ &= \alpha + \underbrace{\frac{2f(1-f)}{\left(f^2+(1-f)^2\right)}}_{\beta} ret_{0\to1}\,. \end{aligned} \tag{A.8}$$

$$\frac{d\beta}{df(1-f)} = \frac{2}{-2f(1-f)+1} + \frac{4f(1-f)}{\left(-2f(1-f)+1\right)^2} > 0 \text{ for } f = [0;1]$$

Momentum described by the return correlation is increasing on f(1-f).

A.3. Prediction

The number of ways of picking a pair of investors out of *N* investors equals ${}_N W_2 = \binom{N}{2}$.

Then

$$\rho_{FE} = \frac{\sum_{1}^{{}_N W_2} \rho_{i,FE}}{{}_N W_2}, \tag{A.9}$$

where $\rho_{i,FE}$ is the correlation in forecast errors for investor pair *i* and ρ_{FE} is the average correlation in forecast errors across all ${}_N W_2$ investor pairs.

Let $\rho_{i,FE}$ *{x,y}* be the correlation in forecast errors for investor pair *i* where one investor is of Type *x* and the other is of Type *y*. Then

$$\rho_{i,FE}\{A,B\} = \rho_{i,FE}\{B,A\} = 0\,, \tag{A.10}$$

$$\rho_{i,FE}\{A,A\} = \rho_{i,FE}\{B,B\} = 1\,. \tag{A.11}$$

(A.10) follows from $A \perp B$ and (A.3) and (A.4).

From (A.10) and (A.11), it follows that the numerator of (A.9), $\sum_{1}^{{}_N W_2} \rho_{i,FE}$, is simply the number of investor pairs where both investors are of the same type. There are *fN* investors of Type A and *(1-f)N* investors of Type B. Therefore,

$$\sum_{1}^{{}_N W_2} \rho_{i,FE} = \binom{fN}{2} + \binom{(1-f)N}{2}, \text{ and} \tag{A.12a}$$

$$\rho_{FE} = \frac{\binom{fN}{2} + \binom{(1-f)N}{2}}{\binom{N}{2}} = \frac{(fN-1)f + \left[(1-f)N-1\right](1-f)}{N-1} \tag{A.12b}$$

$$f(1-f) = \frac{(1-\rho_{FE})(N-1)}{2N}. \tag{A.13}$$

Combining equation (A.13) with equations (A.7) and (A.8) yields the following predictions:

$$\frac{d\sigma_{ret_{0\to1},ret_{1\to2}}}{d\left(1-\rho_{FE}\right)}=\frac{\left(N-1\right)\sigma^{2}}{N}>0$$

$$\frac{d\beta}{d\left(1-\rho_{FE}\right)}=\frac{\left(N-1\right)}{-\left(1-\rho_{FE}\right)\left(N-1\right)+N}+\frac{\left(1-\rho_{FE}\right)\left(N-1\right)^{2}}{\left[-\left(1-\rho_{FE}\right)\left(N-1\right)+N\right]^{2}}>0$$

Momentum described by the return covariance (A.7) is decreasing on ρ_{FE}.

Momentum described by the return correlation (A.8) is decreasing on ρ_{FE}.

A.4. Prediction with Multiple Investor Groups and Signals

In the model of Hong and Stein (1999), there are more than two investor groups and more than two signals. More specifically, the investor population is divided into z groups and dividend innovations are decomposed into z independent subinnovations. The prediction that momentum increases as investor groups become more equal-sized is not restricted to z=2 but, in simulations, also holds for $z > 2$ (simulation results are available upon request).[61] An example conveys the essence. Consider the case of $z = 3$. Let the three investor groups consist of N_1, N_2, and N_3 investors. The three investors groups are hereafter referred to IG_1, IG_2, and IG_3. Let the three subinnovations be A, B, and C. At time t=1, A is observed by IG_1, B is observed by IG_2, and C is observed by IG_3. As in Hong and Stein, at time t=2, the investor groups rotate so that A is observed by IG_2, B is observed by IG_3, and C is observed by IG_1. Finally, at time t=3, A is observed by IG_3, B is observed by IG_1, and C is observed by IG_2. Investors can frictionlessly take either long or short positions. Prices then equal

$$P_{t=1} = \frac{N_1}{N}A + \frac{N_2}{N}B + \frac{N - N_1 - N_2}{N}C\,,$$

$$P_{t=2} = \frac{N_1 + N_2}{N}A + \frac{N - N_1}{N}B + \frac{N - N_2}{N}C\,, \tag{A.14}$$

$$P_{t=3} = A + B + C\,,$$

where $N = N_1+N_2+N_3$. In other words, prices equal signals times the fraction of investors who have observed the respective signals. The price at t=0 before any signals are observed is zero.

[61] In Hong and Stein (1999), investor groups are equal-sized. In that sense, momentum is maximized.

(Dollar) returns equal

$$ret_{0\to1} = \frac{N_1}{N}A + \frac{N_2}{N}B + \frac{N - N_1 - N_2}{N}C,$$

$$ret_{1\to2} = \frac{N_2}{N}A + \frac{N - N_1 - N_2}{N}B + \frac{N_1}{N}C, \qquad (A.15)$$

$$ret_{2\to3} = \frac{N - N_2}{N}A + \frac{N_1 + N_2}{N}B + \frac{N - N_1}{N}C.$$

Assume for simplicity that $\sigma_A^2 = \sigma_B^2 = \sigma_C^2 = 1$. Then covariances equal

$$\sigma_{ret_{0\to1},ret_{1\to2}} = \frac{N_1N_2}{N^2} + \frac{N_2\left(N - N_1 - N_2\right)}{N^2} + \frac{\left(N - N_1 - N_2\right)N_1}{N^2},$$

$$\sigma_{ret_{1\to2},ret_{2\to3}} = \frac{N_2\left(N - N_2\right)}{N^2} + \frac{\left(N - N_1 - N_2\right)\left(N_1 + N_2\right)}{N^2} + \frac{N_1\left(N - N_1\right)}{N^2}. \qquad (A.16)$$

In simulations (1000 iterations), I examine how the fractions $\frac{N_1}{N}$, $\frac{N_2}{N}$, and $\frac{N - N_1 - N_2}{N}$ relate to the average of $\sigma_{ret_{0\to1},ret_{1\to2}}$ and $\sigma_{ret_{1\to2},ret_{2\to3}}$, i.e. I examine how the relative investor group size relates to the average covariance in returns. For the special case of *z*=3, I find that the average covariance is maximized at $\frac{N_1}{N} = \frac{N_2}{N} = \frac{N - N_1 - N_2}{N} = \frac{1}{3}$.

The setup for z>3 is analogous. I derive the *(z-1)* covariance terms and examine how the relative size of the *z* investor groups relates to the average of these *(z-1)* covariance terms. I find that for *z* = [4;50] the average covariance is maximized when $\frac{N_1}{N} = \frac{N_2}{N} = ...\frac{N_z}{N} = \frac{1}{z}$, where *z* is the number of investor groups.

At time *t*=1, forecast errors for IG_1, FE_{IG1}, equal *B*+*C* (investors of IG_1 have observed *A* only). Similarly, FE_{IG2}=*A*+*C*, and FE_{IG3}=*A*+*B*. The correlation in forecast errors between two investors from the same investor group equals one. In contrast, the correlation in forecast errors between two investors from different investor groups equals 0.5. Therefore, similar to (A.12), to calculate the average correlation in forecast errors at time t=1, we add the number of investor pairs from distinct investor groups divided by two to the number of investor pairs from the same investor group and divide the whole sum by the number of all investor pairs.[62] At time t=2, $FE_{IG1}= C$ (investors of IG_1 have observed A and B but not yet C). Similarly, $FE_{IG2}=A$, and $FE_{IG3}= B$. The correlation in forecast errors between two investors from the same investor group equals one. In contrast, the correlation in forecast errors between two investors from different investor groups equals zero. Analogous to (A.12), the average correlation in forecast errors at time t=2 equals the number of investor pairs from the same investor group divided by the number of all investor pairs.

In simulations, I examine how the fractions $\frac{N_1}{N}$, $\frac{N_2}{N}$, and $\frac{N-N_1-N_2}{N}$ relate to the average of the average correlations in forecast errors. I find that the average of the average correlations in forecast errors is minimized at $\frac{N_1}{N}=\frac{N_2}{N}=\frac{N-N_1-N_2}{N}=\frac{1}{3}$. Similarly, for z = [4;50], I find that the average of the average correlations in forecast errors is minimized at $\frac{N_1}{N}=\frac{N_2}{N}=......\frac{N_z}{N}=\frac{1}{z}$.

---

62 $\rho=\dfrac{\dfrac{\#investor\ groups_{distinct}}{2}+\#investor\ groups_{same}}{\#investor\ groups_{all}}$

A.5. Past Returns and Momentum

In Hong and Stein (2007) momentum is described by the covariance between $ret_{0\to1}$ and $ret_{1\to2}$

$$\sigma_{ret_{0\to1},ret_{1\to2}} = f\left(1-f\right)\left(2\sigma^2\right). \qquad \text{(from A.7)}$$

At time 1, we form portfolios based on $ret_{0\to1}$. The portfolio of stocks with the highest $ret_{0\to1}$ is referred to as the winner portfolio; the portfolio of stocks with the lowest $ret_{0\to1}$ is referred to as the loser portfolio. The variance of $ret_{0\to1}$ is given by

$$\sigma^2_{ret_{0\to1}} = \left(f^2 + \left(1-f\right)^2\right)\sigma^2. \qquad \text{(A.17)}$$

As $\sigma^2_{ret_{0\to1}}$ increases, the spread between the average $ret_{0\to1}$ of stocks in the winner portfolio and the average $ret_{0\to1}$ of stocks in the loser portfolio increases. In other words, an increase in $\sigma^2_{ret_{0\to1}}$ is associated with more extreme past returns for both the winner portfolio and the loser portfolio.

$$\frac{d\sigma^2_{ret_{0\to1}}}{df\left(1-f\right)} = -2 < 0$$

The extremity of past returns ($\sigma^2_{ret_{0\to1}}$) is decreasing on f(1-f)

Now consider two economies where

$$\sigma^2_{ret_{0\to1},economy1} = \sigma^2_{ret_{0\to1},economy2}, \qquad \text{(A.18)}$$

$$f_{economy1}\left(1-f_{economy1}\right) > f_{economy2}\left(1-f_{economy2}\right), \qquad \text{(A.19)}$$

that is two economies that have the same extremity in past returns but differ in their level of *f(1-f)*.

From (A.17) and (A.18) it follows that

$$\left(f_{economy1}^2+\left(1-f_{economy1}\right)^2\right)\sigma_{A,economy1}^2=\left(f_{economy2}^2+\left(1-f_{economy2}\right)^2\right)\sigma_{A,economy2}^2$$

$$\sigma_{A,economy1}^2=\frac{\left(f_{economy2}^2+\left(1-f_{economy2}\right)^2\right)}{\left(f_{economy1}^2+\left(1-f_{economy1}\right)^2\right)}\sigma_{A,economy2}^2\,. \tag{A.20}$$

From (A.7) and (A.20), it follows that the covariance for the first economy is

$$\begin{aligned}\sigma_{ret_{0\to1},ret_{1\to2},economy1}&=f_{economy1}\left(1-f_{economy1}\right)2\sigma_{A,economy1}^2\\&=f_{economy1}\left(1-f_{economy1}\right)\frac{\left(f_{economy2}^2+\left(1-f_{economy2}\right)^2\right)}{\left(f_{economy1}^2+\left(1-f_{economy1}\right)^2\right)}2\sigma_{A,economy2}^2\,.\end{aligned} \tag{A.21}$$

The question is whether (A.21) is greater than $\sigma_{ret_{0\to1},ret_{1\to2},economy2}=f_{economy2}\left(1-f_{economy2}\right)2\sigma_{A,economy2}^2$ the covariance for the second economy, or, in other words, whether

$$\underbrace{f_{economy1}\left(1-f_{economy1}\right)}_{(1)}\underbrace{\frac{\left(f_{economy2}^2+\left(1-f_{economy2}\right)^2\right)}{\left(f_{economy1}^2+\left(1-f_{economy1}\right)^2\right)}}_{(2)}>\underbrace{f_{economy2}\left(1-f_{economy2}\right)}_{(3)}\,. \tag{A.22}$$

We assumed that there is more investor heterogeneity in economy1 than in economy2:

$$\underbrace{f_{economy1}\left(1-f_{economy1}\right)}_{(1)}>\underbrace{f_{economy2}\left(1-f_{economy2}\right)}_{(3)}\,. \qquad \text{(from A.19)}$$

Because $\dfrac{d\left[f^2+(1-f)^2\right]}{d\left[f(1-f)\right]}=-2$, we also know that

$$f_{economy1}^2+\left(1-f_{economy1}\right)^2<f_{economy2}^2+\left(1-f_{economy2}\right)^2 \text{ or that } \underbrace{\frac{\left(f_{economy2}^2+\left(1-f_{economy2}\right)^2\right)}{\left(f_{economy1}^2+\left(1-f_{economy1}\right)^2\right)}}_{(2)}>1.$$

Taken together, this implies that (A.22) does indeed hold and that

$$\sigma_{ret_{0\to1},ret_{1\to2},economy1}>\sigma_{ret_{0\to1},ret_{1\to2},economy2}. \tag{A.23}$$

For two stocks with the same extremity of past returns, the stock with higher (1-f) has stronger return covariance (momentum).

A.6. Analyst Dispersion and Momentum

In the framework of Hong and Stein (2007), the momentum effect is fully described by *f(1-f)*, σ_A^2,and σ_B^2 (see equation A.7):

$$momentum\left(f\left(1-f\right),\sigma_A^2,\sigma_B^2\right). \tag{A.24}$$

ρ_{FE} is fully described by *f(1-f)* and *N* (see equation A.12b):

$$\rho_{FE}\left(f\left(1-f\right),N\right). \tag{A.25}$$

Analyst dispersion is fully described by *f(1-f)*, *N*, σ_A^2, and σ_B^2:

$$dispersion\left(f\left(1-f\right),N,\sigma_A^2,\sigma_B^2\right). \tag{A.25}$$

The reasoning for (A.25) is rather intuitive: Holding all else equal, an increase in investor heterogeneity will lead to an increase in the number of investors disagreeing with each other, and, as such, cause forecasts to be more dispersed. Moreover, holding *f(1-f)* constant (and assuming that *f(1-f)* > 0), an increase in the variance of *A* and *B* will cause the realizations of these two random variables and the forecasts based upon them to be more dispersed.

Any association between momentum effect and ρ_{FE} can be attributed to *f(1-f)* (see equations (A.24) and (A.25)). In comparison, any association between momentum effect and dispersion is a joint function of *f(1-f)*, σ_A^2 and σ_B^2 (see equations (A.24) and (A.25)). As a result, for the sake of testing the partial effect of *f(1-f)* on momentum (as opposed to the joint impact of *f(1-f)*, σ_A^2 and σ_B^2 on momentum), ρ_{FE} is probably the preferable measure.

There is one scenario in which ρ_{FE} will also be affected by the variance of signals:[63] Let $Y = A + B + e$, where e is a shock that nobody can see foresee. Forecast errors at time 1 are now equal to $B + e$ for Type A investors and $A + e$ for Type B investors. If $\sigma_e^2 > 0$, forecast errors between investors of *different* type are positively correlated.

ρ_{FE} in this scenario is described by *f(1-f)*, *N*, and σ_e^2:

$$\rho_{FE}\left(f\left(1-f\right), N, \sigma_e^2\right). \tag{A.26}$$

However, because e is unforeseen by investors, e has no effect on the covariance in dollar returns. In other words, the momentum effect is still fully described by *f(1-f),* σ_A^2 and σ_B^2 (equation A.24). As a result, even in the scenario of an unforeseen signal, any association between momentum effect and ρ_{FE} can be attributed to *f(1-f)* (see equations (A.24) and (A.26)).

[63] I would like to thank Jeremy Stein for pointing out this potential scenario.

B. Momentum in Daniel, Hirshleifer and Subrahmanyam (1998)

B.1. Setup (for B.2 to B.3)

In the model of Daniel, Hirshleifer and Subrahmanyam (1998), investors form beliefs about future payoffs denoted by θ. They have a common prior

$$\theta \sim N\left(0, \frac{1}{h}\right), \ \frac{1}{h} = \sigma_\theta^2. \tag{B.1}$$

At time 1, a subset of investors receives private signals s_i represented by

$$s_i = \theta + \varepsilon_i, \ \varepsilon_i \sim N\left(0, \frac{1}{k}\right), \ \frac{1}{k} = \sigma_\varepsilon^2. \tag{B.2}$$

where ε_i is orthogonal to θ, but is allowed to be correlated with ε_j, $i \neq j$, i.e. signal noise terms are allowed to be correlated. For tractability, I impose the assumption that the covariance in signal noise terms, σ, is the same across all investors, i.e. that $\sigma = \sigma_{i,j}$ for all i and j. At time 2, a noisy public signal arrives. At time 3, conclusive public information arrives.

B.2. Momentum

Momentum is increasing on σ, the covariance of investors' signal noise terms.[64]

[64] This prediction is implicit in footnote 6, page 1845, but can also be explicitly derived within their model. In the model of Daniel, Hirshleifer, and Subrahmanyam (1998), signal noise terms are assumed to be perfectly correlated.

B.3. Prediction[65]

At time 1, an (informed) investor's forecast (or his/her conditional expectation) of future payoff θ, μ_i, is a weighted average of common prior and private signal with the respective precisions as the weights

$$\mu_i = \frac{ks_i}{h+k}. \tag{B.3}$$

I introduce the following notation and measures:

$$\mu \equiv \frac{1}{N}\sum_{i=1}^{N}\mu_i, \tag{B.4}$$

$$V_i \equiv E\left[\left(\theta-\mu_i\right)^2\right] \tag{B.5}$$

$$V \equiv \frac{1}{N}\sum_{i=1}^{N}V_i, \tag{B.6}$$

$$C_i \equiv \frac{1}{N-1}\sum_{j\neq 1}^{N}Cov\left(\theta-\mu_i,\theta-\mu_j\right) \tag{B.7}$$

$$C \equiv \frac{1}{N}\sum_{i=1}^{N}C_i, \tag{B.8}$$

$$\rho_{FE} \equiv \frac{C}{V} \tag{B.9}$$

(B.6) is the average expected squared forecast error, (B.8) is the average covariance in forecast errors, and (B.9) is the average correlation in forecast errors (all at time 1).

$$\begin{aligned}
V_i &\equiv E\left[\left(\theta-\mu_i\right)^2\right] = E\left[\left(\theta-\frac{k\left(\theta+\varepsilon_i\right)}{h+k}\right)^2\right] \\
&= E\left(\theta^2\right)+\frac{k^2}{\left(h+k\right)^2}\left[E\left(\theta^2\right)+E\left(\varepsilon^2\right)\right]-\frac{2k}{h+k}E\left[\theta\left(\theta+\varepsilon\right)\right] \\
&= \frac{1}{h}+\frac{k^2}{\left(h+k\right)^2}\left(\frac{1}{h}+\frac{1}{k}\right)-\frac{2k}{\left(h+k\right)}\frac{1}{h}=\frac{1}{h}\left[1+\frac{k^2}{\left(h+k\right)^2}-\frac{2k}{\left(h+k\right)}\right]+\frac{k}{\left(h+k\right)^2} \\
&= \frac{h}{\left(h+k\right)^2}+\frac{k}{\left(h+k\right)^2}=\frac{1}{\left(h+k\right)}
\end{aligned} \tag{B.10}$$

[65] This derivation draws from Barron, Kim, Lim, and Stevens (1998).

$$V \equiv \frac{1}{N}\sum_{i=1}^{N} V_i = \frac{1}{(h+k)} \tag{B.11}$$

$$C_i \equiv \frac{1}{N-1}\sum_{j\neq 1}^{N} Cov(\theta-\mu_i, \theta-\mu_j) = \frac{1}{N-1}\sum_{j\neq 1}^{N} Cov\left(\theta - \frac{k(\theta+\varepsilon_i)}{h+k}, \theta - \frac{k(\theta+\varepsilon_j)}{h+k}\right)$$

$$= \frac{1}{N-1}\sum_{j\neq 1}^{N}\left[\frac{1}{h} - \frac{2k}{h(h+k)} + \frac{k^2}{(h+k)^2}\left(\frac{1}{h}+\sigma\right)\right]$$

$$= \frac{1}{N-1}\sum_{j\neq 1}^{N}\left[\frac{1}{h}\left(1 - \frac{2k}{(h+k)} + \frac{k^2}{(h+k)^2}\right) + \frac{k^2\sigma}{(h+k)^2}\right]$$

$$= \frac{1}{N-1}\sum_{j\neq 1}^{N}\left[\frac{h+k^2\sigma}{(h+k)^2}\right] = \frac{h+k^2\sigma}{(h+k)^2} \tag{B.12}$$

$$C \equiv \frac{1}{N}\sum_{i=1}^{N} C_i = \frac{h+k^2\sigma}{(h+k)^2} \tag{B.13}$$

From (B.9), (B.11) and (B.13), the covariance in signal noise terms can be expressed as a function of the precision of the common prior, the precision of the private signal and the correlation in forecast errors:

$$\rho_{FE} \equiv \frac{C}{V} = \frac{\frac{h+k^2\sigma}{(h+k)^2}}{\frac{1}{h+k}}$$

$$= \frac{h+k^2\sigma}{h+k} \tag{B.14}$$

$$\sigma = \frac{\rho_{FE}(h+k)-h}{k^2} \tag{B.15}$$

Combining equation (B.15) with the prediction in Section B.2. yields the following prediction: *Momentum is increasing on ρ_{FE}.*

C. Estimator for ρ_{FE}[66]

We start with our estimator for ρ_{FE}:

$$\hat{\rho}_{FE} \equiv \frac{\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j\neq 1}^{N}(y-x_i)(y-x_j)}{\frac{1}{N}\sum_{i=1}^{N}(y-x_i)^2}, \tag{C.1}$$

To facilitate notation, I will, hereafter, refer to $(y - x_i)$ as e_i and to $(y - x)$ as e. Further, I will refer to $\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j\neq 1}^{N}(y-x_i)(y-x_j)$ as c, and to $\frac{1}{N}\sum_{i=1}^{N}(y-x_i)^2$ as v.

$$\begin{aligned} s\,e &\equiv (y-x)^2 = e^2 = \left(\frac{1}{N}\sum_{i=1}^{N}e_i\right)^2 \\ &= \frac{1}{N^2}\left(\sum_{i=1}^{N}e_i\right)^2 = \frac{1}{N^2}\left[\sum_{i=1}^{N}e_i^2 + \sum_{i=1}^{N}\sum_{j\neq i}^{N}e_ie_j\right] \\ &= \frac{v+(N-1)c}{N} \end{aligned} \tag{C.2}$$

$$\begin{aligned} d &\equiv \frac{1}{N-1}\sum_{i=1}^{N}(x_i-x)^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left((y-x)-(y-x_i)\right)^2 = \frac{1}{N-1}\sum_{i=1}^{N}(e-e_i)^2 \\ &= \frac{1}{N-1}\sum_{i=1}^{N}\left[e^2+e_i^2-2ee_i\right] \\ &= \frac{1}{N-1}\sum_{i=1}^{N}\left[se+v_i-2ee_i\right] = \frac{N}{N-1}\left[se+v\right] - \frac{2}{N(N-1)}\left[\sum_{i=1}^{N}e_i^2+\sum_{i=1}^{N}\sum_{j\neq i}^{N}e_{i,}e_j\right] \end{aligned}$$

---

[66] This derivation draws from Barron, Kim, Lim, and Stevens (1998).

$$= \frac{N}{N-1}\left[se+v\right] - \frac{2v}{N-1} - 2c$$

$$\begin{aligned} &= \frac{N}{N-1}\left[\left(\frac{v-c}{N}+c\right)+v\right] - \frac{2v}{N-1} - 2c \\ &= v-c \end{aligned} \tag{C.3}$$

$$\begin{aligned} se &= \frac{v-c}{N}+c && \text{|(from C.2)} \\ &= \frac{d}{N}+c && \text{|from (C.3)} && \rightarrow c = \text{se - } \frac{d}{N} \\ & && && \rightarrow v = d+c \\ & && && \quad\;\; = d + \text{se - } \frac{d}{N} \\ & && && \quad\;\; = \left(1-\frac{1}{N}\right)d + se \end{aligned}$$

We can see that

$$\hat{\rho}_{FE} \equiv \frac{\frac{1}{N\left(N-1\right)}\sum_{i=1}^{N}\sum_{j\neq 1}^{N}\left(y-x_i\right)\left(y-x_j\right)}{\frac{1}{N}\sum_{i=1}^{N}\left(y-x_i\right)^2} = \frac{c}{v} = \frac{se-\frac{d}{N}}{\left(1-\frac{1}{N}\right)d+se} . \tag{C.4}$$

References

Adams, Renee B., and Daniel Ferreira, 2007, A Theory of Friendly Boards, *The Journal of Finance* 62, 217-250.

Aggarwal, Rajesh K., and Andrew A. Samwick, 1999, Executive Compensation, Strategic Competition, and Relative Performance Evaluation: Theory and Evidence, *The Journal of Finance* 54, 1999-2043.

Akerlof, George A., 1980, A Theory of Social Custom, of which Unemployment May Be One Consequence, *Quarterly Journal of Economics* 94, 749-775.

Aoki, Kumiko, and Edward J. Downes, 2003, An Analysis of Young People's Use of and Attitudes toward Cell Phones, *Telematics and Informatics* 20, 349-364.

Arrow, Kenneth J., 1972, Models of Job Discrimination, in A.H. Pascal, ed.: *Racial Discrimination in Economic Life* (D.C. Heath, Lexington).

Asness, Clifford S., 1997, The Interaction of Value and Momentum Strategies, *Financial Analysts Journal* 29-36.

Baker, George P., and Brian J. Hall, 2004, CEO Incentives and Firm Size, *Journal of Labor Economics* 22, 767-798.

Baker, George P., Michael C. Jensen, and Kevin J. Murphy, 1988, Compensation and Incentives: Practice vs. Theory, *The Journal of Finance* 43, 593-616.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *The Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *The Journal of Economic Perspective* 21, 129-151.

Ball, Ray, and Philip Brown, 1968, An Empirical Evaluation of Accounting Income Numbers, *Journal of Accounting Research* 6, 159-178.

Banker, Rajiv D., and Srikant M. Datar, 1989, Sensitivity, Precision, and Linear Aggregation of Signals for Performance Evaluation, *Journal of Accounting Research* 27, 21-39.

Barber, Brad M., and Terrance Odean, 2008, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21, 785-818.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Barberis, Nicholas, and Richard Thaler, 2005, A Survey of Behavioral Finance, in George M. Constantinides, Milton Harris, and Rene Stulz, eds.: *Handbook of the Economics of Finance* (North Holland, Amsterdam).

Barron, Orie E., Oliver Kim, Steve C. Lim, and Douglas E. Stevens, 1998, Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment, *The Accounting Review* 73, 421-433.

Bebchuk, Lucian Arye, and Alma Cohen, 2005, The Costs of Entrenched Board, *Journal of Financial Economics* 78, 409-433.

Bebchuk, Lucian Arye, Alma Cohen, and Allen Ferrell, 2004, What Matters in Corporate Governance?, *Harvard University Working Paper*.

Bebchuk, Lucian Arye, and Jesse M. Fried, 2003, Executive Compensation as an Agency Problem, *The Journal of Economic Perspective* 17, 71-92.

Becker, Gary, 1957. *The Economics of Discrimination* (University of Chicago Press, Chicago).

Berk, Jonathan B., and Richard Stanton, 2007, Managerial Ability, Compensation, and the Closed-End Fund Discount, *The Journal of Finance* 62, 529-556.

Bernard, Victor L., and Jacob Thomas, 1989, Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?, *Journal of Accounting Research* 27, 1-36.

Bodurtha, James N., Jr., Dong-Soon Kim, and Charles M. C. Lee, 1995, Closed-end Country Funds and U.S. Market Sentiment, *The Review of Financial Studies* 8, 879-918.

Brennan, Michael, Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns, *Journal of Financial Economics* 49, 345-373.

Brickley, James A., Jeffrey L. Coles, and Rory Terry, 1994, Outside Directors and the Adoption of Poison Pills, *Journal of Financial Economics* 35, 371-390.

Byrd, John W., and Kent A. Hickman, 1992, Do Outside Directors Monitor Managers?, *Journal of Financial Economics* 32, 195-221.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, 2007, Robust Inference with Multi-way Clustering, *University of California, Davis Working Paper*.

Chan, Justin, Dong Hong, and Marti G. Subrahmanyam, 2008, A Tale of Two Prices: Liquidity and Asset Prices in Multiple Markets, *Journal of Banking and Finance* 21, 947-960.

Chan, Justin, Ravi Jain, and Yihong Xia, 2008, Market Segmentation, Liquidity Spillover, and Closed-End Country Fund Discounts, *Journal of FInancial Markets* 11, 377-399.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum Strategies, *The Journal of Finance* 51, 1681-1713.

Chavis, Larry, and Phillip Leslie, 2008, Consumer Boycotts: The Impact of the Iraq War on French Wine Sales in the U.S., *Quantitative Marketing and Economics* 7, 37-67.

Cherkes, Martin, Jacob Sagi, and Richard Stanton, 2009, A Liquidity-Based Theory of Closed-End Funds, *Review of Financial Studies* 22, 257-297.

Cohen, Lauren, Andrea Frazzini, and Christopher J. Malloy, 2007, The Small World of Investing: Board Connections and Mutual Fund Returns, *Journal of Political Economy* 116, 951-979.

Cohen, Lauren, Andrea Frazzini, and Christopher J. Malloy, 2008, Sell Side School Ties, *Harvard University Working Paper*.

Coles, Jeffrey L., Naveen D. Daniel, and Lalitha Naveen, 2008, Boards: Does One Size Fit All?, *Journal of Financial Economics* 87, 329-356.

Core, John E., Robert W. Holthausen, and David F. Larcker, 1999, Corporate Governance, Chief Executive Officer Compensation, and Firm Performance, *Journal of Financial Economics* 51, 371-406.

Cotter, James F., Anil Shivdasani, and Marc Zenner, 1997, Do Independent Directors Enhance Target Shareholder Wealth During Tender Offers?, *Journal of Financial Economics* 43, 195-218.

Crosse, Caroline, and Barbara Hocking, 2004, Social Rehabilitation: What are the Issues?, DVA National Rehabilitation Conference (Canberra, Australia).

Cyert, Richard M., Sok-Hyon Kang, and Praveen Kumar, 2002, Corporate Governance, Takeovers, and Top-Management Compensation: Theory and Evidence, *Management Science* 48, 453-469.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *The Journal of Finance* 53, 1839-1885.

Daniel, Kent, David Hirshleifer, and Siew Hong Teoh, 2002, Investor Psychology in Capital Markets: Evidence and Policy Implications, *Journal of Monetary Economics* 49, 139-209.

Daniel, Kent, and Sheridan Titman, 1999, Market Efficiency in an Irrational World, *Financial Analysts' Journal* 55, 28-40.

De Long, J. Bradford, Andrei Shleifer, L. H. Summers, and Robert J. Waldman, 1990, Noise Trader Risk in Financial Markets, *The Journal of Political Economy* 98, 703-738.

Dechow, Patricia M., Richard G. Sloan, and Amy P. Sweeney, 1996, Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC, *Contemporary Accounting Research* 13, 1-36.

Del Guercio, Diane, 1996, The Distorting Effect of the Prudent Man Law on Institutional Equity Investments, *Journal of Financial Economics* 40, 31-62.

DellaVigna, Stefano, and Joshua M. Pollet, 2008, Investor Inattention and Friday Earnings Announcements, *Journal of Finance, forthcoming*.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of Opinion and the Cross Section of Stock Returns, *The Journal of Finance* 57, 2113-2141.

Doukas, John A., Chansong Kim, and Christos Pantzalis, 2006, Divergence of Opinion and Equity Returns, *The Journal of Financial and Quantitative Analysis* 41, 573-606.

Edmans, Alex, Diego Garcia, and Oyvind Norli, 2007, Sports Sentiment and Stock Returns, *The Journal of Finance* 62, 1967-1998.

Einhorn, Hillel J., 1980, Overconfidence in Judgment, *New Directions for Methodology of Social and Behavioral Science* 4, 1-16.

Elster, Jon, 1989, Social Norms and Economic Theory, *The Journal of Economic Perspective* 3, 99-117.

Faleye, Olubunmi, 2007, Classified Boards, Firm Value, and Managerial Entrenchment, *Journal of Financial Economics* 83, 501-529.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics* 43, 153-193.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting Anomalies, *The Journal of Finance* 63, 1653-1678.

Fama, Eugene F., and Michael C. Jensen, 1983, Separation of Ownership and Control, *Journal of Law and Economics* 26, 301-325.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return and Equilibrium, *Journal of Political Economy* 81.

Fich, Eliezer M., and Anil Shivdasani, 2006, Are Busy Boards Effective Monitors?, *The Journal of Finance* 61, 689-724.

Finkelstein, Sydney, and Donald C. Hambrick, 1989, Chief Executive Compensation: A Study of the Intersection of Markets and Political Processes, *Strategic Management Journal* 10, 121-134.

French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected Stock Returns and Volatility, *Journal of Financial Economics* 19, 3-29.

Friedman, Matthew J., 2005, Veterans' Mental Health in the Wake of War, *New England Journal of Medicine* 352, 1287-1290.

Gaver, Jennifer J., and Kenneth M. Gaver, 1993, Additional Evidence on the Association between the Investment Opportunity Set and Corporate Financing, Dividend, and Compensation Policies, *Journal of Accounting and Economics* 16, 125-160.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate Governance and Equity Prices, *The Quarterly Journal of Economics* 118, 107-155.

Gompers, Paul, and Andrew Metrick, 2001, Institutional Investors and Equity Prices, *Quarterly Journal of Economics* 116, 229-259.

Granovetter, Mark, 2005, The Impact of Social Structure on Economic Outcomes, *The Journal of Economic Perspective* 19, 33-50.

Grinblatt, Mark, and Tobias J. Moskowitz, 2004, Predicting Stock Price Movements from Past Returns: The Role of Consistency and Tax-Loss Selling, *Journal of Financial Economics* 71, 541-579.

Gruber, Martin J., 1996, Another Puzzle: The Growth in Actively Managed Mutual Funds, *The Journal of Finance* 51, 783-810.

Hall, Brian J., and Jeffrey B. Liebman, 1998, Are CEOs Really Paid Like Bureaucrats?, *The Quarterly Journal of Economics* 113, 653-691.

Hallock, Kevin F., 1997, Reciprocally Interlocking Boards of Directors and Executive Compensation, *The Journal of Financial and Quantitative Analysis* 32, 331-344.

Healy, Paul M., 1985, The Effect of Bonus Schemes on Accounting Decisions, *Journal of Accounting and Economics* 7, 261-279.

Hermalin, Benjamin E., and Michael S. Weisbach, 1991, The Effects of Board Composition and Direct Incentives on Firm Performance, *Financial Management* 20, 101-112.

Hermalin, Benjamin E., and Michael S. Weisbach, 1998, Endogenously Chosen Boards of Directors and Their Monitoring of the CEO, *The American Economic Review* 88, 96-118.

Hirshleifer, David, 2001, Investor Psychology and Asset Pricing, *The Journal of Finance* 56, 1533-1597.

Hirshleifer, David, and Tyler Shumway, 2003, Good Day Sunshine: Stock Returns and the Weather, *The Journal of Finance* 58, 1009-1032.

Hong, Harrison, and Marcin Kacperczyk, 2009, The Price of Sin: The Effects of Social Norms on Markets, *Journal of Financial Economics, forthcoming*.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *The Journal of Finance* 55, 265-295.

Hong, Harrison, and Jeremy Stein, 2007, Disagreement and the Stock Market, *The Journal of Economic Perspective* 21, 109-128.

Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *The Journal of Finance* 54, 2143-2184.

Hong, Harrison, Jeremy C. Stein, and Jialin Yu, 2007, Simple Forecasts and Paradigm Shifts, *The Journal of Finance* 62, 1207-1242.

Ingram, Paul, and Peter W. Roberts, 2000, Friendships among Competitors in the Sydney Hotel Industry, *American Journal of Sociology* 106, 387-423.

Ippolito, Richard A., 1992, Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, *Journal of Law and Economics* 35, 45-70.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *The Journal of Finance* 56, 699-720.

Jegadeesh, Narasimhan, and Sheridan Titman, 2002, Cross-Sectional and Time-Series Determinants of Momentum Returns, *The Review of Financial Studies* 15, 143-157.

Jegadeesh, Narasimhan, and Sheridan Titman, 2005, Momentum, in Richard Thaler, ed.: *Advances in Behavioral Finance* (Princeton University Press, New Jersey).

Jensen, Michael C., and Kevin J. Murphy, 1990, Performance Pay and Top-Management Incentives, *The Journal of Political Economy* 98, 225-264.

Jones, Charles P., and Robert H. Litzenberger, 1970, Quarterly Earnings Reports and Intermediate Stock Price Trends, *The Journal of Finance* 25, 143-148.

Kamstra, Mark, Lisa Kramer, and Maurice Levi, 2003, Winter Blues: A SAD Stock Market Cycle, *American Economic Review* 93, 1257-1263.

Kaplanski, Guy, and Haim Levy, 2009, Sentiment and Stock Prices: The Case of Aviation Disasters, *Journal of Financial Economics, forthcoming*.

Karolyi, G. Andrew, 1998, Why Do Companies List Shares Abroad?: A Survey of the Evidence and Its Managerial Implications, *Financial Markets, Institutions & Instruments* 7, 1-60.

Keswani, Aneel, and David Stolin, 2008, Which Money is Smart? Mutual Fund Buys and Sells of Individual and Institutional Investors, *The Journal of Finance* 63, 85-118.

Klein, April, 2002, Audit Committee, Board of Director Characteristics, and Earnings Management, *Journal of Accounting and Economics* 33, 375-400.

Lamont, Owen, and Richard Thaler, 2003, Anomalies: The Law of One Price in Financial Markets, *The Journal of Economic Perspective* 17, 191-202.

Larcker, David F., Scott A. Richardson, Andrew J. Seary, and Irem Tuna, 2005, Back Door Links Between Directors and Executive Compensation, *Stanford University Working Paper*.

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *The Journal of Finance* 46, 75-109.

Lee, Charles M. C., and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, *The Journal of Finance* 55, 2017-2069.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer Confidence and Asset Prices: Some Empirical Evidence, *The Review of Financial Studies* 19, 1499-1529.

Levitt, Steven, 2004, Testing Theories of Discrimination: Evidence from Weakest Link, *Journal of Law and Economics* 47, 431-452.

Linck, James S., Jeffry Netter, and Tina Yang, 2008, The Determinants of Board Structure, *Journal of Financial Economics* 87, 308-328.

Lintner, John, 1965, The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics* 47, 13-37.

Lipton, Martin, and Jay W. Lorsch, 1992, A Modest Proposal for Improved Corporate Governance, *The Business Lawyer* 48, 59-77.

Ljungqvist, Alexander, Felicia Marston, Laura Starks, Kelsey D. Wei, and Hong Yan, 2007, Conflicts of Interest in Sell-Side Research and the Moderating Role of Institutional Investors, *Journal of Financial Economics* 85, 420-456.

Marsden, Peter V., 1987, Core Discussion Networks of Americans, *American Sociological Review* 52, 122-131.

Marsden, Peter V., John S. Reed, Michael D. Kennedy, and Kandy M. Stinson, 1982, American Regional Cultures and Differences in Leisure Time Activities, *Social Forces* 60, 1023-1049.

Masulis, Ronald W., Cong Wang, and F. E. I. Xie, 2007, Corporate Governance and Acquirer Returns, *The Journal of Finance* 62, 1851-1889.

Mayers, David, Anil Shivdasani, and Clifford W. Smith, 1997, Board Composition and Corporate Control: Evidence from the Insurance Industry, *Journal of Business* 70, 33-62.

McDonald, Michael L., and James D. Westphal, 2003, Getting By With the Advice of Their Friends: CEOs' Advice Networks and Firms' Strategic Responses to Poor Performance *Administrative Science Quarterly* 48, 1-32.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook, 2001, Birds of a Feather: Homophily in Social Networks, *Annual Review of Sociology* 27, 415-444.

Mehran, Hamid, 1995, Executive Compensation Structure, Ownership, and Firm Performance, *Journal of Financial Economics* 38, 163-184.

Mills, Judson, and Margaret S. Clark, 1982, Exchange and Communal Relationships, *Review of Personality and Social Psychology* 3, 121-144.

Morse, Adair, and Sophie Shive, 2008, Patriotism in Your Portfolio, *Journal of Financial Markets, forthcoming*.

Murphy, Kevin J., 1999. *Executive Compensation* (North Holland).

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

Papadakis, Vassilis M., Spyros Lioukas, and David Chambers, 1998, Strategic Decision-Making Processes: The Role of Management and Context, *Strategic Management Journal* 19, 115-147.

Paul, Donna L., 2007, Board Composition and Corrective Action: Evidence from Corporate Responses to Bad Acquisition Bids, *The Journal of Financial and Quantitative Analysis* 42, 759-784.

Petersen, Mitchell A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies* 22, 435-480.

Pontiff, Jeffrey, 1996, Costly Arbitrage: Evidence from Closed-End Funds, *Quarterly Journal of Economics* 111, 1135-1152.

Qiu, Lily, and Ivo Welch, 2006, Investor Sentiment Measures, *Brown University Working Paper*.

Reed, John S., 2003, Do Southerners Prefer One Another's Company?, *Southern Cultures* 9, 84-90.

Report of the NACD Blue Ribbon Commission on Director Professionalism, 1996 (National Association of Corporate Directors, Washington, D.C.).

Rosen, Sherwin, 1982, Authority, Control, and the Distribution of Earnings, *The Bell Journal of Economics* 13, 311-323.

Ross, Stephen A., 2002, Neoclassical Finance, Alternative Finance and the Closed End Fund Puzzle, *European Financial Management* 8, 129-137.

Sapp, Travis, and Ashish Tiwari, 2004, Does Stock Return Momentum Explain the "Smart Money" Effect?, *The Journal of Finance* 59, 2605-2622.

Sharpe, William F., 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *The Journal of Finance* 19, 425-442.

Shleifer, Andrei, 2005. *Inefficient Markets* (Oxford University Press, Oxford).

Shleifer, Andrei, and Robert W. Vishny, 1997, The Limits of Arbitrage, *The Journal of Finance* 52, 35-55.

Silver, Allan, 1990, Friendship in Commercial Society: Eighteenth-Century Social Theory and Modern Sociology, *American Journal of Sociology* 95, 1474-1504.

Sirri, Erik R., and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, *The Journal of Finance* 53, 1589-1622.

Smith, Clifford W., and Ross Watts, 1992, The Investment Opportunity Set and Corporate Financing, Dividend, and Compensation Policies, *Journal of Financial Economics* 32, 263-292.

U.S. Census Bureau, 2003, Domestic Migration Across Regions, Divisions, and States: 1995-2000, in Rachel S. Franklin, ed.: Census 2000 Special Reports (Washington, D.C.).

U.S. Census Bureau, 2003, Migration of the Young, Single, and College Educated: 1995-2000, in Rachel S. Franklin, ed.: Census 2000 Special Reports (Washington, D.C.).

U.S. State Department of, 2003. *Portrait of the USA* (Washington, D.C.).

Uzzi, Brian, 1996, The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect, *American Sociological Review* 61, 674-698.

Uzzi, Brian, 1999, Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing, *American Sociological Review* 64, 481-505.

Verardo, Michela, 2007, Heterogeneous Beliefs and Momentum Profits, *Journal of Financial & Quantitative Analysis, forthcoming*.

Villalonga, Belen, and Raphael Amit, 2006, How Do Family Owernship, Control and Management Affect Firm Value?, *Journal of Financial Economics* 80, 385-417.

Wally, Stefan, and J. Robert Baum, 1994, Personal and Structural Determinants of the Pace of Strategic Decision Making, *Academy of Management Journal* 37, 932-956.

Warfield, Terry D., John J. Wild, and Kenneth L. Wild, 1995, Managerial Ownership, Accounting Choices, and Informativeness of Earnings, *Journal of Accounting and Economics* 20, 61-91.

Weisbach, Michael S., 1988, Outside Directors and CEO Turnover, *Journal of Financial Economics* 20, 431-460.

Westphal, James D., 1999, Collaboration in the Boardroom: Behavioral and Performance Consequences of CEO-Board Social Ties, *The Academy of Management Journal* 42, 7-24.

Westphal, James D., Steven Boivie, and Daniel Han Ming Chng, 2006, The Strategic Impetus for Social Network Ties: Reconstituting Broken CEO Friendship Ties, *Strategic Management Journal* 27, 425-445.

Westphal, James D., and Edward J. Zajac, 1995, Who shall govern? CEO Board Power, Demographic Similarity, and New Director Selection *Administrative Science Quarterly* 40, 60-83.

Yermack, David, 1996, Higher Market Valuation of Companies with a Small Board of Directors, *Journal of Financial Economics* 40, 185-211.

Zhang, X. Frank, 2006, Information Uncertainty and Stock Returns, *The Journal of Finance* 61, 105-137.

Zheng, Lu, 1999, Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability, *The Journal of Finance* 54, 901-933.

Table 1
Proportions of directors with conventional or social ties

This table presents pooled means of the proportions of directors with various ties to the CEO or to the firm. Our sample includes all Fortune 100 firms as of 2005 for which we could obtain the necessary financial data. Overall, our data consists of N = 704 firm-years over the period 1996 to 2005. The "Affiliation to CEO" column presents general ways in which a director can be affiliated or dependent to the CEO. A conventional affiliation (i.e., conventional dependence) indicates that the director has a financial or familial tie, as specified by the IRRC, to the CEO or to the firm. A social affiliation (i.e., social dependence) indicates that the director and the CEO share at least two of the following ties: miltary service, alma mater, regional origin, background (i.e., academic discipline), industry of primary employment, or third-party connection through another director. Mutual alma mater must be accompanied by no greater than a three-year age difference to constitute a tie between the director and the CEO. Conventional or social signifies that the director is either conventionally or socially affiliated (or both). The "Proportion of affiliated directors" column presents the pooled means, across all firm-years, of the fraction of the board having the specified general affiliation or dependence to the CEO. The "Proportion of affiliated directors with specific tie" columns present the pooled means, across all firm-years, of the fraction of type-X affiliated directors having the specific tie Y to the CEO.

Affiliation to CEO	Proportion of affiliated directors $\left(\frac{\#\text{ of affiliated directors on the board}}{\#\text{ of all directors on the board}}\right)$	Proportion of affiliated directors with specific tie $\left(\frac{\#\text{ of affiliated directors on the board with specific tie}}{\#\text{ of affiliated directors on the board}}\right)$					
		Military	School	Regional origin	Background	Industry	Third party
Conventional	0.296	0.066	0.390	0.449	0.426	0.660	0.437
Social	0.276	0.089	0.496	0.680	0.602	0.652	0.660
Conventional or social	0.416	0.063	0.310	0.478	0.445	0.522	0.510

Table 2
CEO and board characteristics

This table presents the pooled means of various CEO and board characteristics. *Independent (conventional)* and *Independent (new)* are dummies that equal one if a majority of directors are independent under the classification in question, and zero otherwise. The *conventional measure* classifies a director as affiliated if he has either financial or familial ties, as specified by the IRRC, to the CEO or to the firm. In addition to the conventional criteria, the *new measure* further classifies a director as affiliated if the director and the CEO share at least two of the following ties: miltary service, alma mater, regional origin, background (i.e., academic discipline), industry of primary employment, or third-party connection through another director. Mutual alma mater must be accompanied by no greater than a three-year age difference to constitute a tie between the director and the CEO. The remaining variables are as defined in Appendix B. Column 1 represents all firms, Column 2 represents the subset of firms with conventionally independent boards, Column 3 represents the subset of firms with conventionally-and-socially independent boards, and Column 4 represents the subset of firms with conventionally independent boards that are not conventionally and socially independent.

Variable	All	Conventional	New	Conventional only
Independent (conventional)	0.874	1.000	1.000	1.000
Independent (new)	0.624	0.714	1.000	0.000
CEO Equity Holdings (%)	0.938	0.579	0.547	0.659
CEO Award	0.203	0.218	0.205	0.250
CEO = Chairman	0.835	0.857	0.854	0.864
CEO Tenure	6.777	6.099	5.485	7.631
Board Size	12.298	12.340	12.189	12.717
Old Directors	0.109	0.129	0.118	0.156
Busy Board	0.358	0.387	0.365	0.442
Directors' Equity Holdings (%)	0.289	0.145	0.120	0.207
CEO from Other Company	0.700	0.725	0.736	0.698
Classified Board	0.509	0.515	0.515	0.515
Democracy Firm	0.094	0.079	0.075	0.089
Dictatorship Firm	0.017	0.018	0.018	0.018
Family Firm	0.070	0.054	0.052	0.059
Number of observations	704	615	439	176

Table 3
Determinants of social dependence

This table presents estimates from a pooled regression of the board's social-dependence fraction (i.e., the proportion of directors who are socially dependent to the CEO) on various CEO, board, and firm characteristics. All independent variables are as defined in Appendix B. We include year dummies and industry dummies using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

Variable	Expected sign	Coefficient (*t*-statistic)
$CEO\ Equity\ Holdings_{i,t}$	?	0.000 (0.47)
$CEO\ Award_{i,t}$	+	0.077 (2.12)
$CEO = Chairman_{i,t}$	+	0.015 (0.52)
$CEO\ Tenure_{i,t}$	+	0.007 (2.11)
$ln(Board\ Size)_{i,t}$	+	-0.065 (-1.10)
$Old\ Directors_{i,t}$	+	0.263 (3.12)
$Busy\ Board_{i,t}$	+	0.052 (2.30)
$Directors\ Equity\ Holdings_{i,t}$	?	0.001 (0.13)
$CEO\ from\ Other\ Company_{i,t}$	+	-0.018 (-0.65)
$Classified\ Board_{i,t}$	+	-0.004 (-0.11)
$Democracy\ Firm_{i,t}$	-	0.062 (1.17)
$Dictatorship\ Firm_{i,t}$	+	-0.049 (-0.82)
$Family\ Firm_{i,t}$	+	0.008 (0.12)
$ROA_{i,t-1}$	+	-0.702 (-2.95)
$RET_{i,t-1}$	+	0.025 (1.65)
$ln\left(Total\ Assets_{i,t-1}\right)$	+	0.004 (0.28)
$ln\left(MB_{i,t-1}\right)$	+	0.032 (1.54)
Year/industry dummies		Yes/Yes
Number of observations		704
Adjusted R^2		0.17

Table 4
Firm characteristics and CEO compensation

This table presents the pooled means of CEO compensation and various firm characteristics. Standard deviations are reported in brackets. *Total Assets* (denoted in millions), *MB*, *ROA*, and *RET* are as defined in Appendix B. *Salary + Bonus* is the sum of base salary and bonus in millions. *Total Compensation* is the CEO's total compensation in millions, defined as the sum of base salary, bonus, long-term incentive payouts, the value of restricted stock grants, and the Black-Scholes value of option grants converted into their stock equivalents using the options' median delta. Column 1 represents all firms, Column 2 represents the subset of firms with conventionally independent boards, Column 3 represents the subset of firms with conventionally-and-socially independent boards, and Column 4 represents the subset of firms with conventionally independent boards that are not conventionally and socially independent. A board is classified as independent if a majority of its members are classified as independent. The *conventional measure* classifies a director as affiliated if he has either financial or familial ties, as specified by the IRRC, to the CEO or to the firm. In addition to the conventional criteria, the *new measure* further classifies a director as affiliated if the director and the CEO share at least two of the following ties: miltary service, alma mater, regional origin, background (i.e., academic discipline), industry of primary employment, or third-party connection through another director. Mutual alma mater must be accompanied by no greater than a three-year age difference to constitute a tie between the director and the CEO.

Variable	All	Conventional	New	Conventional only
Total Assets	96,231 [171,692]	98,016 [177,839]	75,655 [135,644]	153,791 [246,030]
MB	4.159 [4.229]	4.093 [4.210]	3.957 [4.086]	4.432 [4.499]
ROA	0.058 [0.056]	0.058 [0.057]	0.061 [0.055]	0.051 [0.061]
RET	0.227 [0.433]	0.214 [0.427]	0.200 [0.435]	0.249 [0.405]
Salary + Bonus	3.778 [3.148]	3.748 [2.950]	3.419 [2.114]	4.569 [4.289]
Total Compensation	12.755 [14.072]	12.931 [13.677]	11.393 [10.781]	16.767 [18.565]
Number of observations	704	615	439	176

Table 5
Board independence and CEO compensation

This table presents estimates from the following pooled regression:

$$C_{i,t} = \alpha + \beta_1 BoardIndependence_{i,t} + X\,\beta_{2\text{-}19} + Year\,\beta_{20\text{-}28} + Industry\,\beta_{29\text{-}32} + \varepsilon_{i,t}.$$

$C_{i,t}$, the dependent variable, is the level of compensation in millions for the CEO of firm i in year t. We use two different measures of compensation: *Salary + Bonus* (Columns 1 and 2) and *Total Compensation* (Columns 3 and 4) calculated as the sum of base salary, bonus, long-term incentive payouts, the value of restricted stock grants, and the Black-Scholes value of option grants converted into their stock equivalents using the options' median delta. $BOARD\ INDEPENDENCE_{i,t}$ is a dummy that equals one if a majority of directors are classified as independent, and zero otherwise. We compare two classification schemes of independence. The *conventional measure* (Columns 1 and 3) classifies a director as affiliated if he has either financial or familial ties, as specified by the IRRC, to the CEO or to the firm. In addition to the conventional criteria, the *new measure* (Columns 2 and 4) further classifies a director as affiliated if the director and the CEO share at least two of the following ties: miltary service, alma mater, regional origin, background (i.e., academic discipline), industry of primary employment, or third-party connection through another director. Mutual alma mater must be accompanied by no greater than a three-year age difference to constitute a tie between the director and the CEO. X is a set of the following control variables: $ln(Total\ Assets_{i,t-1})$, $ln(MB_{i,t-1})$, $ROA_{i,t-1}$, $RET_{i,t-1}$, $\sigma^2_{i,t-1}$, $CEO\ Equity\ Holdings_{i,t}$, $CEO\ Award_{i,t}$, $CEO{=}Chairman_{i,t}$, $CEO\ Tenure_{i,t}$, $ln(Board\ Size_{i,t})$, $Old\ Directors_{i,t}$, $Busy\ Board_{i,t}$, $Directors\ Equity\ Holdings_{i,t}$, $CEO\ from\ Other\ Company_{i,t}$, $Classified\ Board_{i,t}$, $Democracy\ Firm_{i,t}$, $Dictatorship\ Firm_{i,t}$, and $Family\ Firm_{i,t}$, which are as defined in Appendix B. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All t-statistics are calculated using White standard errors adjusted for clustering (by firm).

		Coefficient (t-statistic)			
		Salary + Bonus		*Total Compensation*	
Variable	Expected sign	(1)	(2)	(3)	(4)
$BOARD\ INDEPENDENCE_{i,t,conventional}$	-	-0.755 (-1.16)		0.572 (0.24)	
$BOARD\ INDEPENDENCE_{i,t,new}$	-		-0.780 (-2.31)		-3.347 (-2.50)
$ln(Total\ Assets_{i,t-1})$	+	1.057 (5.38)	1.066 (5.60)	3.337 (4.12)	3.355 (4.47)
$ln(MB_{i,t-1})$	+	0.696 (2.56)	0.631 (2.39)	3.717 (2.44)	3.364 (2.44)
$ROA_{i,t-1}$	+	-1.062 (-0.31)	0.142 (0.04)	2.022 (0.10)	8.403 (0.45)
$RET_{i,t-1}$	+	0.477 (2.05)	0.444 (1.90)	6.315 (4.06)	6.129 (3.92)

$\sigma^2_{i,t-1}$	?	13.024	16.329	196.483	214.860
		(0.42)	(0.53)	(1.07)	(1.10)
CEO Equity Holdings$_{i,t}$	?	-0.141	-0.134	-0.300	-0.269
		(-3.48)	(-3.38)	(-1.45)	(-1.30)
CEO Award$_{i,t}$	+	0.016	-0.070	1.051	0.747
		(0.04)	(-0.19)	(0.51)	(0.38)
CEO = Chairman$_{i,t}$	+	1.097	1.064	3.344	3.722
		(3.33)	(3.39)	(1.60)	(1.84)
CEO Tenure$_{i,t}$	+	0.030	0.025	0.084	0.023
		(1.28)	(0.94)	(0.79)	(0.18)
ln(Board Size)$_{i,t}$	+	-0.048	-0.020	-3.995	-3.799
		(-0.09)	(-0.04)	(-2.00)	(-1.80)
Old Directors$_{i,t}$	+	3.641	3.334	4.798	2.689
		(3.43)	(3.23)	(1.38)	(0.75)
Busy Board$_{i,t}$	+	0.202	0.105	0.178	-0.104
		(0.69)	(0.36)	(0.12)	(-0.07)
Directors Equity Holdings$_{i,t}$	-	0.020	0.012	-0.223	-0.556
		(0.09)	(0.06)	(-0.39)	(-1.05)
CEO from Other Company$_{i,t}$	+	0.356	0.422	2.505	3.108
		(0.75)	(0.94)	(1.62)	(1.99)
Classified Board$_{i,t}$	+	-0.343	-0.350	0.702	0.720
		(-0.94)	(-1.00)	(0.50)	(0.53)
Democracy Firm$_{i,t}$	-	-1.291	-1.285	1.681	1.744
		(-2.17)	(-2.08)	(0.51)	(0.58)
Dictatorship Firm$_{i,t}$	+	1.467	1.494	-3.184	-3.113
		(1.81)	(1.95)	(-1.35)	(-1.42)
Family Firm$_{i,t}$	+	0.880	0.903	3.304	3.309
		(0.74)	(0.78)	(1.07)	(1.27)
Year/industry dummies		Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Number of observations		704	704	704	704
Adjusted R^2		0.35	0.36	0.20	0.21

Table 6
Compensation differential within subsample of conventionally independent boards

This table presents estimates from the following pooled regression, within the subset of firms with conventionally independent boards:

$$C_{i,t} = \alpha + \beta_1\, NOT\ INDEPENDENT_{i,t} + X\,\beta_{2\text{-}19} + Year\,\beta_{20\text{-}28} + Industry\,\beta_{29\text{-}32} + \varepsilon_{i,t}.$$

$C_{i,t}$, the dependent variable, is the level of compensation in millions for the CEO of firm *i* in year *t*. We use two different measures of compensation: *Salary + Bonus* (Column 1) and *Total Compensation* (Column 2). $NOT\ INDEPENDENT_{i,t}$ is a dummy that equals one if the board (despite being conventionally independent) is not conventionally and socially independent, and zero otherwise. *X* is a set of the following control variables: $ln(Total\ Assets_{i,t-1})$, $ln(MB_{i,t-1})$, $ROA_{i,t-1}$, $RET_{i,t-1}$, $\sigma^2_{i,t-1}$, $CEO\ Equity\ Holdings_{i,t}$, $CEO\ Award_{i,t}$, $CEO{=}Chairman_{i,t}$, $CEO\ Tenure_{i,t}$, $ln(Board\ Size_{i,t})$, $Old\ Directors_{i,t}$, $Busy\ Board_{i,t}$, $Directors\ Equity\ Holdings_{i,t}$, $CEO\ from\ Other\ Company_{i,t}$, $Classified\ Board_{i,t}$, $Democracy\ Firm_{i,t}$, $Dictatorship\ Firm_{i,t}$, and $Family\ Firm_{i,t}$, which are as defined in Appendix B. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

		Coefficient (*t*-statistic)	
Variable	Expected sign	*Salary + Bonus* (1)	*Total Compensation* (2)
$NOT\ INDEPENDENT_{i,t}$	+	0.595	4.079
		(1.71)	(2.69)
Year/industry dummies		Yes/Yes	Yes/Yes
Number of observations		615	615
Adjusted R^2		0.35	0.19

Table 7
Excess compensation and subsequent operating performance

This table presents estimates from the following pooled regression, within the subset of firms with conventionally independent boards:

$$Performance_{i,t+1,t+3} = \alpha + PredictedExcessCompensation_{i,t}\,\beta_{1\text{-}2} + X\,\beta_{3\text{-}5} + Year\,\beta_{16\text{-}14} + Industry\,\beta_{15\text{-}18} + \varepsilon_{i,t}.$$

Performance$_{i,t+1,t+3}$, the dependent variable, is the operating performance averaged over the subsequent one-, two-, or three-year period. We use three different measures of operating performance: *Return on Assets (ROA)*, *Return on Sales (ROS)*, and *Return on Equity (ROE)*. *Predicted Excess Compensation*$_{i,t}$ consists of two variables: *Excess(NOT INDEPENDENT*$_{i,t}$*)*, the predicted excess compensation attributed to having a board that is not conventionally and socially independent (despite being conventionally independent); and *Excess(Other Governance Variables*$_{i,t}$*)*, the predicted excess compensation from the remaining governance variables: *CEO Equity Holdings*, *CEO=Chairman*, *ln(Board Size)*, *Old Directors*, *Busy Board*, *Directors' Equity Holdings*, *CEO from Other Company, Classified Board*, *Democracy Firm*, *Dictatorship Firm*, and *Family Firm*, which are as defined in Appendix B. Predicted excess components of total compensation are calculated using the coefficient estimates from Table 6, and are scaled by total compensation. *X* is a set of the following control variables: *ln(Total Assets*$_{i,t}$*)*, *ln(MB*$_{i,t-1}$*)*, and $\sigma^2_{i,t}$, which are also as defined in Appendix B. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

		Coefficient (*t*-statistic)		
Variable	Expected sign	One-year	Two-year	Three-year
Return on Assets (ROA)				
Excess(NOT INDEPENDENT$_{i,t}$*)*	-	-0.010	-0.011	-0.010
		(-1.89)	(-2.10)	(-2.46)
Return on Sales (ROS)				
Excess(NOT INDEPENDENT$_{i,t}$*)*	-	-0.011	-0.012	-0.012
		(-1.72)	(-1.86)	(-2.24)
Return on Equity (ROE)				
Excess(NOT INDEPENDENT$_{i,t}$*)*	-	-0.019	-0.018	-0.016
		(-2.61)	(-2.54)	(-2.08)
Year/industry dummies		Yes/Yes	Yes/Yes	Yes/Yes
Number of observations		602	533	462

Table 8
Pay-performance differential within subsample of conventionally independent boards

This table presents estimates from the following pooled regression, within the subset of firms with conventionally independent boards:

$C_{i,t} = \alpha + \beta_1 Ret_{i,t} + \beta_2 Ret_{i,t}*NOT\ INDEPENDENT_{i,t} + Interact\ \beta_{3\text{-}15} + Year\ \beta_{16\text{-}24} + Industry\ \beta_{25\text{-}28} + \varepsilon_{i,t}$.

$C_{i,t}$, the dependent variable, is the percentage change in the level of compensation for the CEO of firm *i* in year *t*. We use two different measures of compensation: *Salary + Bonus* (Columns 1 and 2) and *Total Compensation* (Columns 3 and 4). $RET_{i,t}$ is the annual stock return from year *t*. $NOT\ INDEPENDENT_{i,t}$ is a dummy that equals one if the board (despite being conventionally independent) is not conventionally and socially independent, and zero otherwise. *INTERACT* is a set of additional interaction terms in which $RET_{i,t}$ is interacted with each of the following variables: $CEO\ Award_{i,t}$, $CEO{=}Chairman_{i,t}$, $CEO\ Tenure_{i,t}$, $ln(Board\ Size_{i,t})$, $Old\ Directors_{i,t}$, $Busy\ Board_{i,t}$, $Directors\ Equity\ Holdings_{i,t}$, $CEO\ from\ Other\ Company_{i,t}$, $Classified\ Board_{i,t}$, $Democracy\ Firm_{i,t}$, $Dictatorship\ Firm_{i,t}$, $Family\ Firm_{i,t}$, and $\sigma^2_{i,t}$, which are as defined in Appendix B. Columns 1 and 3 report results from excluding these interaction terms, and Columns 2 and 4 report results from including these interaction terms. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

		Coefficient (*t*-statistic)			
		Salary + Bonus		*Total Compensation*	
Variable	Expected sign	(1)	(2)	(3)	(4)
$RET_{i,t}$	+	0.268	-0.534	0.636	5.234
		(4.12)	(-1.01)	(2.27)	(2.83)
$RET_{i,t}$ * $NOT\ INDEPENDENT_{i,t}$	-		-0.058		-0.511
			(-0.53)		(-1.83)
Year/industry dummies		Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Number of observations		615	615	615	615
Adjusted R^2		0.08	0.10	0.08	0.16

Table 9
Turnover differential within subsample of conventionally independent boards

This table presents estimates from the following pooled logit model, within the subset of firms with conventionally independent boards:

$$Turnover_{i,t} = \alpha + \beta_1 Ret_{i,t-1} + \beta_2 Ret_{i,t-1}{*}NOT\ INDEPENDENT_{i,t-1} + \beta_3 NOT\ INDEPENDENT_{i,t-1} + Interact\ \beta_{4\text{-}15} + X\ \beta_{16\text{-}28} + Year\ \beta_{29\text{-}36} + Industry\ \beta_{37\text{-}40} + \varepsilon_{i,t}.$$

$Turnover_{i,t}$, the dependent variable, is a dummy that equals one if a CEO turnover occurs at firm *i* in year *t*, and zero otherwise. $RET_{i,t-1}$ is the annual stock return from year *t*-1. $NOT\ INDEPENDENT_{i,t-1}$ is a dummy that equals one if in year *t-1* the board (despite being conventionally independent) is not conventionally and socially independent, and zero otherwise. *X* is a set of the following control variables: $CEO\ Award_{i,t-1}$, $CEO{=}Chairman_{i,t-1}$, $CEO\ Tenure_{i,t-1}$, $ln(Board\ Size_{i,t-1})$, $Old\ Directors_{i,t-1}$, $Busy\ Board_{i,t-1}$, $Directors\ Equity\ Holdings_{i,t-1}$, $CEO\ from\ Other\ Company_{i,t-1}$, $Classified\ Board_{i,t-1}$, $Democracy\ Firm_{i,t-1}$, $Dictatorship\ Firm_{i,t-1}$, $Family\ Firm_{i,t-1}$ (which are as defined in Appendix B), and $CEO\ Age_{i,t-1}$. *INTERACT* is a set of additional interaction terms in which $RET_{i,t-1}$ is interacted with each of the variables in *X*, except for $CEO\ Age_{i,t-1}$. *Year* denotes the year dummies, $Year_{1998}$ through $Year_{2005}$. Because this regression involves lagged board-structure variables, which are unavailable in 1995, we begin our analysis in 1997. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All *p*-values account for clustering (by firm).

		Coefficient (*p*-value)
Variable	Expected sign	Turnover
$RET_{i,t-1}$	-	-2.202
		(0.67)
$RET_{i,t-1}$ * $NOT\ INDEPENDENT_{i,t-1}$	+	1.691
		(0.18)
$NOT\ INDEPENDENT_{i,t-1}$	-	-0.574
		(0.09)
Year/industry dummies		Yes/Yes
Number of observations		601
Likelihood ratio		76.95

Table 10
Bonus differential within subsample of conventionally independent audit committees

This table presents estimates from the following pooled regression, within the subset of firms whose audit committees are composed entirely of conventionally independent directors:

$Bonus_{i,t} = \alpha + \beta_1 NOT\ INDEPENDENT_{i,t} + \beta_2 OtherComp_{i,t} + X\,\beta_{3\text{-}20} + Year\,\beta_{21\text{-}27} + Industry\,\beta_{28\text{-}31} + \varepsilon_{i,t}$.

$Bonus_{i,t}$, the dependent variable, is the bonus in millions for the CEO of firm *i* in year *t*. $NOT\ INDEPENDENT_{i,t}$ is a dummy that equals one if the audit committee (despite being composed entirely of conventionally independent directors) has one or more directors who are socially dependent to the CEO, and zero otherwise. $OtherComp_{i,t}$ is the CEO's total compensation salary minus bonus. *X* is a set of the following control variables: $ln(Total\ Assets_{i,t-1})$, $ln(MB_{i,t-1})$, $ROA_{i,t-1}$, $RET_{i,t-1}$, $\sigma^2_{i,t-1}$, $CEO\ Equity\ Holdings_{i,t}$, $CEO\ Award_{i,t}$, $CEO{=}Chairman_{i,t}$, $CEO\ Tenure_{i,t}$, $ln(Board\ Size_{i,t})$, $Old\ Directors_{i,t}$, $Busy\ Board_{i,t}$, $Directors\ Equity\ Holdings_{i,t}$, $CEO\ from\ Other\ Company_{i,t}$, $Classified\ Board_{i,t}$, $Democracy\ Firm_{i,t}$, $Dictatorship\ Firm_{i,t}$, and $Family\ Firm_{i,t}$, which are as defined in Appendix B. *Year* denotes the year dummies, $Year_{1999}$ through $Year_{2005}$. Because this regression involves audit committee data (which are not available until after 1997), we begin our analysis in 1998. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

		Coefficient (*t*-statistic)
Variable	Expected sign	Bonus
$NOT\ INDEPENDENT_{i,t}$	+	0.734 (1.75)
Year/industry dummies		Yes/Yes
Number of observations		507
Adjusted R^2		0.35

Table 11
Sensitivity tests

This table presents the results from a range of sensitivity tests examining different specifications of board-independence cutoffs. As in Table V, we estimate the following pooled regression:

$$C_{i,t} = \alpha + \beta_1 BoardIndependence_{i,t} + X\,\beta_{2\text{-}19} + Year\,\beta_{20\text{-}28} + Industry\,\beta_{29\text{-}32} + \varepsilon_{i,t}.$$

We use two different measures of $C_{i,t}$ (in millions): *Salary + Bonus* (Panel A) and *Total Compensation* (Panel B). In Columns 1 through 3, $BOARD\ INDEPENDENCE_{i,t}$ is a dummy that equals one if the board is classified as independent (under the criteria in question), and zero otherwise. In Column 1, we require that a 50% majority of directors be independent; in Column 2, we require that a 60% majority of directors be independent; and in Column 3, we require that all members of the compensation committee be independent. In regressions using the 60% cutoff, we also include a mixed-board dummy that equals one if the percentage of independent directors is between 40% and 60%, and zero otherwise. For regressions involving compensation committee information, our analyses begin in 1998 in accordance with data availability. In Column 4, we define $BOARD\ INDEPENDENCE_{i,t}$ as the fraction of directors that are independent. In Column 5, we define $BOARD\ INDEPENDENCE_{i,t}$ as the board's average number of ties per director, which is calculated by dividing the total number of director-CEO ties by the number of directors for that firm-year. For each of these measures of board independence, we present the results from using two different specifications of director independence. In the first row, we consider only the conventional ties, and in the second row, we augment the conventional criteria with our social criteria (consisting of restrictions on mutual alma mater, military service, regional origin, discipline, industry, and third-party connections). X is a set of control variables as listed in Table 5. *Year* denotes the year dummies, $Year_{1997}$ through $Year_{2005}$. *Industry* denotes the industry dummies using the Fama-French (1997) five-industry classification. All *t*-statistics are calculated using White standard errors adjusted for clustering (by firm).

	Coefficient (t-statistic)				
	Independent if ≥ 50% of directors independent	Independent if ≥ 60% of directors independent	Independent if all compensation committee members independent	Fraction of independent directors	Average number of ties
	(1)	(2)	(3)	(4)	(5)
Expected sign	-	-	-	-	+
		Panel A. *Salary + Bonus*			
Conventional ties only	-0.755	-1.695	-0.410	-1.291	1.291
	(-1.16)	(-1.65)	(-0.78)	(-0.74)	(0.74)
Conventional and social ties	-0.780	-1.424	-0.917	-2.335	0.808
	(-2.31)	(-2.38)	(-2.24)	(-2.09)	(1.76)
		Panel B. *Total Compensation*			
Conventional ties only	0.572	-3.574	-1.559	0.876	-0.876
	(0.24)	(-0.87)	(-0.76)	(0.19)	(-0.19)
Conventional and social ties	-3.347	-5.353	-3.018	-6.983	3.522
	(-2.50)	(-2.35)	(-1.96)	(-1.94)	(2.21)

Table 12
Country Closed-End Fund Premia/(Discounts) and Countries' Popularities

This table presents coefficient estimates from regressions of monthly country closed-end fund premia/(discounts) on a country's popularity among Americans and various control variables. The sample includes 23 country closed-end funds from 14 countries over the period 1993:12 to 2006:06. The *Country Popularity Score* is concurrent and equal to the sum of the percentage of survey participants (in the US) thinking (1) very favorably of a country multiplied by four, (2) mostly favorably of a country multiplied by three, (3) mostly unfavorably of a country multiplied by two, and (4) very unfavorably of a country multiplied by one. *Inverse Security Price (Price < NAV)* [*(Price > NAV)*] is one over the fund's lagged price level if the fund trades at a discount [premium], and zero otherwise. *Dividend Yield (Price < NAV)* [*(Price > NAV)*] is dividends-per-share paid by the country closed-end fund over the previous 12 months scaled by the funds' lagged net asset value if the fund trades at a discount [premium], and zero otherwise. *Turnover Ratio* is the ratio of the concurrent median turnover of US stocks over the concurrent median turnover of stocks in a country closed-end fund's respective home market. *Home Market Index Returns* are concurrent monthly value-weighted index returns in local currency of a country closed-end fund's respective home market. *US Market Index Returns* are concurrent monthly value-weighted index returns for the US. *t*-statistics are reported in parentheses. For columns 1 and 2, they are calculated using White standard errors adjusted for clustering (by year-month and fund); for column 3, they are calculated using Newey-West (1987) standard errors with twelve lags. Column 1 reports estimates obtained under Fixed-Effects; column 2 under First-Differencing; and column 3 under Fama-MacBeth.

Variables	Expected Sign	Coefficient (*t*-statistic)		
		(1)	(2)	(3)
Country Popularity Score	+	0.052	0.039	0.030
		(1.97)	(2.58)	(3.69)
Inverse Security Price (Price < NAV)	-	-0.426	0.139	-0.315
		(-4.21)	(0.60)	(-2.23)
Inverse Security Price (Price > NAV)	+	0.842	1.246	1.341
		(5.03)	(2.00)	(5.51)
Dividend Yield (Price < NAV)	+	-0.011	-0.025	-0.554
		(-0.04)	(-0.00)	(-1.78)
Dividend Yield (Price > NAV)	-	1.355	-0.250	-8.098
		(2.43)	(-0.71)	(-1.12)
Turnover Ratio	+	0.001	-0.002	0.001
		(0.36)	(-3.27)	(0.59)
Home Market Index Returns	?	0.144	0.109	0.168
		(2.08)	(2.03)	(1.55)
US Market Index Returns	+	0.273	0.412	
		(2.38)	(5.08)	
Number of Observations		1,939	1,910	151
Adjusted R^2		0.56	0.15	

Table 13
Country Closed-End Fund Premia/(Discounts) and Countries' Popularities
Alternative Aggregation of Country Popularity

This table presents coefficient estimates from regressions of monthly country closed-end fund premia/(discounts) on a country's popularity among Americans and various control variables. The sample includes 23 country closed-end funds from 14 countries over the period 1993:12 to 2006:06. The *% Survey Participants* is concurrent and equal to the sum of the percentage of survey participants (in the US) thinking very or mostly favorably of a country (Panel A); or equal to the sum of the percentage of survey participants (in the US) thinking very or mostly unfavorably of a country (Panel B). Other independent variables include: *Inverse Security Price (Price < NAV)*, *Inverse Security Price (Price > NAV)*, *Dividend Yield (Price < NAV)*, *Dividend Yield (Price > NAV)*, *Turnover Ratio*, *Home Market Index Returns*, and *US Market Index Returns*. *t*-statistics are reported in parentheses. For columns 1 and 2, they are calculated using White standard errors adjusted for clustering (by year-month and fund); for column 3, they are calculated using Newey-West (1987) standard errors with twelve lags. Column 1 reports estimates obtained under Fixed-Effects; column 2 under First-Differencing; and column 3 under Fama-MacBeth.

Variables	Expected Sign	Coefficient (*t*-statistic)		
		(1)	(2)	(3)
Panel A: Very Favorably or Mostly Favorably				
% Survey Participants	+	0.343 (2.23)	0.218 (2.60)	0.160 (4.20)
Panel B: Very Unfavorably or Mostly Unfavorably				
% Survey Participants	-	-0.210 (-1.49)	-0.170 (-2.07)	-0.220 (-4.33)

Table 14
ADR Premia/(Discounts) and Countries' Popularities

This table presents coefficient estimates from regressions of monthly ADR premia/(discounts) on a country's popularity among Americans and various control variables. The sample includes 309 ADRs from 19 countries over the period 1992:11 to 2006:06. The *Country Popularity Score* is concurrent and equal to the sum of the percentage of survey participants (in the US) thinking (1) very favorably of a country multiplied by four, (2) mostly favorably of a country multiplied by three, (3) mostly unfavorably of a country multiplied by two, and (4) very unfavorably of a country multiplied by one. *Inverse Security Price (Price < NAV)* [*(Price > NAV)]* is one over the ADR's lagged price level if the ADR trades at a discount [premium], and zero otherwise. *Dividend Yield (Price < NAV)* [*(Price > NAV)*] is dividends-per-share paid by the ADR over the previous 12 months scaled by the ADRs' lagged price if the ADR trades at a discount [premium], and zero otherwise. *Turnover Ratio* is the ratio of the ADR's concurrent turnover in the US over the ADR's underlying asset's concurrent turnover in the ADR's respective home market. *Home Market Index Returns* are concurrent monthly value-weighted index returns in local currency of an ADR's respective home market. *US Market Index Returns* are concurrent monthly value-weighted index returns for the US. *t*-statistics are reported in parentheses. For columns 1 and 2, they are calculated using White standard errors adjusted for clustering (by year-month and fund); for column 3, they are calculated using Newey-West (1987) standard errors with twelve lags. Column 1 reports estimates obtained under Fixed-Effects; column 2 under First-Differencing; and column 3 under Fama-MacBeth.

Variables	Expected Sign	Coefficient (*t*-statistic)		
		(1)	(2)	(3)
Country Popularity Score	+	0.002	0.004	0.001
		(1.74)	(1.55)	(0.80)
Inverse Security Price (Price < NAV)	-	-0.094	0.036	-0.117
		(-11.83)	(1.55)	(-13.19)
Inverse Security Price (Price > NAV)	+	0.091	0.079	0.114
		(8.07)	(2.55)	(13.23)
Dividend Yield (Price < NAV)	+	-0.036	-0.034	-0.112
		(-1.88)	(-0.65)	(-4.79)
Dividend Yield (Price > NAV)	-	0.050	0.078	0.121
		(1.96)	(1.51)	(5.23)
Turnover Ratio	+	0.000	-0.000	0.000
		(1.09)	(-1.03)	(1.43)
Home Market Index Returns	?	0.002	-0.003	-0.037
		(1.24)	(-0.71)	(-1.39)
US Market Index Returns	+	0.038	0.040	
		(1.89)	(2.21)	
Number of Observations		21,932	21,596	164
Adjusted R^2		0.46	0.01	

Table 15
Fund Flows and Countries' Popularities

This table presents coefficient estimates from a pooled regression of monthly normalized fund flows on a country's popularity among Americans and various control variables. The sample includes 29 mutual funds investing predominantly in a single country (other than the US) from 5 countries over the period 1992:12 to 2006:12. The dependent variable is the normalized monthly cash flow computed as the dollar monthly cash flow for the fund divided by the TNA at the beginning of the month (adjusted for mergers). The *Country Popularity Score* is concurrent and equal to the sum of the percentage of survey participants (in the US) thinking (1) very favorably of a country multiplied by four, (2) mostly favorably of a country multiplied by three, (3) mostly unfavorably of a country multiplied by two, and (4) very unfavorably of a country multiplied by one. *Past Year Return* is the holding period return over the past 12 months. *MarketCap* is the fund's TNA at the beginning of the month. *Average Flow* is the concurrent equal-weighted mean fund flow (adjusted for mergers) across all mutual funds in the CRSP universe. All *t*-statistics are reported in parentheses and calculated using White standard errors adjusted for clustering (by year-month and fund).

Variables	Expected Sign	Coefficient (*t*-statistic)
Country Popularity Score	+	0.047
		(2.06)
Past Year Return	+	0.046
		(2.65)
Ln(MarketCap)	-	-0.047
		(-4.50)
Average Flow	+	3.233
		(3.95)
Fund Dummies		Yes
Number of Observations		2,618
Adjusted R^2		0.05

Table 16
Institutional Holdings and Countries' Popularities

This table presents coefficient estimates from a pooled regression of quarterly institutional holdings on a country's popularity among Americans and various control variables for country closed-end funds (column 1) and ADRs (column 2). The sample includes 23 country closed-end funds from 14 countries over the period 1993:12 to 2006:06 and 309 ADRs from 19 countries over the period 1992:10 to 2006:06. *Institutional Holdings* is the fraction of shares held by institutions in the US. The *Country Popularity Score* is concurrent and equal to the sum of the percentage of survey participants (in the US) thinking (1) very favorably of a country multiplied by four, (2) mostly favorably of a country multiplied by three, (3) mostly unfavorably of a country multiplied by two, and (4) very unfavorably of a country multiplied by one. For country closed-end funds, *Inverse Security Price* is one over the fund's lagged price level, and *Dividend Yield* is dividends-per-share paid by the country closed-end fund over the previous 12 months scaled by the funds' lagged net asset value. For ADRs, *Inverse Security Price* is one over the ADR's lagged price level, and *Dividend Yield* is dividends-per-share paid by the ADR over the previous 12 months scaled by the ADR's lagged price. All *t*-statistics are reported in parentheses and calculated using White standard errors adjusted for clustering (by year-month and fund).

		Coefficient (*t*-statistic)	
Variables	Expected Sign	Closed-End Funds (1)	ADRs (2)
Country Popularity Score	-	-0.054	-0.010
		(-2.34)	(-1.37)
Inverse Security Price	-	-0.580	0.004
		(-3.11)	(0.07)
Dividend Yield	+	0.038	-0.452
		(1.19)	(-1.62)
Year Dummies		Yes	Yes
Number of Observations		368	6,584
Adjusted R^2		0.10	0.00

Table 17
Subsequent Monthly $\hat{\rho}_{FE}$ for Portfolios Sorted on Past 6 Months Returns and $\hat{\rho}_{FE}$

This table reports subsequent monthly $\hat{\rho}_{FE}$ for portfolios based on six-month lagged returns and $\hat{\rho}_{FE}$. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I rank stocks independently in ascending order on the basis of six-month lagged returns and $\hat{\rho}_{FE}$ as of the portfolio formation date. I then form equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentile. The portfolios are held for 6 months. *t*-statistics are reported in parentheses where standard errors are Newey-West adjusted with 12 lags.

	low past return		high past return
low $\hat{\rho}_{FE}$	0.425	0.413	0.423
	0.461	0.449	0.466
high $\hat{\rho}_{FE}$	0.505	0.510	0.531
high minus low $\hat{\rho}_{FE}$	0.080	0.097	0.107
	(14.73)	(12.57)	(8.93)

Table 18
Monthly Returns for Portfolios Sorted on Past 6 Months Returns

This table reports monthly returns for portfolios based on lagged returns. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I form equally-weighted decile portfolios of stocks based on six-month lagged returns. The portfolios are held for 6 months. P1 is the portfolio of stocks in the worst performing 10%, P10 is the portfolio of stocks in the best performing 10%. *t*-statistics are reported in parentheses.

Past	Monthly Returns	
P1	0.82%	(1.32)
P2	1.11%	(2.52)
P3	1.20%	(3.19)
P4	1.25%	(3.75)
P5	1.28%	(4.16)
P6	1.26%	(4.25)
P7	1.29%	(4.36)
P8	1.33%	(4.40)
P9	1.41%	(4.25)
P10	1.81%	(4.22)
P10-P1	0.99%	(2.55)

Table 19
Monthly Returns and Alphas for Portfolios Sorted on Past 6 Months Returns and $\hat{\rho}_{FE}$

This table reports monthly returns and alphas for portfolios based on six-month lagged returns and $\hat{\rho}_{FE}$. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I rank stocks independently in ascending order on the basis of six-month lagged returns and $\hat{\rho}_{FE}$ as of the portfolio formation date. I then form equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentile. The portfolios are held for 6 months. *t*-statistics are reported in parentheses. Panel A reports monthly returns. Panel B reports monthly alphas from regressing the portfolio returns minus the risk-free rate on the Fama-French (1993) factors.

	low past return		high past return	high minus low past return
Panel A: Monthly Returns				
low $\hat{\rho}_{FE}$	1.15%	1.27%	1.41%	0.26%
				(1.00)
	1.00%	1.27%	1.46%	0.47%
				(1.72)
high $\hat{\rho}_{FE}$	0.99%	1.27%	1.67%	0.68%
				(2.81)
high minus low $\hat{\rho}_{FE}$				0.42%
				(4.38)
Panel B: Monthly Alphas				
low $\hat{\rho}_{FE}$	-0.03%	0.18%	0.42%	0.44%
				(1.78)
	-0.19%	0.17%	0.45%	0.64%
				(2.39)
high $\hat{\rho}_{FE}$	-0.18%	0.17%	0.66%	0.84%
				(3.52)
high minus low $\hat{\rho}_{FE}$				0.39%
				(4.12)

Table 20

Monthly Returns for Portfolios Based on Past Returns, $\hat{\rho}_{FE}$, and Firm Characteristics

This table reports differences in monthly returns for portfolios based on six-month lagged returns, $\hat{\rho}_{FE}$, and firm characteristics. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I rank stocks independently in ascending order on the basis of six-month lagged returns, $\hat{\rho}_{FE}$, and firm characteristics. I then form equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentile. The portfolios are held for 6 months. The reported returns are differences in monthly returns between winners and losers. *t*-statistics are reported in parentheses. In Panel A the firm characteristic is market capitalization; in Panel B, it is book-to-market ratio; in Panel C, it is number of analysts; in Panel D, it is the stock return volatility; in Panel E, it is cash-flow volatility; in Panel F, it is institutional holdings. In Panel G and H the firm characteristic is turnover averaged over the previous 6 months as of the portfolio formation date. Panel G reports results for NYSE/AMEX stocks only. Panel H reports results for NASDAQ stocks only.

	low		high	high minus low
Panel A: Market Capitalization				
low $\hat{\rho}_{FE}$	0.63%	0.15%	0.19%	-0.44%
	(2.44)	(0.53)	(0.68)	(-2.11)
	1.04%	0.38%	0.19%	-0.85%
	(3.67)	(1.31)	(0.66)	(-4.07)
high $\hat{\rho}_{FE}$	1.08%	0.59%	0.32%	-0.76%
	(4.36)	(2.31)	(1.04)	(-2.98)
high minus low $\hat{\rho}_{FE}$	0.46%	0.44%	0.14%	
	(2.85)	(3.15)	(0.86)	
Panel B: Book-to-Market				
low $\hat{\rho}_{FE}$	0.28%	0.14%	0.18%	-0.01%
	(1.00)	(0.58)	(0.68)	(-0.43)
	0.68%	0.28%	0.35%	-0.27%
	(2.33)	(1.07)	(1.23)	(-1.25)
high $\hat{\rho}_{FE}$	0.89%	0.58%	0.51%	-0.38%
	(3.37)	(2.50)	(1.85)	(-1.58)
high minus low $\hat{\rho}_{FE}$	0.61%	0.43%	0.33%	
	(3.58)	(2.97)	(2.06)	

	low		high	high minus low
Panel C: Number of Analysts				
low $\hat{\rho}_{FE}$	0.48%	0.18%	0.09%	-0.39%
	(1.91)	(0.71)	(0.30)	(-2.02)
	0.82%	0.38%	0.30%	-0.51%
	(3.16)	(1.39)	(0.98)	(-2.87)
high $\hat{\rho}_{FE}$	0.68%	0.67%	0.61%	-0.07%
	(3.02)	(2.62)	(1.79)	(-0.33)
high minus low $\hat{\rho}_{FE}$	0.19%	0.49%	0.51%	
	(1.28)	(3.21)	(2.74)	
Panel D: Stock Return Volatility				
low $\hat{\rho}_{FE}$	0.10%	0.27%	0.61%	0.52%
	(0.62)	(1.59)	(2.31)	(2.32)
	0.12%	0.45%	0.94%	0.82%
	(0.77)	(2.36)	(3.38)	(3.46)
high $\hat{\rho}_{FE}$	0.13%	0.58%	1.20%	1.08%
	(0.74)	(3.44)	(4.73)	(4.48)
high minus low $\hat{\rho}_{FE}$	0.03%	0.30%	0.60%	
	(0.22)	(2.78)	(3.30)	
Panel E: Cash Flow Volatility				
low $\hat{\rho}_{FE}$	-0.11%	0.31%	0.34%	0.45%
	(-0.49)	(1.26)	(1.29)	(2.24)
	0.05%	0.39%	0.49%	0.43%
	(0.21)	(1.46)	(1.75)	(2.08)
high $\hat{\rho}_{FE}$	0.26%	0.51%	0.88%	0.62%
	(1.09)	(2.10)	(3.78)	(2.67)
high minus low $\hat{\rho}_{FE}$	0.37%	0.20%	0.54%	
	(2.35)	(1.34)	(2.57)	

	low		high	high minus low
Panel F: Institutional Holdings				
low $\hat{\rho}_{FE}$	0.23%	0.33%	0.12%	-0.11%
	(0.76)	(1.26)	(0.48)	(-0.49)
	0.75%	0.42%	0.27%	-0.48%
	(2.39)	(1.46)	(0.98)	(-2.13)
high $\hat{\rho}_{FE}$	0.61%	0.67%	0.70%	0.09%
	(2.13)	(2.74)	(2.67)	(0.38)
high minus low $\hat{\rho}_{FE}$	0.38%	0.35%	0.57%	
	(2.09)	(2.71)	(3.79)	
Panel G: Turnover – NYSE/AMEX				
low $\hat{\rho}_{FE}$	-0.02%	0.16%	0.59%	0.60%
	(-0.09)	(0.82)	(2.44)	(2.86)
	0.01%	0.12%	0.67%	0.65%
	(0.08)	(0.62)	(2.66)	(3.17)
high $\hat{\rho}_{FE}$	0.32%	0.36%	0.81%	0.49%
	(1.72)	(1.76)	(3.12)	(2.23)
high minus low $\hat{\rho}_{FE}$	0.34%	0.20%	0.22%	
	(2.39)	(1.54)	(1.80)	
Panel H: Turnover – NASDAQ				
low $\hat{\rho}_{FE}$	0.04%	0.73%	0.57%	0.43%
	(0.12)	(2.24)	(1.38)	(1.01)
	0.79%	1.11%	1.12%	0.28%
	(2.27)	(3.26)	(2.98)	(0.68)
high $\hat{\rho}_{FE}$	0.72%	0.72%	1.27%	0.59%
	(2.36)	(2.22)	(3.10)	(1.33)
high minus low $\hat{\rho}_{FE}$	0.68%	-0.08%	0.72%	
	(1.87)	(-0.28)	(1.88)	

Table 21
Returns for Portfolios Sorted on Past 6 Months Returns and Institutional Holdings

This table reports differences in monthly returns for portfolios based on six-month lagged returns, $\hat{\rho}_{FE}$, and institutional holdings. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I rank stocks independently in ascending order on the basis of six-month lagged returns, $\hat{\rho}_{FE}$, and institutional holdings. I then form equally-weighted portfolios of stocks. The breakpoints for past returns and $\hat{\rho}_{FE}$ are the 30th and the 70th percentile. The breakpoints for institutional holdings are the 40th, 60th, and 80th percentile. The portfolios are held for 6 months. The reported returns are differences in monthly returns between winners and losers. *t*-statistics are reported in parentheses.

	< 40th	40th – 60th	60th – 80th	80th – 100th
	Institutional Holdings			
low $\hat{\rho}_{FE}$	0.26%	0.34%	0.18%	0.19%
	(0.90)	(1.24)	(0.69)	(0.72)
	0.60%	0.44%	0.31%	0.37%
	(1.99)	(1.47)	(1.07)	(1.38)
high $\hat{\rho}_{FE}$	0.63%	0.72%	0.54%	0.74%
	(2.31)	(2.78)	(1.96)	(2.76)
high minus low $\hat{\rho}_{FE}$	0.37%	0.38%	0.35%	0.55%
	(2.48)	(2.09)	(2.05)	(2.90)
Mean Inst. Holdings	30.14%	53.74%	66.01%	81.11%

Table 22
Returns for Portfolios Sorted on Past 6 Months Returns and Turnover

This table reports returns for portfolios based on six-month lagged returns and turnover for NYSE/AMEX firms with a stock price of at least $1. The sample period is 1925-2005. I rank stocks independently in ascending order on the basis of six-month lagged returns and turnover averaged over the previous 6 months as of the portfolio formation date. I then form equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentile. The portfolios are held for 6 months. *t*-statistics are reported in parentheses. Panel A reports monthly returns. Panel B reports cumulative past returns (past 6 months).

	low		high	high minus low
Panel A: Monthly Returns				
low turnover	1.58%	1.43%	1.63%	0.05%
				(0.38)
	1.26%	1.31%	1.57%	0.31%
				(2.27)
high turnover	0.76%	1.10%	1.41%	0.65%
				(4.66)
high minus low turnover				0.60%
				(6.25)
Panel B: Cumulative Past Returns (6 months)				
low turnover	-15.73%	4.48%	30.14%	45.87%
				(65.46)
	-17.39%	4.82%	34.07%	51.46%
				(75.80)
high turnover	-20.91%	4.97%	45.29%	66.20%
				(92.71)
high minus low turnover				20.34%
				(56.94)

Table 23
Fama-MacBeth Regression Estimates

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The sample period is 1926-2005 and the sample consists of NYSE/AMEX stocks with a stock price of at least $1. The dependent variable is the excess risk-adjusted return using the FF (1993) factors. BM is the logarithm of the book-to-market ratio. Size represents the logarithm of market capitalization in billions of dollars. 1/P is one over the stock price. Turnover is turnover averaged over the previous six months. RET1-6 is the cumulative returns over the first through sixth months. RET1-6 is interacted with turnover dummies where the dummy equals one if the variable is below the 30th percentile, two if the variable is between the 30th and 70th percentile, and three if the variable is above the 70th percentile. All variables are lagged by two months. All coefficients are multiplied by 100. I do not report the intercept. *t*-statistics are reported in parentheses.

Variable	(1)	(2)	(3)	(4)
BM	0.133	0.136	0.139	0.116
	(3.77)	(3.84)	(3.97)	(3.68)
Size	-0.039	-0.039	-0.044	-0.013
	(-2.13)	(-2.07)	(-2.48)	(-0.87)
1/P				0.262
				(0.56)
RET1-6	0.662		1.291	1.564
	(4.13)		(4.40)	(5.82)
RET1-6 * $\text{Turnover}_{\text{Dummy}}$		0.229	-0.232	-0.307
		(3.72)	(-2.16)	(-2.98)

Table 24
Monthly Returns and Alphas for Portfolios Sorted on SUE and $\hat{\rho}_{FE}$

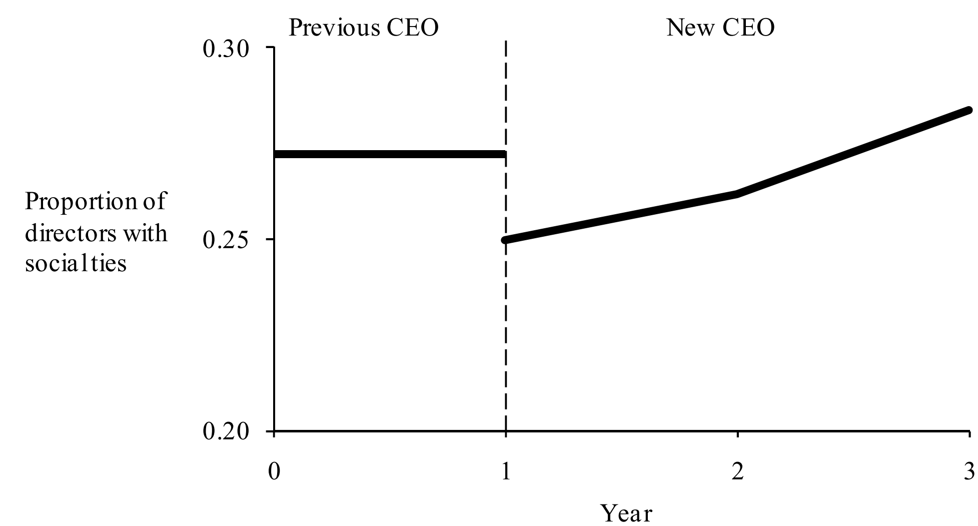
This table reports monthly returns and alphas for portfolios based on SUE and $\hat{\rho}_{FE}$. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I rank stocks independently in ascending order on the basis of SUE and $\hat{\rho}_{FE}$ as of the portfolio formation date. I then form equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentile. The portfolios are held for 6 months. *t*-statistics are reported in parentheses. Panel A reports monthly returns. Panel B reports monthly alphas from regressing the portfolio returns minus the risk-free rate on the Fama-French (1993) factors.

	low SUE		high SUE	high minus low SUE
		Panel A: Monthly Returns		
low $\hat{\rho}_{FE}$	1.25%	1.31%	1.30%	0.05% (0.58)
	1.19%	1.25%	1.33%	0.15% (1.45)
high $\hat{\rho}_{FE}$	1.07%	1.39%	1.50%	0.43% (4.13)
high minus low $\hat{\rho}_{FE}$				0.38% (4.54)
		Panel B: Monthly Alphas		
low $\hat{\rho}_{FE}$	0.12%	0.18%	0.26%	0.14% (1.71)
	0.06%	0.15%	0.26%	0.20% (1.98)
high $\hat{\rho}_{FE}$	-0.06%	0.28%	0.46%	0.51% (4.99)
high minus low $\hat{\rho}_{FE}$				0.37% (4.24)

Figure 1

Evolution of social dependence surrounding the appointment of a new CEO

Using an unbalanced panel of 81 CEO appointments, this figure demonstrates the evolution of the board's social dependence from the year preceding (t = 0) to the three years following (t = 3) the appointment of a new CEO. In Panel A, we plot the average fraction of socially dependent directors. This average fraction is calculated as the average of the number of directors on the board who are socially dependent to the incumbent CEO divided by the total number of directors on the board. In Panel B, we plot the percentage change in the average fraction of socially dependent directors relative to time t = 0.



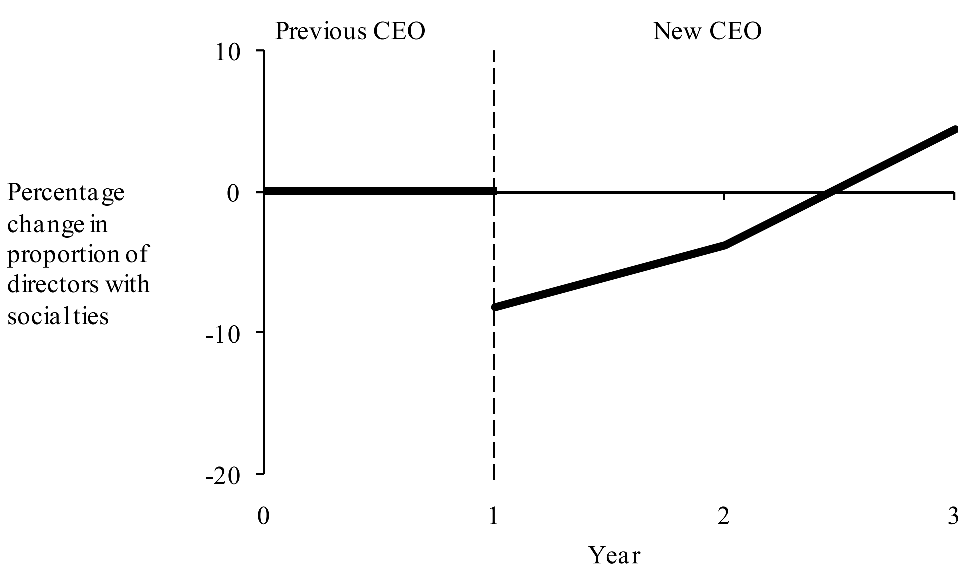


Figure 2
Long-run horizon results

This figure plots monthly excess returns for portfolios based on past returns and $\hat{\rho}_{FE}$. The sample period is 1984-2005. The sample consists of all NYSE/AMEX/NASDAQ stocks that have the necessary data to estimate ρ_{FE}. I rank stocks independently in ascending order on the basis of six-month lagged returns and $\hat{\rho}_{FE}$ as of the portfolio formation date. I then form equally-weighted portfolios of stocks. The breakpoints are the 30th and the 70th percentile. The portfolios are held for 18 months. In Panel A, I plot monthly returns of the high $\hat{\rho}_{FE}$ portfolios ($\hat{\rho}_{FE}$ above the 70th percentile) in excess of monthly returns of all securities in my sample. In Panel B, I plot monthly returns of the low $\hat{\rho}_{FE}$ portfolios ($\hat{\rho}_{FE}$ below the 30th percentile) in excess of monthly returns of all securities in my sample.