To my family

INSTITUTIONAL INVESTMENT HORIZON, HERDING, AND STOCK RETURNS

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

MUHAMMAD SABEEH IQBAL

In Partial Fulfillment of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY IN MANAGEMENT

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November 2020

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ABSTRACT

INSTITUTIONAL INVESTMENT HORIZON, HERDING, AND STOCK RETURNS

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Ph.D. in Department of Management
Supervisor: Assoc. Prof. Dr. Levent Akdeniz

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This thesis investigates the interaction between the herding behavior of institutions classified by their investment horizons and the role of investment horizon of institutions in driving the book-to-market effect. First, we examine the price impact of the herding behavior of short- and long-horizon institutional investors. We categorize the institutional herding as same-side herding when both types of institutions herd on the buy-side or sell-side together and as opposite-side herding when short-horizon institutions buy while the long-horizon institutions sell or vice versa. We find that the previously documented destabilizing impact of long-horizon institutional herding is only observed on opposite-side herding. Moreover, short-horizon institutional herding improves the stock price discovery process confirming the belief that they are more informed. Second, we investigate the differential contribution of institutions with different investment horizons in book-to-market effect. We find that long-horizon institutions tend to buy (sell) stocks with positive (negative) past intangible information. This behavior exacerbates market overreaction and magnifies intangible return reversals and thus contributes to book-to-market effect. On the other hand, short-horizon institutions trade independent of intangible information, and their trading in the direction of intangible information does not contribute to book to market effect. Moreover, our findings also support that short-horizon institutions are better informed than long-horizon institutions.

Keywords: Asset Pricing, Institutional Investors, Investment Horizon, Market Overreaction, Stock Returns

ÖZET

Kurumsal Yatırım Süresi, Sürü Davranışıve Hisse Senedi Getirileri

Iqbal, Muhammad Sabeeh
Doktora, İşletme
Tez Danışmanı: Doç. Dr. Levent Akdeniz

Kasım 2020

Bu tez, yatırım vadesine göre sınıflandırılan yatırım kurumların sürü davranışları ile kurumların yatırım vadesinin piyasa-defter değerine etkisi arasındaki etkileşimi incelemektedir. İlk olarak, kısa ve uzun vadeli yatırım yapan kurumsal yatırımcıların sürü davranışının hisse fiyatlarına etkisini inceliyoruz. Hem kısa vadeli yatırım yapan hem de uzun vadeli yatırım yapan kurumlar alım ve satımlarda aynı yönde haraket ediyorsa bu durumu aynı yön sürü hareketi olarak kategorize ediyoruz. Aynı şekilde uzun vadeli yatırım yapan kurumlar satış yaparken kısa vadeli yatırım yapan kurumlar alım yapıyorsa (yada tam tersi) bunu da tersine sürü hareketi olarak kategorize ediyoruz. Uzun vadeli yatırım yapan kurumsal sürü davranışının daha önce literatürde belgelenmiş istikrarsızlaştırıcı etkisinin sadece tersine sürü hareketinde geçerli olduğunu gösteriyoruz. Ayrıca, bizim bulgularımız, yine daha önce literatürde belgelenmiş kısa vadeli yatırım yapan kurumsal sürü hareketinin daha bilgili olduğu ve hisse senedi denge fiyatını bulma sürecini geliştirdiğini desteklemektedir. İkinci olarak, farklı yatırım vadelerine sahip olan kurumların piyasa-defter değeri etkisine diferansiyel katkılarını araştırıyoruz. Tezimizde, uzun vadeli yatırım yapan kurumların, maddi olmayan bilgisi pozitif olan hisse senetlerini satın almak, maddi olmayan bilgisi negatif olan hisse senetlerini satmak eğiliminde olduğunu buluyoruz. Bu davranış, piyasanın aşırı tepkisini

daha da derinleştirerek maddi olmayan getiri geri dönüşlerini büyütmekte ve piyasa-defter değeri etkisinin açıklanmasına katkı sağlamaktadır. Öte yandan, kısa vadeli yatırım yapan kurumlar alım-satım kararlarını maddi olmayan bilgilerden bağımsız olarak vermekte dolayısıyla piyasa-defter değeri etkisine bir katkı yapmamaktadır. Ayrıca bulgularımız, kısa vadeli yatırım yapan kurumların uzun vadeli yatırım yapan kurumlara nazaran daha fazla bilgiyle yatırım yaptıkları tezini de desteklemektedir.

Anahtar Sözcükler: Kurumsal Yatırımcılar, Piyasa Aşırı Tepkisi, Stok Dönüşü, Varlık Fiyatlandırması, Yatırım Vadesi,

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CHAPTER I

INTRODUCTION

1.1 Overview

Financial institutions hold a large portion (almost 63% in 2018) of the stock market. The swings in demands by such a large proportion of investors while imitating each other can impact the stock prices greatly.[1] However, the nature of the impact depends on the informativeness of these institutions. For example, if institutional trading is based on information, it stabilizes stock prices; that is, it moves prices towards intrinsic values. On the other hand, if institutions trade for reasons that are not related to information about firm's fundamentals, they move the prices away from intrinsic values.

Sophisticated institutions hypothesis states that institutions are rational investors that trade on information. Presuming institutions as informed investors, their herding should improve market efficiency. A number of studies (e.g., Lakonishok et al., 1992; Wermers, 1999; Sias, 2004) find that institutional herding improves the stock price discovery process while other studies (e.g., Dasgupta et al., 2011a; Jiang, 2010) arrive at the opposite conclusion. Hence, a

[1]Herding is defined as the imitation in trading decisions by a group of investors over some period of time (Sias, 2004).

conclusive evidence on the price impact of institutional herding is absent in the literature.

One way to reconcile these conflicting findings is to delve into the heterogeneity across institutions since the previous studies mostly investigate herding by institutions as one group and ignore the heterogeneity across these institutions. Institutions can be heterogeneous in many aspects including types such as banks, insurance, investment companies, investment advisers, and so on or in investment horizons. We focus specifically on investment horizon of institutions due to the findings in Yan & Zhang (2009) that the short-horizon institutions are better informed than long-horizon institutions. We explore the potential of these differences in informativeness to explain the price impact of institutional herding. Specifically, we focus on the trading strategies of institutions with different investment horizons and uncover their implications for stock returns.

We explore two ways in which institutional trading can effect stock returns; the direct impact of short- and long-horizon institutional herding and the impact of these by exacerbating the market overreaction. We investigate the interaction between the herding behavior of short- and long-horizon institutions in chapter 3. Our data show that while sometimes the short- and long-horizon institutions buy or sell together, other times they trade in opposite directions (e.g., short-horizon institutions buy while their long-horizon counterparts sell or vice versa). We call the former as same-side herding and the later as opposite-side herding. Then, we investigate the role of these trading strategies of short- and long-horizon institutions in stock price formation.

The coincidence of trading strategies could have different implication for the stock price formation for these institutions could be following each other due to their correlated private information or due to the preference of long-horizon institutions to follow the better informed short-horizon institutions. In either of these scenarios, the informational herding models predict that the long-horizon institutions should not destabilize stock prices. Therefore, we hypothesize that the same-side herding of both short- and long-horizon institutions do not destabilize stock prices, whereas the opposite-side herding of only long-horizon institutions destabilizes stock prices. We test these hypotheses by investigating the relationship between short- and long-horizon institutional herding and stock returns in the same- and opposite-direction subsamples that represent same- and opposite-side herding, respectively.[2]

We find an insignificant relationship between same-side short- and long-horizon institutional herding and future returns. This suggests that the same-side herding of both types of institutions do not destabilize stock prices, unlike the evidence in previous studies. Furthermore, we find a negative relationship between opposite-side long-horizon institutional herding and future stock returns and an insignificant relationship between opposite-side short-horizon institutional herding and future stock returns. This evidence indicates that the opposite-side herding of only long-horizon institutions destabilizes stock prices.

Then, we explore a second channel, contribution to the value effect, through which institutional herding affects stock returns. Daniel & Titman (2006) document that high book-to-market stocks have poor past intangible returns (the returns independent of firm's fundamentals) to which the market overreacts that leads to the reversal of intangible returns. Jiang (2010) reports that institutions buy stocks with high past intangible returns and sell those with poor past intangible returns and while trading this way they magnify the market overreaction. We argue that only long-horizon institutions, due to their tendency to trade for non-informational reasons, drive the market overreaction to intangible information. Moreover, we do an in-depth analysis of same- and opposite-side trading of these institutions in contributing to the book-to-market

[2]Same-direction subsample represents the group of stocks in which both short- and long-horizon institutions herd on the buy side or sell-side together whereas opposite-direction subsample represents the group of stocks in which if the short-horizon institutions are herding on the buy side, long-horizon institutions herd on the sell side or vice versa.

effect.

We disentangle the contribution of institutions with different investment horizons in driving book-to-market effect in chapter 4. We find that the short-horizon institutions do not trade in this manner and the previous findings can be attributed to long-horizon institutions only. We find an insignificant relationship between intangible information and short-horizon institutional trading and significant positive relationship between intangible information and long-horizon institutional trading.

Furthermore, we test whether short- and long-horizon institutional trading in the direction of intangible information magnify the associated returns reversals. We find that only long-horizon institutional trading magnify the intangible return reversals. These findings suggest that the long-horizon institutions exacerbate the market overreaction and drive the value effect. Overall, our results highlight that the short-horizon institutions are better informed and that the long-horizon institutional trading can be behaviorally biased.

The contributions of our studies are manifold. First, it increases the understanding of institutional behavior. We identify the same- and opposite-side herding of short- and long-horizon institutions and its consequences for market efficiency. Second, our study increases the understanding of the value effect. We highlight the role of the institutional investment horizon in the book-to-market effect. Third, we confirm the previous findings that the short-horizon institutions are better informed than long-horizon institutions.

CHAPTER II

REVIEW OF RELEVANT LITERATURE

Friedman (1953) argues that irrational investors trade in the direction of market trends, i.e., they buy when securitys price is high in the market or sell when the price is low, which causes mispricing. He further argues that rational investors improve market efficiency by trading against the direction of the market. Sophisticated institutions hypothesis (SIH) asserts that institutions are sophisticated investors that trade on fundamental information, and therefore institutions presumably improve market efficiency. However, there is conflicting evidence in the literature on the price impact of institutional herding (a form of trading by institutions in which they imitate each other). Some studies find that herding by institutional investors stabilize stock prices while other studies find the contrary evidence. It is argued in the literature that the impact of herding on stock prices depends on the reasons to herd given as follows.

2.1 Why do Institutions Herd?

Lakonishok et al. (1994) argue that the price impact of institutional herding, whether stabilizing or destabilizing, depends on the reasons for their herding. In other words, if institutions follow each other due to informational reasons, i.e., if they herd due to correlated private information, the price impact of such behavior could be stabilizing or non-destabilizing. We will refer to this type of herding as informational herding. On the other hand, the price impact of institutional herding could be destabilizing if institutions follow each other due to behavioral reasons, such as their reputational concerns or agency problems. We will refer to this type of herding as behavioral herding. The studies presenting informational and behavioral herding models are presented as follows.

2.1.1 Informational Herding Models

Following models of herding explain why institutions could follow each other due to informational reasons. Bikhchandani et al. (1992) derive a model of informational cascades that explains the convergence towards uniform social behavior. In their sequential models, it may be optimal for individuals to discard their private information and follow those, better informed, who are ahead of them. Hence, their actions do not convey information to the later individual that leads to a cascade. Once a cascade starts, individuals actions do not contribute to the public information pool resulting in blockage in the aggregation of information. Moreover, a cascade can be shattered by the release of a little information at a later stage.

In the model of Froot et al. (1992), herding on similar information can be a rational choice as trading by other similarly informed investors impounds the information into prices when speculators have shorter horizons. Besides, when speculators have longer horizons, more information is already incorporated that renders the trading on different information useful. However, there are informational inefficiencies in the sense that speculators may avoid diverse sources of information and that they may study information that is completely independent of fundamentals. In a similar work by Hirshleifer et al. (1994), investors herd on the same information, but their results do not depend on the investment horizon of investors. Specifically, the investors tend to investigate those stocks that are followed by a large number of investors, whereas they ignore those that are otherwise identical but relatively ignored. Moreover, the increase in the assessed probability of the investor that he will acquire the information early is associated with an increase in expected payoff associated with the stocks followed by others. The investors with overconfidence or reputational concerns assign high probabilities to their early informativeness. Therefore, their tendency to follow popular stocks or herding increases.

2.1.2 Behavioral Herding Models

On the other hand, herding can also be observed due to behavioral reasons. Scharfstein & Stein (1990) argue that managers consider moving away from the herd detrimental to their reputation. They explained that managers follow the herd because of the sharing the blame effect, which implies that if the managers experience misfortune following others due to systematic unpredictable shock, it is not bad for their reputation. In other words, managers give up investments with positive expected values if the herd has done the same before them. Falkenstein (1996) posits that institutions herding can be the result of their preference towards stocks with specific characteristics. He documents that open-ended funds have nonlinear preferences towards stocks with high volatility, and they avoid transaction costs as suggested by their aversion towards low-price stocks and demand for liquidity. Moreover, these funds are found to neglect stocks having little information, and other than those mutual funds that are specialized in the small-cap sector, they are found to prefer large stocks in his study. He further argues that herding by institutions must be occurring in those stocks that begin to show certain stock characteristics, and the institutions might not be under-weighing their private information.

2.2 Herding and Stock Returns

Behavioral herding moves the price away from fundamental value whereas informational herding pushes the price towards it. Hence, the implications of these two types of herding for securities prices are different. The former brings a temporary shift in prices; that is, if institutions buy overpriced stocks due to behavioral reasons, it will increase their prices, although temporarily. In this case, the relationship between herding and future returns will be negative. Contrarily, informational herding brings a permanent shift and therfore predicts high subsequent returns. The empirical evidence on the relationship between herding and stock returns are presented below.

2.2.1 Evidence on Price Stabilization

In the empirical literature, evidence on the impact of herding on stock returns is mixed. Less recent studies, including those by Kraus & Stoll (1972), Lakonishok et al. (1994), Grinblatt et al. (1995), and Nofsinger & Sias (1999) find weak evidence of herding among institutional traders and those by Wermers (1999), and Sias (2004) find relatively strong evidence of herding among institutional investors. Kraus & Stoll (1972) found that parallel trading by institutions, which is referred to as herding, is only occurring by chance. They found that the returns are positively associated with parallel trading in the current month and negatively associated with one month lagged parallel trading. They argue that their results are inconsistent with perfectly efficient markets.

Lakonishok et al. (1994) investigated herding behavior in tax-exempt funds pension funds and find that these funds herd little in stocks with large market capitalization where 95% of their trading happens, and relatively more in small stocks. They found a weak positive correlation between excess institutional trading (referred to as herding) and size-adjusted returns in small size stocks, suggesting that pension funds do not destabilize stock prices. They explain a small price impact with the view that institutions follow a variety of strategies that counterbalance each other, i.e., enough positive feedback traders can offset negative feedback traders. Grinblatt et al. (1995) find a weak evidence of herding among mutual funds, however, momentum investing is reported as a predominant trading strategy of mutual funds. The herding strategies of mutual funds improve mutual funds performance, but once the momentum investing is controlled, the positive performance goes away. A more comprehensive study was conducted by Wermers (1999), who finds little herding among all mutual funds (when they are investigated collectively) in an average stock and a high level of herding among the growth-oriented mutual funds. He also uncovers positive feedback trading, such as momentum as a potential source of mutual funds herding. In addition, he finds that mutual funds are equally likely to herd on the buy-side as on the sell-side. On the price impact of herding, he finds that stocks exhibiting buy herding by mutual funds outperform stocks exhibiting sell herding. These results are consistent with the predictions of informational herding models. Finally, he finds a comparatively higher level of herding in small stocks. He associates this evidence to informational cascades since they are more likely to occur in small stocks because of less precise information. Nofsinger & Sias (1999) disentangle the price impact of positive feedback trading from institutional herding and finds that changes in institutional ownership has its own impact. They investigate herding in both institutional investors and individual investors and report that stocks exhibiting institutional herding does not lead to return reversals in the following two-year period.

While the previous studies mainly estimate herding by looking at the proportionally large number of traders on one side of the market, Sias (2004) opts for a different approach to investigate herding. He looks at the cross-sectional correlation between the proportion of institutional buyers in adjacent quarters. His methodology allows him to decompose herding into the part that results from institutional money managers following other institutions and the part that results from individual institutions mimicking their trades of the previous period. He finds a positive relationship between institutional demand and next years returns that he associates it to informational cascades due to the prevalence of herding in small stocks.

2.2.2 Evidence on Price Destabilization

Dasgupta et al. (2011a) empirically investigate the price impact of institutional herding using a measure based on multiple quarters. They argue that institutional herding causes persistence in institutional trading, which they capture using the number of persistent quarters in which institutions trade on one side of the market. In other words, if institutions persistently buy (sell) stock in the last three quarters, including the current quarter, they assign +3 (-3) trade persistence to such stocks. They find that stocks that exhibit herding show long-term return reversals, which are concentrated in small stocks and are stronger in high institutional ownership stocks. The stocks with high institutional ownership show a stronger negative association between herding and long-term returns. Their findings suggest that herding pushes the price of security away from the value suggested by its fundamentals. Similarly, Coval & Stafford (2007) and Frazzini & Lamont (2008) report a negative association between net mutual fund flows and long-term returns.

We said earlier that the institutions prefer certain stock characteristics, which may lead them to herd. Frazzini & Lamont (2008) and Sharma et al. (2008) report the institutional tendency to buy growth stocks and sell value stocks. Similarly, the evidence in Jiang (2010) indicates that institutions tend to buy stock with positive intangible information and sell stocks with negative intangible news. Institutions are documented to magnify the mispricing when they trade in the direction of various anomalies. For example, in Jiang (2010), institutional tendency to trade in the direction of intangible information magnify the market overreaction to intangible information and therefore cause the reversals in intangible returns. Although he does not rule out the behavioral biases of institutional investors, he associates his findings to their reputational concerns. In a more recent study by Edelen et al. (2016), institutions are documented to trade contrary to the anomaly prescriptions, i.e., they buy stocks that anomaly prescribes as overpriced and sell those that an anomaly prescribes as underpriced. They attribute this evidence to institutional preferences of stock characteristics that are driven by their reputational concerns.

Moreover, the stabilizing and destabilizing impact is also investigated in the literature dealing with the volatility of stock returns. Avramov et al. (2006) provide a trading based explanation of the asymmetric volatility effect (the negative relationship between returns and volatility). They define herding trades as those selling activities which are followed by positive returns and contrarian trades as those selling activities which are followed by negative returns. They find that herding causes high volatility, and anti-herding trades decrease volatility. They attribute contrary behavior to superior information. In Dennis & Strickland (2002), evidence suggests herding on days when the stock market exhibits big moves in prices. They find that institutional herding during these days move the stocks prices away from their intrinsic values, and therefore contribute to the market volatility. Blasco et al. (2012) report a positive relationship between herding and volatility, and Chang & Dong (2006) find a positive relationship between herding and idiosyncratic risk.

2.3 Reconciliation Attempts

It appears that the relationship between institutional trading and returns depends on the horizons over which returns and trading by institutions are estimated. For example, Wermers (1999) and Sias (2004), the studies using quarterly horizons, report the evidence of a positive relationship, whereas Kaniel et al. (2008) find a negative relation between institutional trading and subsequent monthly returns. Campbell et al. (2009) also reports similar evidence. Dasgupta et al. (2011b) attempt to reconcile this conflicting evidence by presenting a model that explains that if institutional investors have reputational concerns, it is possible to observe a stabilizing impact in the short run, whereas a destabilizing impact in the long term.

Furthermore, earlier studies do not take into account the heterogeneity across institutional subgroups. For example, short- and long-horizon institutions (SHIs and LHIs) are found to be heterogeneous in many aspects. Yan & Zhang (2009) empirically investigate the informativeness of institutions classified by their investment horizon. They find that SHIs have superior information, and their trading significantly predicts future stock returns. Similarly, Chichernea et al. (2015) investigate the effect of institutional ownership on idiosyncratic risk conditional on the investment horizon of institutional investors. They empirically find that there is enough heterogeneity across institutions in terms of their preferences and effects of their trading. High SHIs ownership increases idiosyncratic risk suggesting a preference for stocks with high idiosyncratic risk, whereas high LHIs ownership decreases idiosyncratic risk suggesting a preference towards low idiosyncratic risk stocks.

Yuksel (2015) investigates the impact of herding conditional on the investment horizon of institutions. He finds that herding by LHIs is a negative predictor of subsequent returns (both in the short term and long term), whereas herding by

SHIs is positively associated with future returns. He attributes these findings to LHIs uninformed behavior and to SHIs relatively informed trading.

2.4 Areas for Future Research

We review a number of studies on institutional herding behavior and its consequences for market efficiency and do not see a conclusive evidence on the price impact of institutional herding. On one hand, earlier studies Lakonishok et al. (1994); Sias (2004) conclude that institutional herding does not destabilize stock prices. On the other hand, the evidence in the later studies (Dasgupta et al., 2011a; Gutierrez & Kelley, 2009; Jiang, 2010) is against the role of institutional herding in improving the price discovery process. Although some studies (e.g., Yuksel, 2015) attempt to reconcile these conflicting results, some methodological issues still need to be addressed. For instance, the interactions between institutions classified by their investment horizons can provide further insights into the price impact of institutional herding. In other words, they could be herding on the same sides or opposite sides to each other. If the herding strategies of short- and long-horizon institutions coincide, which could be due to their correlated private information or due to the superior information of short-horizon institutions, the impact of herding by might not be destabilizing, unlike Yuksel (2015) and Dasgupta et al. (2011a). Similarly, following a similar argument, the destabilizing impact of herding should be true only for long-horizon institutions while trading in the opposite direction to short-horizon institutions.

Finally, the characteristics herding (herding due to institutional following of certain stock characteristics) by short- and long-horizon institutions requires further exploration. For example, the preference of long-horizon institutions for intangible information may be contributing to the market overreaction since it is argued that they might be motivated by their behavioral biases, such as reputational concerns. In contrast, since short-horizon institutions presumably trade on information, they should not magnify the market overreaction. Hence, it remains an open question of whether the overreaction to intangible information can be lead by short-horizon institutions also.

Lakonishok et al. (1992) argue that trades of heterogeneous institutions counter balance each other, such as the positive feedback traders offset the price impact brought upon by negative feedback traders. Kyle (1985) explains the adjustment of information into stock prices when informed and uninformed noise traders exist in the market. In his model, information is adjusted gradually into stock prices as a result of informed trading by insiders. However, an ex ante increase in the quantity traded by noise traders do not affect prices but allows informed traders to benefit from an increase in depth of the market. Madura & Richie (2004) suggest that informed traders mitigate the overreaction generated by uninformed noise traders. These studies suggest that the interaction of informed and uninformed investors in the market has implications for the overreaction and the resulting price impact. Therefore, we investigate these implication for the same- and opposite-side herding by short- and long-horizon institutions.

The literature investigates institutions as a group; therefore, an in-depth analysis of the trading strategies of short- and long-horizon institutions is required. We provide only those studies which we consider relevant to our discussion. For detailed studies on herding literature, one can refer to Hirshleifer & Hong Teoh (2003), Spyrou (2013), and Kumar & Goyal (2015). We summarize the evidence on price impact of herding in the literature in Table 2.1.

Table 2.1: Studies on the Price Impact of Institutional Herding

Study	**Sample**	**Data**	**Impact**
Kraus & Stoll (1972)	Bank trust departments; investment companies (mutual funds and closed-end companies); banks and investment companies.	Jan. 1968-Sept. 1969	Destabilizing
Lakonishok et al. (1994)	Tax-Exempt Pension Funds	March 1985-Dec. 1989	Non-destabilizing
Grinblatt et al. (1995)	Mutual Funds	Dec. 1975-Dec. 1984	Stabilizing
Wermers (1999)	Mutual Funds	Dec. 1974-Dec. 1994	Stabilizing
Nofsinger & Sias (1999)	Individual Investors Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	Jan. 1977-Dec. 1996	Non-destabilizing

Table 2.1: (cont'd)

Study	**Sample**	**Data**	**Impact**
Dennis & Strickland (2002)	Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	Jan. 1988-Dec. 1996	Destabilizing
Sias (2004)	Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	March 1983-Dec. 1997	Stabilizing
Avramov et al. (2006)	Daily Trades of all stocks from TAQ	Jan. 1993-December 1998	Destabilizing
Chang & Dong (2006)	Institutional ownership data of non-financial firms in Japan	Jan. 1975-Dec. 2002	Destabilizing

Table 2.1: (cont'd)

Study	**Sample**	**Data**	**Impact**
Coval & Stafford (2007)	Mutual Funds	March 1980-Dec. 2004	Destabilizing
Frazzini & Lamont (2008)	Mutual Funds	March 1980-Dec. 2003	Destabilizing
Jiang (2010)	Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	March 1981-Dec. 2004	Destabilizing
Dasgupta et al. (2011a)	Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	March 1983-Dec. 2004	Destabilizing
Blasco et al. (2012)	Intraday trades data of Spanish stock market	Jan. 1997-Dec. 2003	Destabilizing

Table 2.1: (cont'd)

Study	Sample	Data	Impact
Yuksel (2015)	Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	March 1981-Dec. 2012	Destabilizing for long-horizon institutions & stabilizing for short-horizon institutions
Edelen et al. (2016)	Mutual Funds; Banks, Insurance Companies, Investment Companies, Investment Advisors, Others (Education Endowment Funds etc)	Dec. 1980-June 2011	Destabilizing
Cai et al. (2019)	Mutual Funds; Insurance Companies, Pension Funds	July 1998-Sept. 2014	Buy herding stabilizing & sell herding destabilizing

CHAPTER III

THE PRICE IMPACT OF SAME- AND OPPOSING-DIRECTION HERDING BY INSTITUTIONS WITH DIFFERENT INVESTMENT HORIZONS[1]

3.1 Introduction

Institutional investors tend to follow each other (Lakonishok et al., 1992), and the implications of such behavior, referred to as herding, has been studied in many papers. A number of studies have found that institutional herding improves price discovery (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004). In contrast, Dasgupta et al. (2011a) and Gutierrez & Kelley (2009) have reported a destabilizing impact of such behavior. Moreover, Yuksel (2015) suggests that the impact of institutional herding, whether stabilizing or destabilizing, is conditional on the investment horizon of institutions. He shows that herding by long-horizon institutions (LHIs) is a negative predictor of subsequent return whereas herding by short-horizon institutions (SHIs) is positive. He attributes these results to uninformed behavior of LHIs that moves prices away from their fundamental value and to informed trading decisions of

[1]This chapter is published in Iqbal et al. (2020).

SHIs that move prices in the direction as suggested by the stock's fundamentals. This evidence is in line with Yan & Zhang (2009) who finds that the trades of SHIs are better informed than those of LHIs.

A meticulous analysis of our data for institutional herding reveals that, in some cases, both SHIs and LHIs herd to take long/short positions together in some stocks. Similarly, in other cases, while one type of institution herds on the buy-side the other herds on the sell-side. We call the former as "same-side herding" and the latter as "opposite-side herding". This observation has motivated us to decompose herding based on the sides of herdings and re-examine the impact of herding on price stability. To the best of our knowledge, previous studies have not decomposed herding into directions of herding. In this study, we investigate the effect of the direction of herding on price discovery.

Bikhchandani et al. (1992) argue that individuals discard their private information and follow those who are better informed. Since the SHIs are believed to be better informed, in some cases, LHIs may follow them while herding, and thus form an informational cascade. Similarly, Froot et al. (1992) argue that investors follow each other as the private information they possess is correlated. Lakonishok et al. (1992) argue that herding due to informational reasons does not necessarily exert a destabilizing force on stock prices. We therefore hypothesize in this chapter that the LHIs do not destabilize stock prices when they trade in the same direction with SHIs since SHIs are better informed but cause destabilization when they herd in opposite direction.

In this study, we investigate the differential price impact of same- and opposite-side herding by short- and long-horizon institutions. We use quarterly institutional data from the CDA/Spectrum database, accounting data from Compustat, and stock market data from CRSP for the period 1980Q1 to 2018Q4. We first classify institutions into SHIs and LHIs following Yan &

Zhang (2009). We measure SHIs' and LHIs' herding following Dasgupta et al. (2011a). Dasgupta et al. (2011a) recognize that herding causes persistence in institutional trading. Accordingly, in our measure, if institutions persistently buy or sell a stock for three quarters, then the stock's trading persistence is +3 or -3, respectively. The maximum trade persistence attributed to a stock is +5 (-5). Then, we divide stocks into same- and opposite-direction subsamples to obtain same- and opposite-side herding, respectively. The former subsample consists of stocks in which both SHIs and LHIs are herding together on either the buy-side or sell-side. The later subsample comprises stocks in which only one type of institution, LHIs or SHIs, is herding on either the buy-side or the sell-side. Specifically, SHIs trade persistence and LHIs trade persistence have the same signs for stocks in the same-direction subsample and opposite signs for stocks in the opposite-direction subsample. Finally, we regress market-adjusted returns on SHIs' trade persistence, LHIs' trade persistence, and other control variables both in the subsamples and the full sample.

We find that the trade persistence for both SHIs and LHIs are insignificant in predicting future returns in the same-direction subsample. Contrarily, LHIs' trade persistence is a negative predictor of future returns in the opposite-direction subsample. On the other hand, SHIs' trade persistence is insignificant in the opposite-direction subsample. Our findings are robust to the inclusion of other control variables and various methodological concerns.

Investment strategy implications based on the results of the previous studies is that if an investor buys stocks that are consistently sold by LHIs and sells stocks that are consistently bought by LHIs, s/he will be able to generate abnormal positive returns. However, our results suggest that the success of this strategy depends on the careful decomposition of the direction of the herding of these institution types with respect to each other. If an investor buys (sells) stocks that are consistently sold (bought) by both LHIs and SHIs, he will not be able to generate any abnormal returns. The above strategy will only work if while one type of institution is consistently buying (selling), the other is consistently selling (buying). As such, our study contributes to the debate on the role of institutions in determining price stability. We show that LHIs do not destabilize prices when they herd in the same direction as SHIs.

The remainder of the chapter is as follows; section 2 describes data and methodology, section 3 reports results, and section 4 concludes the chapter.

3.2 Data and Methodology

Our sample includes all common stocks in CRSP that have quarterly institutional holdings in Thompson Financial and annual accounting information in Compustat.[2] The data spans the period from 1980Q1 to 2018Q4. Moreover, we remove penny stocks to mitigate the effect of bid-ask spread on our results.

3.2.1 Classification of Institutions

Following Yan & Zhang (2009), we classify institutions into short- and long-horizon institutions on the basis of their four-quarter average churn rate (portfolio turnover) as follows.

$$CR_{k,t} = \frac{min(Buy_{k,t}, Sell_{k,t})}{\sum_{i=1}^{N_k} \frac{S_{k,i,t}P_{i,t}+S_{k,i,t-1}P_{i,t-1}}{2}}, \tag{3.1}$$

[2]All institutions managing more than \$100 million are required to disclose their holdings to SEC.

where $CR_{k,t}$ is the churn rate for institution k in quarter t. $Buy_{k,t}$ and $Sell_{k,t}$ are given as

$$Buy_{k,t} = \sum_{i=1, S_{k,t} > S_{k,t-1}}^{N_k} |S_{k,i,t}P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\delta P_{i,t}|, \tag{3.2}$$

$$Sell_{k,t} = \sum_{i=1, S_{k,t} < S_{k,t-1}}^{N_k} |S_{k,i,t}P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\delta P_{i,t}|, \tag{3.3}$$

where $P_{i,t}$ is the closing share price for security i in quarter t, and $S_{k,i,t}$ is the number of split-adjusted shares, held by institutional investor k at the end of quarter t.[3] Next, we obtain average churn rate as follows:

$$AVGCR_{k,t} = \frac{1}{4}\sum_{j=0}^{3} CR_{k,t-j}. \tag{3.4}$$

A four-quarter average handles any idiosyncratic shock that could temporarily affect the institution's chosen horizon. Each quarter, we rank institutions into terciles based on their $AVGCR_{k,t}$. Institutions with $AVGCR_{k,t}$ in top (bottom) tercile are classified as short-horizon (long-horizon) institutions. Among 7,008 short- and long-horizon institutions, 5,463 remain consistent with their chosen investment horizons whereas 1,545 (40) institutions change their investment horizons at least once (five times) over the sample period. We keep only those institutions that remain consistent in their choices.[4]

3.2.2 Short- and Long-Horizon Institutional Trade Persistence

We obtain short- and long-horizon institutional trade persistence following Dasgupta et al. (2011a). Unlike other one- or two-quarter herding measures,

[3] This churn rate measure mitigates the effect of cash flows induced trading on portfolio turnover. Alexander et al. (2007) document that the cash flows induced trading contains little information. Besides, CRSP uses a similar turnover measure for mutual funds.

[4] Our findings do not change if we keep all institutions.

such as those by Lakonishok et al. (1992) and Sias (2004), the measure proposed by Dasgupta et al. (2011a) is better at capturing the dynamic aspects of herding discussed in theoretical herding models of Bikhchandani et al. (1992) and Scharfstein & Stein (1990). Specifically, in these models, the persistence in investors trading decisions results when agents take a specific action over multiple periods.

To estimate the trade persistence, the change in holdings is measured as

$$\Delta Hold_{i,t}^{SHI(LHI)} = Hold_{i,t}^{SHI(LHI)} - Hold_{i,t-1}^{SHI(LHI)},$$

where $Hold_{i,t}^{SHI(LHI)}$ is the number of shares of stock i in the aggregate portfolio of SHIs or LHIs in quarter t. A positive (negative) $\Delta Hold_{i,t}$ shows that the stock is net bought (net sold) in quarter t. TP^{SHI} (TP^{LHI}) is the number of recent quarters in which a stock is consecutively bought or sold by SHIs (LHIs). In other words, if SHIs have bought a stock in quarter t and quarter *t-1* but have sold it in quarter *t-2*, its $TP_{i,t}^{SHI}$ is +2. A stock has a maximum trade persistence of +5 (-5). $IO_{i,t}^{SHI}$ ($IO_{i,t}^{LHI}$) is $Hold_{i,t}^{SHI}$ ($Hold_{i,t}^{LHI}$) divided by the number of shares outstanding.

Among other control variables, size (CAP) is the log of market capitalization of stock i at the end of quarter t. Share turnover (TURN) is trading volume divided by number of shares outstanding at the end of quarter t.
Book-to-market (B/M) is the book value of equity divided by market equity. Earnings to price ratio (E/P) is the income before extraordinary items divided by market equity. Cash Flows to Price (CF/P) is earnings before extraordinary items plus deferred taxes plus equity's share of depreciation divided by the market equity, where equity's share is equal to market equity divided by total assets minus book equity plus market equity. Sales to Price (Sale/P) is sales divided by market equity. The accounting values in these price scaled ratios are

Table 3.1: Pooled Summary Statistics

Variables	Mean	sd	P05	Median	P95	N
TP^{LHI}	-0.005	2.346	-4	-1	4	448,975
TP^{SHI}	0.012	2.191	-4	-1	4	426,055
IO^{LHI}	0.091	0.086	0	0.068	0.253	486,889
IO^{SHI}	0.078	0.084	0	0.052	0.245	486,889
TURN	0.125	0.191	0.007	0.072	0.404	487,906
B/M	0.697	1.079	0.089	0.555	1.647	468,707
CSI	0.052	0.376	-0.330	-0.007	0.674	372,801
$Ret_{t-15,t}$	0.984	2.241	-0.576	0.524	3.817	375,293
EG	-0.002	0.444	-0.163	0.006	0.133	439,026
E/P	0.033	0.282	-0.139	0.052	0.156	468,322
Sale/P	1.674	3.561	0.089	0.853	5.428	466,735
CF/P	0.113	0.374	-0.104	0.089	0.413	403,628
CAP	5.835	1.941	2.938	5.695	9.271	487,840

Note: This table reports the summary statistics of the pooled sample. N represents the number of observations (stock-quarter) available for a given variable. sd represents standard deviation. P.05 and P.95 represent the 5th and 95th percentiles, respectively. The data covers the period 1980Q1 to 2018Q4.

from fiscal year that ends in calendar year Y-1, and the market equity is from the end of the calendar year Y-1. Moreover, we employ these ratios starting from the second quarter of year Y to 1st quarter of year Y+1. Earnings Growth (EG) is the annual change in earnings before extraordinary items (EBI) in year Y-1 divided by the calendar-year end market equity. $R_{i,t-15:t}$ is the cumulative return from quarter t-15 to t to capture the return reversals effect documented in Bondt & Thaler (1985).[5] Composite Stock issuance (CSI) measures growth in the market value that is not associated with returns. CSI is measured as $CSI_{i,t} = log(ME_{i,t}/ME_{i,t-15}) - r_{i,t-15:t}$, where $ME_{i,t}$ is the market equity of stock i in quarter t and $r_{i,t-15:t}$ is the cumulative log return from quarter *t-15* to *t*.

[5]Fama & French (1996) suggest skipping one year after the formation period for better contrarian results. Using $R_{i,t-15:t-4}$ instead of $R_{i,t-15:t}$ does not change our findings.

Table 3.2: Average No. of Stocks in Persistence Categories

TP^{SHI}/TP^{LHI}	-5	-4	-3	-2	-1	1	2	3	4	5
-5	4	3	5	11	19	18	8	4	2	3
-4	4	3	6	12	25	23	10	5	3	4
-3	8	6	12	26	51	49	22	13	7	8
-2	16	14	25	50	111	100	52	26	14	17
-1	34	28	52	103	243	234	106	54	29	35
1	34	29	52	104	224	241	101	50	26	32
2	16	14	26	51	102	105	58	25	13	16
3	8	7	13	23	49	50	25	16	7	9
4	4	4	6	11	23	25	12	6	5	5
5	4	3	5	10	21	20	10	6	4	5

Note: This table reports the quarterly average of the number of stocks in 100 portfolios based on stock level TP^{SHI} and TP^{LHI}. SHIs' trade persistence is given in the first column, and LHIs' trade persistence is given in the columns headings. The data covers the period 1980Q1 to 2018Q4.

3.2.3 Descriptive Statistics

Table 3.1 reports descriptive statistics of herding measures and various stock characteristics in the pooled sample. The average trade persistence by long- and short-horizon institutions is -0.005 and 0.012, respectively. As these statistics are close to zero, most of the observations (stock-quarter) do not exhibit herding. Average short-horizon (long-horizon) institutional ownership is 9.1% (7.8%).

Each quarter, we divide our sample into two subsamples. One includes stocks in which both SHIs and LHIs herd in the same direction. Particularly, TP^{SHI} and TP^{LHI} have similar signs for these stocks. We call this subsample as "same-direction subsample" and this phenomenon as "same-side herding". Contrarily, the opposite direction subsample consists of stocks for which TP^{SHI} and TP^{LHI} have opposite signs; that is, if one type of institution buys the other sells. We call this phenomenon "opposite-side herding".

Each quarter, we rank stocks into hundred portfolios on the basis of their SHIs' trade persistence and LHIs' trade persistence. The time-series average of the number of stocks in these portfolios is reported in Table 3.2. We found that the average number of stocks decreases with increasing persistence. Most of the stocks are concentrated in portfolios with the least persistence. Table 3.2 shows that there is a huge number of stocks in which persistent trading by both LHIs and SHIs does not exceed one. Dasgupta et al. (2011a) assign a zero trade persistence to such cases. We also run our analysis after removing stocks in portfolios ($\mathrm{TP}^{\mathrm{SHI}}$=-1 , $\mathrm{TP}^{\mathrm{LHI}}$=-1), ($\mathrm{TP}^{\mathrm{SHI}}$=1 , $\mathrm{TP}^{\mathrm{LHI}}$=1) , ($\mathrm{TP}^{\mathrm{SHI}}$=-1 , $\mathrm{TP}^{\mathrm{LHI}}$=1), and ($\mathrm{TP}^{\mathrm{SHI}}$=1 , $\mathrm{TP}^{\mathrm{LHI}}$=-1) that hereafter is referred as stocks with minimum trade persistence, however, our findings do not change.

3.3 Empirical Results

In this section, we analyze the impact of short- and long-horizon institutional trade persistence on stock returns in the same- and opposite-direction subsamples using following regression model.

$$\begin{aligned} R_{i,t+1:t+h} = \alpha &+ \beta_1 TP_{i,t}^{SHI} + \beta_2 TP_{i,t}^{LHI} + \beta_3 IO_{i,t}^{LHI} + \beta_4 IO_{i,t}^{SHI} \\ &+ \beta_5 CF/P_{i,t} + \beta_6 Sale/P + \beta_7 E/P_{i,t} + \beta_8 EG_{i,t} + \beta_9 B/M_{i,t} \\ &+ \beta_{10} CAP_{i,t} + \beta_{11} TURN_{i,t} + \beta_{12} Ret_{i,t-15:t} + \beta_{13} CSI_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{3.5}$$

where h can be 1 or 8. The coefficients are estimated as in Fama & Macbeth (1973).[6]

[6]We adjust the autocorrelation in standard errors following Newey & West (1987). The number of lags is equal to the integer value of $T^{1/4}$ (see, e.g., Greene (2003)), where T represents the number of quarters.

Table 3.3: Persistent Trading Strategies of Institutions

	Market-Adjusted Returns					
	Ret_{t+1}			$Ret_{t+1,t+8}$		
	(SD)	(OD)	(FULL)	(SD)	(OD)	(FULL)
Panel A. All stocks						
TP^{SHI}	0.001	0.0001	0.001***	-0.003	-0.006**	-0.001
	(0.001)	(0.0004)	(0.0003)	(0.003)	(0.003)	(0.002)
TP^{LHI}	-0.0001	-0.002***	-0.001***	-0.003	-0.009***	-0.005***
	(0.0004)	(0.0005)	(0.0003)	(0.002)	(0.003)	(0.002)
IO^{LHI}	0.002	0.007	0.005	-0.028	0.061	0.024
	(0.012)	(0.012)	(0.010)	(0.051)	(0.054)	(0.049)
IO^{SHI}	0.038***	0.056***	0.047***	0.214***	0.103	0.152***
	(0.014)	(0.014)	(0.013)	(0.058)	(0.076)	(0.058)
Avg. N	989	998	1987	904	912	1816
Observations	137,534	138,678	276,212	119,382	120,376	239,758
R^2	0.108	0.116	0.100	0.110	0.098	0.093
Panel B. Excluding stocks with minimum trade persistence						
TP^{SHI}	0.001	0.0002	0.001***	-0.002	-0.006**	-0.001
	(0.001)	(0.0004)	(0.0003)	(0.003)	(0.003)	(0.002)
TP^{LHI}	-0.00004	-0.002***	-0.001**	-0.002	-0.009***	-0.004**
	(0.0005)	(0.001)	(0.0003)	(0.002)	(0.003)	(0.002)
IO^{LHI}	-0.001	0.011	0.006	-0.017	0.043	0.018
	(0.013)	(0.012)	(0.010)	(0.053)	(0.057)	(0.050)
IO^{SHI}	0.039**	0.048***	0.046***	0.150**	0.096	0.121*
	(0.016)	(0.017)	(0.014)	(0.071)	(0.081)	(0.068)
Avg. N	753	749	1502	687	683	1370
Observations	104,691	104,090	208,781	90,649	90,154	180,803
R^2	0.114	0.122	0.103	0.134	0.106	0.105
Control	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports coefficients and standard errors (in brackets) from the regression of one- and eight-quarter cumulative market-adjusted returns on TP^{SHI}, TP^{LHI}, and other control variables following Fama & Macbeth (1973) in same direction subsample (SD), opposite-direction subsample (OD) and full sample (FULL). TURN, B/M, CSI, $Ret_{t-15,t}$, EG, E/P, Sale/P, CF/P, and CAP are used as control variables in all columns. The data covers the period 1980Q1 to 2018Q4. *, **, and *** represent the statistical significance of coefficients at 10%, 5%, and 1%, respectively.

3.3.1 Institutional Trade Persistence and Returns

The regression in equation 3.5 is estimated for the same-direction subsample (SD), the opposite-direction subsample (OD), and the full sample (FULL). Coefficients and their standard errors (in parenthesis) are reported in Table 3.3. Our dependent variable is the one-quarter-ahead (eight-quarter-ahead) stock return in columns 2-4 (5-7). We report the analysis of all stocks in Panel A and the analysis of stocks excluding those with minimum trade persistence in Panel B.

The results show that the short- and long-horizon institutional trade persistence is insignificant in predicting one-quarter returns in the same-direction subsample. By contrast, LHIs' trade persistence significantly predicts short-term return reversals in the opposite-direction subsample. One-quarter increase in the trade persistence by LHIs predicts a 0.2% decrease in one-quarter returns. As before, SHIs' trade persistence does not have predictive power for one-quarter returns in the opposite-direction subsample. Our full-sample results show that the significant negative impact of long-horizon institutional trade persistence is smaller compared to that in the opposite-direction subsample.

Studies by Smith (1996), Gaspar et al. (2005), and Chen et al. (2007) argue that LHIs influence firms' management to improve long-term performance. Moreover, Yan & Zhang (2009) argue that LHIs might have long-term information. Since LHIs could be herding due to information about the long-term value, the short-term destabilization impact of their persistent trading decisions might revert in the long-run. To analyse that, we use eight-quarter returns as our dependent variable and re-estimate the regression in equation 3.5. Porter (1992), Bushee (1998, 2001), Yan & Zhang (2009), and Yuksel (2015) show that SHIs focus on short-term information. Therefore, the impact of their herding on short-term returns seems more relevant to argue about their informativeness. As before, high persistent trading by LHIs is associated with low eight-quarter returns in the opposite-direction subsample and the entire sample. As can be seen from the table, the effect of LHIs' trade persistence is more pronounced in the opposite-direction subsample. Hence, LHIs herding continues to destabilize prices even in the long run. The findings in Panel B are similar to those of Panel A.

These findings are in sharp contrast to Dasgupta et al. (2011a) and Yuksel (2015); LHIs destabilise stock prices only when they trade in the opposite direction to SHIs. We confirm the previous findings regarding SHIs as informed investors. That is, their same- and opposite-side herding do not destabilize stock prices in the short run.

Among control variables, IO^{SHI} is positive and significant, as in Yan & Zhang (2009). Sale/P is a positive predictor of long-term returns except in column 1. Composite stock issuance (CSI) predicts short- and long-term return reversals.

3.3.2 Robustness Check: Returns over different horizons

In previous section, we reported results for one- and eight-quarter returns. However, one quarter might be too short for the prices to revert whereas eight-quarter period could be too long for short-horizon institutions. To eliminate these concerns, we conduct a similar analysis to that in Panel B of Table 3.3 except we replace the dependent variables by two- and four-quarter returns. The results are reported in Table 3.4. The results in this section confirm our previous findings that only opposite-side herding by LHIs destabilize stock prices.

Table 3.4: Robustness Check: Returns of different Horizons

	Market-Adjusted Returns			
	$Ret_{t+1,t+2}$		$Ret_{t+1,t+4}$	
	(SD)	(OD)	(SD)	(OD)
TP^{SHI}	0.002^{**}	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)
TP^{LHI}	-0.001	-0.003^{***}	-0.002	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
IO^{LHI}	0.001	0.007	-0.003	0.061^{*}
	(0.020)	(0.020)	(0.036)	(0.034)
IO^{SHI}	0.081^{***}	0.069^{**}	0.116^{***}	0.084^{*}
	(0.023)	(0.027)	(0.038)	(0.050)
Avg. N	747	743	731	725
Observations	103,142	102,595	99,394	98,664
R^2	0.123	0.119	0.117	0.113
Control	Yes	Yes	Yes	Yes

Note: This table reports coefficients and standard errors (in brackets) from the regression of two- and four-quarter cumulative market-adjusted returns on TP^{SHI}, TP^{LHI}, and other control variables following Fama & Macbeth (1973) in same direction subsample (SD), opposite-direction subsample (OD) and full sample (FULL). TURN, B/M, CSI, $Ret_{t-15,t}$, EG, E/P, Sale/P, CF/P, and CAP are used as control variables. The data covers the period 1980Q1 to 2018Q4. *, **, and *** represent the statistical significance of coefficients at 10%, 5%, and 1%, respectively.

3.3.3 Informational Advantage of Institutions

Our results are in line with informational herding models. LHIs could be following SHIs due to their superior information (as in Bikhchandani et al. (1992)) or correlated private information (as in Froot et al. (1992)). We check for the informational advantage of each institutional type to distinguish between these explanations.

Following Yan & Zhang (2009), we incorporate change in SHIs' ownership (informational advantage of SHIs), lagged SHIs' ownership (SHIs' demand shock), change in LHIs' ownership (informational advantage of LHIs), and lagged LHIs' ownership (LHIs' demand shock) in equation 3.5. The results are

Table 3.5: Persistent Trading Strategies and Informational Advantage of Institutions

	Market-Adjusted Returns					
	Ret_{t+1}			$Ret_{t+1,t+8}$		
	(SD)	(OD)	(FULL)	(SD)	(OD)	(FULL)
TP^{SHI}	0.0005	0.0002	0.001***	-0.002	-0.005**	-0.001
	(0.001)	(0.0004)	(0.0002)	(0.002)	(0.003)	(0.001)
TP^{LHI}	-0.0004	-0.001***	-0.001*	-0.002	-0.009***	-0.004**
	(0.0005)	(0.001)	(0.0004)	(0.002)	(0.003)	(0.002)
ΔIO^{LHI}	-0.041	0.005	-0.008	0.012	0.129	0.125
	(0.030)	(0.032)	(0.024)	(0.167)	(0.113)	(0.113)
IO^{LHI}_{t-1}	-0.001	0.013	0.006	-0.021	0.036	0.017
	(0.014)	(0.011)	(0.011)	(0.056)	(0.062)	(0.052)
ΔIO^{SHI}	0.126***	0.055	0.093***	0.196	0.018	0.167
	(0.037)	(0.034)	(0.028)	(0.150)	(0.144)	(0.114)
IO^{SHI}_{t-1}	0.024	0.045***	0.038***	0.138*	0.109	0.115
	(0.015)	(0.017)	(0.014)	(0.073)	(0.084)	(0.071)
Avg. N	753	749	1502	687	683	1370
Observations	104,691	104,090	208,781	90,649	90,154	180,803
R^2	0.118	0.125	0.105	0.139	0.109	0.107
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports coefficients and standard errors (in brackets) from the regression of one- and eight-quarter cumulative market-adjusted returns on TP^{SHI}, TP^{LHI}, and other control variables following Fama & Macbeth (1973) in same direction subsample (SD), opposite-direction subsample (OD) and full sample (FULL). TURN, B/M, CSI, $Ret_{t-15,t}$, EG, E/P, Sale/P, CF/P, and CAP are used as control variables. The data covers the period 1980Q1 to 2018Q4. *, **, and *** represent the statistical significance of coefficients at 10%, 5%, and 1%, respectively.

reported in Table 3.5. Our main findings are robust to introducing new variables. The change in SHIs' ownership is positively associated with future returns in the same-direction subsample suggesting that SHIs have an informational advantage in the same-side herding. In contrast, lagged SHIs' ownership is positive and significant in the opposite-direction subsample. These results complement those in Yan & Zhang (2009). The change in LHIs' ownership and lagged LHIs' ownership are insignificant suggesting that LHIs neither have short-term information nor long-term information. This evidence rules out the herding due to correlated private information and supports the informational cascade hypothesis for same-side herding.

3.4 Conclusion

We categorize the herding by short- and long-horizon institutions as same-side herding when both types of institutions herd together on the buy-side or sell-side and as opposite-side herding when one type of institution buys while the other sells. We show that the same-side herding of both long- and short-horizon institutions do not destabilize stock prices, and opposite-side herding of only long-horizon institutions destabilize stock prices.

This study increases our understanding of the pricing implications of the herding behavior of institutional investors. We highlight that the interaction of trading behavior between different type of institutions that differ in investment horizon give us clues about the price discovery process. A follow up study might shed light on why and when these institutions herd together from an informational efficiency perspective.

CHAPTER IV

INSTITUTIONS AND THE BOOK-TO-MARKET EFFECT: THE ROLE OF INVESTMENT HORIZON

4.1 Introduction

There is now a considerable empirical evidence on the positive relation between book-to-market ratio and stock returns. However, the channels through which book-to-market affects stock returns and the underlying economic causes are still not clear. On one hand, Bondt & Thaler (1985) and Lakonishok et al. (1994) argue that the book-to-market effect results from investor overreaction to past fundamental performance. On the other hand, Daniel & Titman (2006) argue that while a stock's future return is unrelated to the firm's past accountingbased performance, it is strongly negatively related to the intangible return, which is proxied by the booktomarket ratio.

Many behavioral theorists associate the overreaction to investors' psychological biases (see, e.g., Daniel et al., 1998; Barberis et al., 1998). Since institutions are often assumed as sophisticated investors, their role in driving the overreaction is often undermined.[1] In contrast, recent evidence in Jiang (2010) suggests that

[1]Sophisticated investors, under the efficient markets hypothesis, trade on information.

institutional money managers could be exacerbating market overreaction to intangible information. He reports that institutions tend to buy (sell) shares in response to positive (negative) intangible information and the observed book-to-market effect is due to the reversal of the intangible returns. Moreover, he finds that this effect is large and significant in stocks with intense past institutional trading but non-existent in stocks with moderate institutional trading. Thus, he argues that institutional trading in the direction of intangible information magnifies the mispricing. These findings contradict with the predictions of the sophisticated institutions hypothesis which argues that a skilled investor exerts a correcting force on stock prices.

Another important perspective that can contribute to this debate is the finding about heterogeneous trading behavior of institutions with respect to their investment horizon. Yan & Zhang (2009) claim that short-horizon institutions are better informed than long-horizon institutions, thus trade more often to exploit their informational advantage.[2] Given this evidence, we would expect short-horizon institutions to trade in a way that mitigates market overreaction. Conversely, long-horizon institutions that are prone to be led by their behavioral motivations could exacerbate the market overreaction and possibly move the prices further away from the fundamental value. In other words, short-horizon institutions should mitigate rather than contribute to the book-to-market effect, and long-horizon institutions should mainly contribute to the effect. We investigate the above hypothesis by examining the response of each type of institution to changes in intangible information. We believe that this analysis will improve our understanding of the contribution of institutional trading in price discovery process. The mere evidence of the link between intangible information and institutional trading is not enough to conclude that these institutions contribute to the documented book-to-market effect because

[2]Yuksel (2015) reports that short-horizon institutional herding stabilizes stock price, whereas long-horizon institutional herding destabilizes it.

there could be an under-reaction in the market and the institutions could be making an informed decision. Therefore, we also examine whether institutional trading in the direction of intangible information magnifies or mitigates the return reversals associated with intangible information.

Furthermore, Lakonishok et al. (1992) argue that institutional investors represent a heterogeneous group of investors whose trading strategies might offset each other, i.e., trend chasers are counterbalanced by enough number of negative feedback traders. Our data show that although sometimes short- and long-horizon institutions trade in the opposite directions (i.e., one type of institution buys and the other sells or vice versa), other times their investment strategies coincide (i.e., both types of institutions buy or sell together).[3] Therefore, these institutions could reinforce each other and further exacerbate the market overreaction while trading in the same-direction or offset each other and reduce the market overreaction while trading in the opposite direction. In other words, we might not find a net book-to-market effect if these institutions offset each other or find an enhanced net effect if these institutions reinforce each other. An investigation of the interaction between trading by both types of institutions presents an opportunity not only to identify the primary contributor of the book-to-market effect but also to increase the understanding of the behavior of institutions that are trading in tandem.

All common stock in the US available in CRSP stock universe from January 1980 to December 2018 form our sample. The quarterly trading measures are from Lakonishok et al. (1992), and composite equity issuance, a proxy for intangible information, is from Daniel & Titman (2006).

The cross-sectional regression tests show a significant positive relationship between one quarter lagged intangible information and long-horizon

[3]We use a similar methodology to Iqbal et al. (2020) that is explained later in introduction section.

institutional buying in quarter t. Similarly, a negative correlation exists between past intangible information and future long-horizon institutional selling. On the other hand, an insignificant relationship exists between past intangible information and short-horizon institutional buying or selling.

Next, we obtain the same- and opposite-side trading following a methodology similar to Iqbal et al. (2020) and divide our sample into the same- and opposite-direction subsamples.[4] Then, we run the cross-sectional regressions in each subsample. We find that long-horizon institutions trade in the direction of intangible information whereas short-horizon institutions trade independent of intangible information in both subsamples. This evidence has important implications. One, it suggests that short-horizon institutions do not further enhance the market overreaction by reinforcing the long-horizon institutional trading. Second, they also do not mitigate market overreaction by countering the moves of long-horizon institutions. Therefore, it is the long-horizon institutions that mainly contribute to the market overreaction.

Then, we explore the price impact of institutional trading in the direction of intangible information. We find that stocks with increased composite equity issuance coupled with a subsequent proportionally large long-horizon institutional buyers exhibit more significant return reversals than those with increased composite equity issuance alone. Contrarily, short-horizon institutional selling following a decrease in composite equity issuance reduces the return reversals. Increased composite equity issuance combined with a subsequent large proportion of short-horizon institutional buyers or long-horizon institutional sellers do not contribute to the return reversals. In summary, long-horizon institutional buys in the direction of intangible information

[4] The same-direction subsample consists of those stocks in which both short- and long-horizon institutions are trading in the same direction (i.e., both types are either buying or selling). The opposite-direction subsample contains the stocks in which short- and long-horizon institutions are trading in the opposite direction (i.e., one type of institution is buying and the other type is selling).

exacerbate the market overreaction, and short-horizon institutional sells counter it. Therefore, the findings in Jiang (2010) are mainly driven by the long horizon institutional trading activity and is not attributable to all institutions.

Moreover, we also check the price impact of institutional trading in the direction of intangible information in the subsamples. Our results show that long-horizon institutional buys magnify the return reversals in both same- and opposite-direction subsamples. It is expected since these institutions always follow intangible information, i.e., whether they trade on the same- or opposite-side. In contrast, short-horizon institutional trading is insignificant in explaining the returns in both subsamples which is in line with our earlier findings that they trade independent of intangible information. In other words, the same-side trading of short-horizon institutions neither offsets nor reinforces the book-to-market effect. Similarly, short-horizon institutions are unable to significantly counter the market-overreaction exacerbated by long-horizon institutions in the opposite-direction subsample.

Market overreaction is attributed to the behavioral biases of individual investors in a number of studies (Daniel et al., 1998; Barberis et al., 1998), and therefore we propose that one explanation of our results could be the long-horizon institutions' behavioral motivations. Alternatively, long-horizon institutions might have reputational concerns as explained in Scharfstein & Stein (1990). They argue that institutional investors tend to follow others due to "sharing the blame" effect. That is, their reputation is not much affected when they make an unprofitable decision while following others. On the other hand, the informativeness of short-horizon institutions is not rejected in our studies.

This study contributes to the debate about the link between institutional trading and the book-to-market effect, that is driven by the reversal of intangible returns, by highlighting the role of the institutional investment horizon. In addition, we show that returns react asymmetrically to buy and sell trades of institutional investors. Next, we conduct an in-depth analysis of the interaction between the trading activities of long- and short-horizon institutions. Last, our evidence contributes to the debate on institutional tendency to exploit anomalies such as intangible information. We find that short-horizon institutions trade independent of intangible information, unlike Jiang (2010) and Edelen et al. (2016). In contrast, long-horizon institutions trade against the prescriptions of changes in intangible information by buying overpriced and selling underpriced stocks.

In the rest of the chapter, section 2 describes data, variables, and summary statistics. Section 3 investigates the institutional trading in response to intangible information. Section 4 examines whether institutions enhance the reversals related to intangible information. Section 5 investigates the same- and opposite-side trading and section 6 concludes.

4.2 Data, Methodology, and Summary

4.2.1 Data and Sample

Our data include all stocks from the CRSP stock universe and cover the period from January 1980 to December 2018. A stock must have institutional holdings data in 13-F CDA/Spectrum database and accounting data in COMPUSTAT to be included in the sample. We use only common stocks with share codes (CRSP header SHRCD) equal to 10 or 11 and eliminate those with negative book equity values as in Jiang (2010). To reduce the concern reported in other studies regarding the effects of the bid-ask spread on the empirical results, we remove penny stocks from the sample with prices below $5.[5]

[5] Kaul & Nimalendran (1990) find little evidence of market overreaction after controlling for the bid-ask spread. Besides, they find that there is a strong negative correlation between stock price and bid-ask spread. Many studies report that bid-ask spread explains the return reversals (see, e.g., Jegadeesh & Titman, 1995; Ball et al., 1995). Bowman & Iverson (1998) report that

Table 4.1: Descriptive Statistics: Institutions

	All Institutions			LHI		SHI	
	Assets	Turnover	N	Assets	Turnover	Assets	Turnover
Year	$mill.	%		$mill.	%	$mill.	%
1982	885.96	11.12	450	842.61	3.82	832.00	19.62
1984	992.53	9.02	511	1078.17	3.04	875.27	16.65
1986	1252.42	10.32	593	1464.70	3.66	939.87	19.29
1988	1241.22	8.79	685	1506.26	3.06	948.01	16.32
1990	1293.45	8.79	785	1631.04	2.60	928.52	17.17
1992	1943.84	9.38	851	2565.84	2.91	1542.41	18.04
1994	2022.06	9.78	834	2148.86	2.96	1795.65	19.14
1996	3625.02	11.41	923	3584.65	3.28	1983.70	22.67
1998	4828.60	11.80	1139	4280.68	3.29	3232.33	23.65
2000	5309.60	11.25	1383	5463.42	3.01	2606.36	22.60
2002	3578.19	12.14	1390	3545.50	2.87	1478.82	25.70
2004	4276.35	13.80	1769	4777.75	3.34	1863.30	29.50
2006	4795.08	13.73	2135	6040.03	3.11	1692.18	28.93
2008	2564.73	11.92	2440	2858.23	3.02	1013.07	23.35
2010	3602.05	13.03	2420	3751.11	2.72	1409.13	27.77
2012	3719.08	11.47	2805	4589.58	2.38	1399.22	24.69
2014	4802.98	11.30	3242	6344.44	2.28	1724.71	24.23
2016	4625.25	11.07	3509	6106.91	2.15	1714.11	24.44
2018	4028.35	9.02	3887	4965.25	2.02	1942.02	19.28

Note: This table reports the average value of institutional holdings (Assets), average portfolio turnover (Turnover), and the number of managers (N) for all institutions as a group and short- and long-horizon institutions separately in the last quarter of even years. It shows all managers whose portfolio holdings of the past five quarters (including current quarter) are available. Each quarter, institutions are ranked into terciles based on their average churn rate in the past four quarters, as in Yan & Zhang (2009). Short-horizon institutions (long-horizon institutions) are those who fall in the top (bottom) tercile. Our data covers the period 1980Q1 to 2018Q4.

4.2.2 Classification of Institutions

We employ an approach similar to Yan & Zhang (2009) to classify institutions into short- and long-horizon institutions based on their past four-quarter average portfolio turnover. The methodology is described in chapter 3 (section 3.2).

Table 4.1 reports the average value of institutional holdings (Assets), average turnover, and the number of institutions (N) in the last quarter of even years for all institutions and the subsamples of short- and long-horizon institutions.

bid-ask spread related reversals exist in the penny stocks which disappear after removing less than 2% of the sample.

An average institution held approximately $886 million worth of assets in 1982 that grew to $4,028.35 million in 2018. The total number of institutions grew from 450 to 3,887 during the same period. Each quarter, one third of the number of institutions are included in the subsamples of short- and long-horizon institutions. Both types of institutions increase their average holdings over the sample period. An average long-horizon institution holds a maximum of $6,344.44 million in 2014, whereas an average short-horizon institution holds a smaller value in its portfolio in all these years and carries a maximum of $3,232.33 million in 1998.

The sample consists of 7,008 short- and long-horizon institutional money managers. 1,545 (40) managers change their horizons, from short to long or vice versa, at least once (five times). We include only 5,463 managers in our analysis who remain consistent in their choices of investment horizons during the sample period.

4.2.3 Institutional Trading Measure

We use the institutional trading measure proposed by Lakonishok et al. (1992), which we hereafter refer to as LSV measure. LSV measure captures the trading imbalance created by a large proportion of institutions buying or selling a stock, which Lakonishok et al. (1992) define as herding. For stock i in quarter t, we estimate LSV measure as follows:

$$Herd_{it} = |BP_{it} - \overline{BP}_{it}| - AF_{it}. \tag{4.1}$$

BP_{it} is the proportion of institutions buying stock i in quarter t. Specifically, BP is equal to the number of institutions increasing their holdings of stock i divided by the total number of institutions trading (either increasing or decreasing their holdings) stock i in quarter t . $\overline{BP}_{it}$ represents the expected value of BP_{it} proxied by the average of BP across all stocks in quarter t.[6] Following Wermers (1999), we require at least five institutions trading stock i. Changing the minimum number of active institutions in a stock does not effect our findings.

An adjustment factor is subtracted from the absolute demeaned proportion of buyers. In the absence of herding, we expect non-zero variation around the expected proportion. To compute AF_{it}, the number of institutional buyers are assumed to follow a binomial distribution. Given this assumption, each institution buys with probability equal to $\overline{BP}_{it}$. AF_{it} is estimated as

$$AF_{it} = \sum_{b=0}^{K_{it}} p_{ib} \left| \frac{b}{K_{it}} - \overline{BP}_{it} \right|, \tag{4.2}$$

where b corresponds to the number of institutional buyers which takes values from 0 to K_{it} (the total number of institutions trading in stock i during quarter t) and p_b is the binomial probability estimated as follows:

$$p_{ib} = \binom{K_{it}}{b} \rho^b (1-\rho)^{(K_{it}-b)} \tag{4.3}$$

for $b \in \{0, \ldots, K_{it}\}$. ρ equals the average proportion of buying institutions. In other words, p_{i0} is the probability that there are zero institutional buyers for stock i.

We obtain buy- and sell-side herding measures following Wermers (1999) as

$$BHerd_{it} = H_{it} | BP_{it} > \overline{BP}_{it} \quad and \quad SHerd_{it} = H_{it} | BP_{it} < \overline{BP}_{it}. \tag{4.4}$$

The adjustment factor for $BHerd_{it}$ ($SHerd_{it}$) is re-estimated with the expected buyers' proportion equal to the average proportion across stocks exhibiting buy-side (sell-side) herding. In line with Brown et al. (2014), we estimate an

[6] Wermers (1999) and Sias (2004) use a similar proxy.

adjusted herding measure that equals $BHerd_{it} - min(BHerd_{it})$ for stocks that exhibit buy-side herding and $-1 \times (SHerd_{it} - min(SHerd_{it}))$ for stocks that exhibit sell-side herding. Then, short- and long-horizon institutions' herding is estimated as

$$Herd_{it}^{SHI(LHI)} = |BP_{it}^{SHI(LHI)} - \overline{BP}_{it}^{SHI(LHI)}| - AF_{it}^{SHI(LHI)}, \qquad (4.5)$$

where BP_{it}^{SHI} and BP_{it}^{LHI} represent the number of short- and long-horizon institutional buyers of stock i as a proportion of the total number of short- and long-horizon institutional traders of stock i in quarter t, respectively. $\overline{BP}_{it}^{SHI}$ and $\overline{BP}_{it}^{LHI}$ are the cross-sectional averages of the proportions of short- and long-horizon institutional buyers in quarter t, respectively. AF_{it}^{SHI} and AF_{it}^{LHI} are computed separately for each type. We measure buy- and sell-herding measures represented as $BHerd_{it}^{SHI(LHI)}$ and $SHerd_{it}^{SHI(LHI)}$ for short-horizon (long-horizon) institutions. Finally, we compute the adjusted herding measures represented as $ADJH_{it}^{SHI(LHI)}$ as before.

4.2.4 Composite Equity Issuance

Daniel & Titman (2006) argue that the firm managers are likely to issue shares in response to favorable intangible information and repurchase shares against the realization of negative intangible information. Therefore, they propose composite equity issuance (CEI) as a proxy for intangible information. CEI increases with employees' stock options, seasoned equity offerings, and share-based acquisitions, and decreases with share repurchases and distribution of dividends. Positive CEI implies the realization of favorable intangible news such as an increase in growth opportunities due to a decrease in the discount rate, and negative CEI implies unfavorable intangible information. We measure

Table 4.2: Descriptive Statistics: Stock Characteristics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
CEI	0.057	0.355	−3.454	−0.126	0.162	5.870
B/M	−0.760	0.791	−9.872	−1.194	−0.232	3.323
Cap	7.182	1.538	1.524	6.061	8.104	13.886
Turn	0.162	0.181	0.001	0.060	0.201	8.901
$Ret_{t-2:t}$	0.075	0.327	−0.980	−0.098	0.212	18.209
Age	287.834	213.452	49	128	381	1,117
$Ret_{t-15:t-4}$	0.784	1.916	−0.999	−0.002	1.016	155.794
Number of LHI	49.618	66.259	5	18	53	970
$BHerd^{LHI}$	0.023	0.089	−0.162	−0.041	0.071	0.450
$SHerd^{LHI}$	0.033	0.091	−0.186	−0.035	0.087	0.579
$ADJH^{LHI}$	−0.027	0.183	−0.745	−0.168	0.118	0.593
IO^{LHI}	0.137	0.084	0.000	0.074	0.187	2.276
ΔIO^{LHI}	0.002	0.030	−1.881	−0.006	0.009	1.938
Number of SHI	52.073	48.606	5	20	67	665
$BHerd^{SHI}$	0.025	0.086	−0.164	−0.034	0.070	0.501
$SHerd^{SHI}$	0.026	0.082	−0.164	−0.031	0.070	0.483
$ADJH^{SHI}$	−0.012	0.171	−0.627	−0.145	0.126	0.626
IO^{SHI}	0.105	0.080	0.000	0.045	0.145	2.205
ΔIO^{SHI}	0.000	0.037	−1.888	−0.014	0.014	1.627

This table reports the mean, standard deviation (St. Dev.), minimum (Min), 25th percentile (Pctl(25)), 75th percentile (Pctl(75)), and maximum (Max) of various stock characteristics and institutional trading measures in the pooled sample. There are 224,358 observations, and the unit of observation is the stock-quarter. We measure CEI following Daniel & Titman (2006) as $CEI_{i,t} = log(me_{i,t}/me_{i,t-15}) - r_{i,t-15:t}$, where $r_{i,t-15:t}$ is the cumulative log returns. B/M, in June of year T, is the natural log of fiscal-year end book-value divided by the calendar-year end market value in year T-1. Cap is the natural log of market equity at the end of quarter t. TURN is the trading volume divided by shares outstanding at the end of quarter t. $\mathrm{Ret}_{\mathrm{i,t\text{-}2:t}}$ is the cumulative return from quarter *t-2* to quarter *t*, and $\mathrm{Ret}_{\mathrm{i,t\text{-}15:t\text{-}4}}$ is the cumulative return from quarter t-15 to quarter t-4. Age is the number of months since the stock first appears in monthly CRSP data. Stock level institutional trading measures are from Lakonishok et al. (1992). We classify institutions as short- and long-horizon based on the past four-quarter average churn rate, as in Yan & Zhang (2009). $HERD^{LHI}$ and $HERD^{SHI}$ are the LSV herding measures. $BHerd^{LHI}$ ($BHerd^{SHI}$) and $SHerd^{LHI}$ ($SHerd^{SHI}$) are the conditional LSV herding measures representing buy and sell herding by long-horizon (short-horizon) institutions, respectively. IO_t^{SHI} (IO_t^{LHI}) is the number of shares held by SHIs (LHIs) divided by the number of outstanding shares. ΔIO^{SHI} (ΔIO^{LHI}) is equal to IO_t^{SHI} minus IO_{t-1}^{SHI} (IO_t^{LHI} minus IO_{t-1}^{LHI}). Adjusted herding measures $ADJH^{SHI}$ and $ADJH^{LHI}$ combine the buy and sell herding measures of short- and long-horizon institutions, respectively. E.g., $ADJH^{SHI}$ is equal to $BHerd_{it}^{SHI} - min(BHerd_{it}^{SHI})$ for stocks that exhibit buy-side herding and $-1 \times (SHerd_{it}^{SHI} - min(SHerd_{it}^{SHI}))$ for stocks that exhibit sell-side herding. The data covers the period from January 1980 to December 2018.

CEI as

$$CEI_{i,t} = log(me_{i,t}/me_{i,t-15}) - r_{i,t-15:t}, \tag{4.6}$$

where me represents market equity and $r_{i,t-15:t}$ represents the log returns cumulated over 4 years. 4 years are consistent with the measurement period for $Ret_{t-15:t-4}$ that controls for return reversals. Appendix B provides details regarding other control variables.

4.2.5 Summary Statistics

Table 4.2 reports mean, standard deviation (St. Dev.), minimum (Min), 25th percentile (Pctl(25)), 75th percentile (Pctl(75)), and maximum (Max) of the various stock characteristics and the stock-level institutional measures in the pooled sample. In the data, 224,358 observations span the period 1984Q1 to 2018Q4. Average composite equity issuance that is the growth in market equity not attributed to returns is 5.7% suggesting a realization of positive intangible information on average. Average long-horizon institutional ownership is 13.7%, whereas short-horizon institutional ownership is 10.5%. An average stock has 50 active long-horizon institutional traders against a maximum of 970. The average number of short-horizon traders is 52, and the maximum number of short-horizon institutions that trade in a stock is 665. Average long-horizon institutional buy (sell) herding is 2.3% (3.3%), whereas average short-horizon institutional buy (sell) herding is 2.5% (2.6%).

4.2.6 Portfolios based on Composite Equity Issuance

In this sub-section, we analyze institutional trading in CEI-sorted portfolios. In each quarter, we rank stocks into deciles based on their one-quarter lagged composite equity issuance. Table 4.3 reports the pooled averages of various trading measures for portfolios based on one quarter lagged composite equity issuance. Average CEI_{t-1} is -0.415 for decile 1 (the lowest decile) and 0.803 for decile 10 (the highest decile). $CEI_{t-1}(OD)$ represents the composite equity issuance in the subsample where short- and long-horizon institutions trade in the opposite direction, i.e., one type of institution is buying and the other is selling. On the other hand, $CEI_{t-1}(SD)$ represents the composite equity issuance in the same-direction subsample, i.e., both types of institutions are either buying or selling together. The reported average CEI_{t-1} values in the same- and opposite-direction subsamples are similar to those of the full sample.

Long-horizon institutional trading measures in CEI deciles show that they trade in the direction of intangible information. ΔIO^{LHI} increases from 0.001 in the lowest decile to 0.003 in the highest decile. The adjusted herding measure ($ADJH^{LHI}$) is -0.095 for the lowest decile suggests selling by long-horizon institutions in response to negative intangible news. A monotonous increase of $ADJH^{LHI}$ from left to right reaching 0.046 in the highest decile indicates that long-horizon institutions tend to buy stocks that realize positive intangible news and sell those that realize negative intangible information. Long-horizon institutional trading trend does not change in the same- and opposite-direction subsample. A more in-depth look into their buy- and sell-herding measures further confirms our claim.

The trading behavior of short-horizon institutions exhibits a different pattern than that of long-horizon institutions. ΔIO^{SHI} (unlike ΔIO^{LHI}) shows no specific trend. Furthermore, short-horizon institutional herding is lower than that of long-horizon institutions in the comparable deciles. $BHerd^{SHI}$ in decile 1 and decile 10 is 0.025 and 0.029, respectively. Similarly, $SHerd^{SHI}$ in decile 1 is smaller than that in decile 10. However, buy and sell herding measures do not show clear trends in any direction. Only when we classify the sample into the same- and opposite-direction subsamples, the trading strategies of short-horizon

Table 4.3: Composite Equity Issuance Sorted Portfolios

CEI deciles	1	2	3	4	5	6	7	8	9	10
CEI_{t-1}	-0.415	-0.192	-0.129	-0.078	-0.032	0.014	0.070	0.156	0.306	0.803
$CEI_{t-1}(OD)$	-0.393	-0.191	-0.128	-0.079	-0.033	0.015	0.071	0.153	0.302	0.781
$CEI_{t-1}(SD)$	-0.394	-0.191	-0.128	-0.078	-0.033	0.016	0.073	0.154	0.304	0.791
Long-Horizon Institutions' Trading Measures										
ΔIO^{LHI}	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.003
$ADJH^{LHI}$	-0.095	-0.086	-0.064	-0.046	-0.026	-0.014	0.000	0.012	0.025	0.046
$ADJH^{LHI}(OD)$	-0.096	-0.091	-0.068	-0.045	-0.025	-0.011	0.007	0.019	0.033	0.054
$ADJH^{LHI}(SD)$	-0.110	-0.103	-0.079	-0.060	-0.036	-0.022	-0.010	0.001	0.015	0.037
$BHerd^{LHI}$	0.011	0.009	0.011	0.014	0.018	0.019	0.023	0.027	0.033	0.045
$SHerd^{LHI}$	0.058	0.051	0.042	0.035	0.026	0.022	0.018	0.016	0.014	0.016
Short-Horizon Institutions' Trading Measures										
ΔIO^{SHI}	0.001	0.001	0.001	0.001	0.000	0.001	0.000	-0.001	-0.001	-0.001
$ADJH^{SHI}$	-0.070	-0.067	-0.053	-0.041	-0.025	-0.016	-0.011	-0.005	0.008	0.019
$ADJH^{SHI}(OD)$	0.053	0.053	0.038	0.022	0.008	-0.002	-0.016	-0.025	-0.035	-0.052
$ADJH^{SHI}(SD)$	-0.092	-0.085	-0.070	-0.052	-0.030	-0.013	-0.008	0.002	0.015	0.046
$BHerd^{SHI}$	0.025	0.025	0.024	0.027	0.026	0.029	0.027	0.027	0.028	0.029
$SHerd^{SHI}$	0.026	0.022	0.023	0.026	0.026	0.026	0.029	0.030	0.029	0.030
Stock-Quarter	35,326	35,261	35,249	35,257	35,278	35,235	35,242	35,264	35,246	35,317

This table reports the average institutional trading measures in portfolios based on composite equity issuance in quarter *t-1*. Composite equity issuance (CEI) in quarter t is measured as $CEI_{i,t} = log(me_{i,t}/me_{i,t-15}) - r_{i,t-15:t}$. Stock level institutional trading measures are from Lakonishok et al. (1992). We classify institutions as short- and long-horizon based on the past four-quarter average churn rate, as in Yan & Zhang (2009). $HERD^{LHI}$ and $HERD^{SHI}$ are the LSV herding measures. $BHerd^{LHI}$ ($BHerd^{SHI}$) and $SHerd^{LHI}$ ($SHerd^{SHI}$) are the conditional LSV herding measures representing buy and sell herding by long-horizon (short-horizon) institutions, respectively. IO_t^{SHI} (IO_t^{LHI}) is the number of shares held by SHIs (LHIs) divided by the number of outstanding shares. ΔIO^{SHI} (ΔIO^{LHI}) is equal to IO_t^{SHI} minus IO_{t-1}^{SHI} (IO_t^{LHI} minus IO_{t-1}^{LHI}). Adjusted herding measures $ADJH^{SHI}$ and $ADJH^{LHI}$ combine the buy and sell herding measures of short- and long-horizon institutions, respectively. E.g., $ADJH^{SHI}$ is equal to $BHerd_{it}^{SHI} - min(BHerd_{it}^{SHI})$ for stocks that exhibit buy-side herding and $-1 \times (SHerd_{it}^{SHI} - min(SHerd_{it}^{SHI}))$ for stocks that exhibit sell-side herding. The data covers the period from January 1980 to December 2018.

institutions become apparent. $ADJH^{SHI}(OD)$ shows a decrease from 0.053 in the lowest decile to -0.052 in the highest decile. Contrarily, $ADJH^{SHI}(SD)$ shows an increase from left to right. The division of the sample clarifies that short-horizon institutions do not always follow intangible information. In the opposite-direction subsample, they seem to counter the market overreaction to intangible news by trading in the opposite direction. Next, we use regression methodology to test whether institutional trading in the direction of intangible information is statistically significant.

4.3 Institutional Trading and Intangible Information

In this section, we investigate the institutional trading in response to intangible information using Fama & Macbeth (1973) methodology. We run the following quarterly regressions of institutional trading measures on one-quarter lagged issuance measure and other control variables.

$$\begin{aligned} Trade_{i,t} = \alpha + \beta_1 CEI_{i,t-1} + \beta_2 Trade_{i,t-1} + \beta_3 Ret_{i,t-16:t-5} + \beta_4 Cap_{i,t-1} \\ + \beta_5 TURN_{i,t-1} + \beta_6 Ret_{i,t-3:t-1} + \beta_7 Age_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{4.7}$$

where Trade is one of the trading measures, including $BHerd^{LHI}$, $SHerd^{LHI}$, $BHerd^{SHI}$, and $SHerd^{SHI}$. Lagged trading measures are included due to the evidence reported in Sias (2004) that the institutions follow their own trades in subsequent quarters. The averages of betas from quarterly regressions are the final estimates. Standard errors are corrected for serial correlation as in Newey & West (1987).[7] The following sub-sections report and discuss our findings.

[7]The integer value of $T^{1/4}$ gives the number of lags for Newey-West correction, where T is the total number of quarters (Greene, 2003).

Table 4.4: Long-Horizon Institutional Trading and Intangible Information

	Trading by LHI					
	$BHerd_t^{LHI}$			$SHerd_t^{LHI}$		
	(1) (Full)	(2) (Same)	(3) (Opposite)	(4) (Full)	(5) (Same)	(6) (Opposite)
CEI_{t-1}	0.018***	0.024***	0.013***	−0.022***	−0.022***	−0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$BHerd_{t-1}^{LHI}$	0.077***	0.078***	0.075***			
	(0.006)	(0.008)	(0.009)			
$SHerd_{t-1}^{LHI}$				0.206***	0.225***	0.191***
				(0.010)	(0.011)	(0.013)
$Ret_{t-16:t-5}$	0.001***	0.001	0.002***	−0.006***	−0.007***	−0.007***
	(0.0003)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)
Cap_{t-1}	−0.001	−0.001	−0.001	0.010***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turn_{t-1}	−0.003	0.009	−0.003	0.042***	0.046***	0.014*
	(0.009)	(0.012)	(0.007)	(0.012)	(0.011)	(0.008)
$Ret_{t-3:t-1}$	0.014***	0.011***	0.013***	−0.022***	−0.018***	−0.022***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Age_{t-1}	−0.0003***	−0.0003***	−0.0003***	0.0002***	0.0002***	0.0002***
	(0.00004)	(0.0001)	(0.00005)	(0.00003)	(0.00003)	(0.00003)
Constant	0.031***	0.031***	0.029***	−0.047***	−0.049***	−0.057***
	(0.007)	(0.009)	(0.007)	(0.005)	(0.005)	(0.005)
Avg. N	443	200	200	601	314	253
Observations	61,631	27,789	27,791	83,535	43,624	35,128
R^2	0.082	0.113	0.102	0.187	0.220	0.222

Note: This table reports coefficients and autocorrelation-adjusted standard errors (in brackets) from the regression of long-horizon institutional herding on lagged composite equity issuance (CEI_{t-1}) and other control variables following the methodology in Fama & Macbeth (1973). Our dependent variable is buy-side herding in columns 1-3 and sell-side herding in columns 4-6. We classify institutions as short- and long-horizon based on the past four-quarter average churn rate, as in Yan & Zhang (2009). $BHerd^{LHI}$ and $SHerd^{LHI}$ are the conditional LSV herding measures representing buy and sell herding by long-horizon institutions, respectively. Columns 1 and 4 report the results from the entire sample. Columns 2 and 5 (Columns 3 and 6) report the analysis of same-direction (opposite-direction) subsample. Same-direction (opposite-direction) subsample contains those stocks in which both types of institutions herd on the buy side or sell side together (opposite sides). We measure CEI following Daniel & Titman (2006) as $CEI_{i,t} = log(me_{i,t}/me_{i,t-15}) - r_{i,t-15:t}$, where $r_{i,t-15:t}$ is the cumulative log returns. Other control variables are defined in appendix B. The data covers the period from January 1980 to December 2018. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

4.3.1 Long-Horizon Institutional Trading in response to CEI

Table 4.4 reports mean coefficients and Newey-West corrected standard errors (in parenthesis) from regressions specified in equation 4.7. The dependent variable is $BHerd^{LHI}$ in columns (1)-(3) and $SHerd^{LHI}$ in columns (4)-(6). Columns (2) and (5) report results from regressions in same-direction subsample and columns (3) and (6) present results from the analyses of opposite-direction subsamples. Our variable of interest is one-quarter lagged CEI, which is positively related to long-horizon institutional buying in the full-sample and the same- and opposite-direction subsamples. On the other hand, cei_{t-1} is negatively related to selling by long-horizon institutions, as suggested by the results reported in columns (4)-(6). The effects are statistically significant. One standard deviation (0.355) increase in CEI in quarter *t-1* increases buy-herding by 0.64% and decreases sell-herding by 0.78% in the full sample. One standard deviation increase in CEI_{t-1} increases buy-herding by 0.85% and 0.46% in the same- and opposite-direction subsamples, respectively. On the other hand, we observe a decrease in sell-herding by 0.78% and 0.92% in the same- and opposite-direction subsamples, respectively. These results suggest that long-horizon institutions buy in response to positive intangible news proxied by an increase in CEI_{t-1} and sell in response to negative intangible news proxied by a decrease in CEI_{t-1}.

4.3.2 Short-Horizon Institutional Trading in response to CEI

Table 4.5 reports results from the regression of short-horizon institutional trading on composite equity issuance and other control variables. As before, the dependent variable is $BHerd^{SHI}$ in columns (1)-(3) and $SHerd^{SHI}$ in columns (4)-(6). Columns (2) and (5) (columns (3) and (6)) present analyses of the same-direction (opposite-direction) subsample. Short-horizon institutional trading in quarter t is not effected by CEI in quarter *t-1*. Analyses of the same- and opposite-direction subsamples confirm these findings. These results suggest that short-horizon institutions do not follow intangible information. However,

Table 4.5: Short-Horizon Institutional Trading and Intangible Information

	Trading by SHI					
	$BHerd_t^{SHI}$			$SHerd_t^{SHI}$		
	(1) (Full)	(2) (Same)	(3) (Opposite)	(4) (Full)	(5) (Same)	(6) (Opposite)
CEI_{t-1}	0.003*	0.001	−0.003	0.001	0.004*	0.0002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
$BHerd_{t-1}^{SHI}$	0.023***	0.022***	0.014*			
	(0.005)	(0.007)	(0.008)			
$SHerd_{t-1}^{SHI}$				0.025***	0.030***	0.019**
				(0.007)	(0.008)	(0.008)
$Ret_{t-16:t-5}$	−0.002***	−0.002***	−0.003***	0.001**	0.002***	0.001
	(0.0004)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)
Cap_{t-1}	−0.001**	0.0004	−0.002***	−0.001	−0.0003	−0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turn_{t-1}	−0.022***	−0.031***	−0.006	0.039***	0.054***	0.036***
	(0.006)	(0.008)	(0.010)	(0.007)	(0.010)	(0.012)
$Ret_{t-3:t-1}$	0.024***	0.027***	0.018***	−0.025***	−0.021***	−0.026***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Age_{t-1}	−0.0001***	−0.0001***	−0.0001*	−0.00001	−0.00003	−0.00003
	(0.00003)	(0.00005)	(0.00004)	(0.00002)	(0.00002)	(0.00004)
Constant	0.037***	0.028***	0.039***	0.028***	0.025***	0.030***
	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Avg. N	379	177	180	459	264	177
Observations	52,684	24,562	25,015	63,854	36,681	24,662
R^2	0.052	0.077	0.074	0.053	0.091	0.073

Note: This table reports coefficients and autocorrelation-adjusted standard errors (in brackets) from the regression of short-horizon institutional herding on lagged composite equity issuance (CEI_{t-1}) and other control variables following the methodology in Fama & Macbeth (1973). Our dependent variable is buy-side herding in columns 1-3 and sell-side herding in columns 4-6. We classify institutions as short- and long-horizon based on the past four-quarter average churn rate, as in Yan & Zhang (2009). $BHerd^{SHI}$ and $SHerd^{SHI}$ are the conditional LSV herding measures representing buy and sell herding by short-horizon institutions, respectively. Columns 1 and 4 report the results from the entire sample. Columns 2 and 5 (Columns 3 and 6) report the analysis of same-direction (opposite-direction) subsample. Same-direction (opposite-direction) subsample contains those stocks in which both types of institutions herd on the buy side or sell side together (opposite sides). We measure CEI following Daniel & Titman (2006) as $CEI_{i,t} = log(me_{i,t}/me_{i,t-15}) - r_{i,t-15:t}$, where $r_{i,t-15:t}$ is the cumulative log returns. Other control variables are defined in appendix B. The data covers the period from January 1980 to December 2018. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

the effect of intangible information is weaker on short-horizon institutional buying compared to that of long-horizon institutions. Additionally, unlike our portfolio analysis, we do not see a significant counter trading by institutions with shorter investment horizon in the opposite direction subsample.

Overall, long-horizon institutions buy stocks with positive intangible information and sell stocks with negative intangible information whereas short-horizon institutions trade independent of intangible information. This evidence suggest that institutions heterogeneous in investment horizons behave differently to intangible information, unlike Jiang (2010). This evidence complements the results in Edelen et al. (2016) which finds that institutions trade against the prescriptions of anomalies, i.e., they buy stocks prescribed as overvalued and sell stocks prescribed as undervalued by the anomaly. In our study, we find that this is true only for long-horizon institutions which trade against the prescriptions of composite equity issuance anomaly whereas although short-horizon institutions trade both according to and against the prescriptions of anomalies, their trading is not statistically significant. Since long-horizon institutions trade in the direction of intangible information, they may exacerbate the market overreaction and therefore contribute to the book-to-market effect. Alternatively, there might be under-reaction in the market. In that case, we might see a reduction in book-to-market effect. Similarly, short-horizon institutional trading may or may not improve the stock price discovery process. In the next section, we investigate whether trading by each type of institution in response to intangible information enhances or mitigates the return reversals associated with intangible information.

4.3.3 Other Trading Preferences of Institutions with Different Investment Horizons

The coefficients of other control variables exhibit both differences and similarities in preferences of both types of institutions. Both types of institutions tend to follow their lag trades. There is a strong positive correlation between the institutional trades in adjacent quarters, as shown by Tables 4.4 and 4.5. Both types of institutions tend to follow recent winners and sell recent losers as indicated by the coefficients on $Ret_{t-3,t-1}$ that controls for momentum. Hence, in line with Sias (2005), Bennett et al. (2003), and Yan & Zhang (2009), we find that these institutions are momentum traders.

Long-term past returns ($Ret_{t-16,t-5}$) are positively associated with long-horizon institutional buying negatively associated with long-horizon institutional selling suggesting that they buy winners and sell. Yan & Zhang (2009) also find that change in long-horizon institutional ownership is positively associated with past long-term returns. However, they could not find statistically significant results. Contrarily, short-horizon institutions tend to buy long-term past losers and sell long-term past winners. This suggest that they trade to exploit the predictions of past returns. These results are in sharp contrast with the evidence of a positive relationship between change in short-horizon institutional ownership and past long-term returns in Yan & Zhang (2009). They, however, found a weak evidence since only 25 out 94 coefficients are positive.

Long-horizon institutions tend to sell large, liquid, and old stocks and buy young stocks. Short-horizon institutions tend to buy small, illiquid, and young stocks and sell liquid stocks. Despite the methodological differences this evidence is mostly in line with Yan & Zhang (2009). Moreover, our findings are not robust across the subsamples.

4.4 The Price Impact of Trading driven by Intangible Information

Institutions tend to herd in a destabilizing manner and damage the stock price discovery (Dasgupta et al., 2011a; Gutierrez & Kelley, 2009). In contrast, Wermers (1999), Sias (2004), and several other studies document institutions as sophisticated investors. An in depth look into the dichotomy between long- and short-horizon institutions reconciles the two strands of literature. Studies (Yan & Zhang, 2009; Yuksel, 2015) find that short-horizon institutions represent the sophisticated portion of investors. In contrast, long-horizon institutions are price destabilizers. We find evidence of intangible information-motivated long-horizon institutional buying and selling, but short-horizon institutions trade independent of intangible news. If these institutions trade this way since they know the true value of the stocks or, in other words, they have private information, we should expect them to correct prices or to impact prices permanently. The behavioral literature associates market overreaction to the behavioral biases of the investors (Barberis et al., 1998; Daniel et al., 1998). Hence, if they are following intangible information due to behavioral concerns such as reputation (see, e.g., Scharfstein & Stein (1990)), then we should expect prices to move further away from the intrinsic value. In this section, we investigate the price impact of the trading strategies of each institution type. We use a regression methodology similar to section 5 to test our hypotheses. The regression model is

$$\begin{aligned} R_{i,t+1:t+h} = \alpha + \beta_1 CEI_t + \beta_2 CEI_{i,t-1} * BHerd^{LHI}_{i,t} + \beta_3 CEI_{i,t-1} * SHerd^{LHI}_{i,t} \\ + \beta_4 CEI_{i,t-1} * BHerd^{SHI}_{i,t} + + \beta_5 CEI_{i,t-1} * SHerd^{SHI}_{i,t} + \beta_6 BHerd^{LHI}_{i,t} + \beta_7 SHerd^{LHI}_{i,t} \\ + \beta_8 BHerd^{SHI}_{i,t} + \beta_9 SHerd^{SHI}_{i,t} + \beta_{10} \Delta IO^{SHI}_{i,t} + \beta_{11} IO^{SHI}_{i,t-1} + \beta_{12} \Delta IO^{LHI}_{i,t} + \beta_{13} IO^{LHI}_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{4.8}$$

where R is the market-adjusted returns cumulated over quarters *t+1* to *t+h*, and h can be 2 or 8. The eight-quarter returns are investigated since the correction in stock prices may be observed beyond one year. CEI controls for market overreaction to intangible information. Interaction between CEI in quarter *t-1* and institutional trading measures in quarter *t* captures institutional trading in the direction of intangible information. Since adjusted herding measures can not be used directly in our specification, we interact CEI with buy and sell trading measures. This way allows us to model the asymmetric impact of buying and selling. We replace missing values of $BHerd_{i,t}$ and $SHerd_{i,t}$ with zeroes. $CEI_{i,t-1} * BHerd_{i,t}^{LHI}$ and $CEI_{i,t-1} * SHerd_{i,t}^{LHI}$ capture buying and selling of long-horizon institutions in the direction of intangible information . If $\beta 2$ is positive (negative) than our specification suggests that long-horizon institutional buying in response to intangible news reduces (exacerbates) the mispricing. A positive (negative) $\beta 3$ suggests enhanced (decreased) return reversals against institutional selling following intangible news. Similarly, $CEI_{i,t-1} * BHerd_{i,t}^{SHI}$ and $CEI_{i,t-1} * SHerd_{i,t}^{SHI}$ capture short-horizon institutional trading in the direction of intangible information.

We use $\Delta IO_{i,t}^{SHI}$ and $\Delta IO_{i,t}^{LHI}$ to control for the informational advantages of short- and long-horizon institutions. Besides, lagged institutional ownership controls for institutional demand shocks. Gompers & Metrick (2001) argue that the change in institutional ownership and one quarter lagged institutional ownership track the source of the positive price impact of the institutional-ownership. If the change in institutional ownership is positive and significant, then the "informational advantage" of institutions drives the positive price impact of institutional ownership. On the other hand, Gompers & Metrick (2001) attribute the impact to institutions' "temporal demand shock" if the coefficient of lagged institutional ownership is positive.[8]

Table 4.6 reports regressions of two-quarter returns in columns 1-3 and eight-quarter returns in columns 4-6. We run the regressions for the entire sample (Full), the same-direction subsample (SD), and the opposite-direction subsample (OD). Negative and significant coefficients of CEI_t suggest that high intangible information predicts low future returns. The negative effect is significant on eight-quarter returns as well. The following sub-section discusses the role of the investment horizon in driving the book-to-market effect. In the

[8]We also included other control variables in our specification to check for robustness. To control for the value effect, we use sales to price and earnings to price ratios. Additionally, we control for variables such as earnings growth (EG), size (CAP), liquidity (Turn), and past returns ($Ret_{i,t-15:t-4}$ and $Ret_{i,t-2:t}$). The control variables are defined in the appendix. They do not change our results, and since these variables are insignificant mostly, we do not use them in our main results here.

later section, we will discuss the same- and opposite-side trading.

4.4.1 The Role of Investment Horizon

In this subsection, we analyze the price impact of intangible information-driven institutional trading using the entire sample.

4.4.1.1 Long-Horizon Institutions

In column 1 of Table 4.6, $CEI_{i,t-1} * BHerd_{i,t}^{LHI}$ negatively predicts two-quarter returns in the full sample. One standard deviation increase in CEI followed by one standard deviation increase in long-horizon institutional trading in quarter t results in 0.272% (0.355×0.089×0.086) lower two-quarters returns, compared to the return reversals associated with CEI alone.

(Yan & Zhang, 2009) posit that LHIs might possess information about the long-term value of the firm; hence, LHIs could be trading based on information and the short-term destabilizing impact might revert in the long-run. Additionally, previous studies argue that LHIs are more concerned with long-term performance, and therefore they influence the firms' managers to improve it (see, e.g., Smith, 1996; Gaspar et al., 2005; Chen et al., 2007). To test that, we re-estimate equation 4.8 using eight-quarter returns as dependent variable. The coefficient of interaction term explaining eight-quarter returns is negative and significant (column 4). One standard deviation increase in CEI predicts a decrease in eight-quarter returns by 3.12%. The drop will be 3.85% (0.355×0.089×0.232+0.0312) if a similar increase in CEI is followed by one standard deviation increase in long-horizon institutional buying. These results suggest that buying by long-horizon institutions magnifies the mispricing caused by market overreaction. Long-horizon institutional selling does not magnify the

Table 4.6: Institutional Trading and Stock Price

	Market-Adjusted Returns					
	$Ret_{t+1,t+2}$			$Ret_{t+1,t+8}$		
	(1) (Full)	(2) (Same)	(3) (Opposite)	(4) (Full)	(5) (Same)	(6) (Opposite)
CEI_t	-0.029^{***}	-0.031^{***}	-0.029^{***}	-0.088^{***}	-0.088^{***}	-0.094^{***}
	(0.006)	(0.006)	(0.008)	(0.023)	(0.022)	(0.027)
$CEI_{t-1} * BHerd_t^{LHI}$	-0.089^{***}	-0.113^{**}	-0.054	-0.232^{**}	-0.237	-0.339^{**}
	(0.033)	(0.055)	(0.060)	(0.111)	(0.166)	(0.149)
$CEI_{t-1} * SHerd_t^{LHI}$	0.001	-0.007	0.062	0.002	0.068	-0.158
	(0.057)	(0.070)	(0.060)	(0.138)	(0.155)	(0.202)
$CEI_{t-1} * BHerd_t^{SHI}$	0.026	0.033	0.076	0.054	0.123	0.076
	(0.041)	(0.060)	(0.083)	(0.100)	(0.138)	(0.193)
$CEI_{t-1} * SHerd_t^{SHI}$	-0.107^{**}	-0.110^{**}	-0.075	0.050	-0.003	0.104
	(0.044)	(0.053)	(0.073)	(0.104)	(0.165)	(0.181)
$BHerd_t^{LHI}$	-0.008	0.001	-0.014	-0.083^{*}	-0.104^{**}	-0.045
	(0.019)	(0.020)	(0.025)	(0.042)	(0.051)	(0.062)
$SHerd_t^{LHI}$	0.005	-0.005	0.021	0.078	0.116	0.030
	(0.016)	(0.020)	(0.019)	(0.066)	(0.074)	(0.065)
$BHerd_t^{SHI}$	0.041^{**}	0.032^{*}	0.051^{***}	0.104^{***}	0.083	0.141^{***}
	(0.017)	(0.019)	(0.019)	(0.034)	(0.052)	(0.047)
$SHerd_t^{SHI}$	-0.027^{**}	-0.032^{**}	-0.022	0.022	0.014	0.022
	(0.012)	(0.015)	(0.020)	(0.045)	(0.050)	(0.055)
ΔIO_t^{SHI}	0.145^{***}	0.098	0.210^{***}	0.116	-0.074	0.354^{**}
	(0.048)	(0.060)	(0.047)	(0.109)	(0.139)	(0.141)
IO_{t-1}^{SHI}	0.046	0.042	0.053	0.073	0.023	0.142
	(0.036)	(0.039)	(0.036)	(0.103)	(0.105)	(0.107)

Table 4.6: (Cont'd)

	Market-Adjusted Returns					
	$Ret_{t+1,t+2}$			$Ret_{t+1,t+8}$		
	(1) (Full)	(2) (Same)	(3) (Opposite)	(4) (Full)	(5) (Same)	(6) (Opposite)
ΔIO_t^{LHI}	−0.022	0.014	−0.063	−0.054	−0.054	−0.049
	(0.037)	(0.041)	(0.051)	(0.087)	(0.119)	(0.081)
IO_{t-1}^{LHI}	−0.004	−0.015	0.007	−0.092	−0.148**	−0.035
	(0.018)	(0.019)	(0.023)	(0.059)	(0.063)	(0.065)
Constant	0.008	0.009	0.007	0.038	0.048*	0.026
	(0.009)	(0.009)	(0.010)	(0.029)	(0.028)	(0.030)
Avg. N	1569	827	742	1444	763	681
Observations	214,980	113,360	101,620	189,172	99,937	89,235
R^2	0.071	0.082	0.083	0.064	0.075	0.078

This table reports coefficients and Newey-West corrected standard errors (in brackets) from the regression of two- or eight-quarter cumulative returns on institutional trading measures interacted with composite equity issuance and other explanatory variables following the methodology in Fama & Macbeth (1973). We classify institutions as short- and long-horizon based on the past four-quarter average churn rate, as in Yan & Zhang (2009). $BHerd^{LHI}$ ($BHerd^{SHI}$) and $SHerd^{LHI}$ ($SHerd^{SHI}$) are the conditional LSV herding measures representing buy and sell herding by long-horizon (short-horizon) institutions, respectively. Same-direction subsample (columns 2 & 5) contains those stocks in which both types of institutions herd in the same direction (sign($ADJH^{SHI}$)=sign($ADJH^{LHI}$). The opposite-direction subsample (columns 3 & 6) is the subsample of stocks for which sign($ADJH^{SHI}$)≠sign($ADJH^{LHI}$. CEI is $CEI_{i,t} = log(me_{i,t}/me_{i,t-15}) - r_{i,t-15:t}$, where $r_{i,t-15:t}$ is the cumulative log returns. The data covers the period 1980Q1 to 2018Q4. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

CEI related return reversals as suggested by the coefficients of $CEI_{i,t-1} * SHerd_{i,t}^{LHI}$ in columns 1 and 4. These results are in line with Gutierrez & Kelley (2009), who study institutions as a group and observes return reversals against herding on the buy side only. However, in Cai et al. (2019), institutional buy-herding (which is less pronounced than sell-herding) improves price discovery process in the bond market.

In summary, the evidence suggests that the long-horizon institutional buying driven by intangible information is behaviorally biased. In contrast, their selling activity seems neither informed nor behaviorally motivated. Overall, we side with Yan & Zhang (2009) regarding the informativeness of long-horizon institutions.

4.4.1.2 Short-Horizon Institutions

Short-horizon institutional buying driven by intangible news does not predict future returns, as indicated by an insignificant coefficient on $CEI_{i,t-1} * BHerd_{i,t}^{SHI}$. Unlike long-horizon institutions, short-horizon institutions do not magnify CEI related reversals. $CEI_{i,t-1} * SHerd_{i,t}^{SHI}$ is negative and significant. One standard deviation decrease in CEI followed by one standard deviation increase in short-horizon institutional herding in quarter t results in 0.31% (0.355×0.082×0.107) higher two-quarters returns, compared to the return reversals associated with CEI alone. The price impact is not observed in the long-run suggesting that eight-quarter period is too long of a horizon for short-horizon institutions. These results commensurate with previous studies (Porter, 1992; Bushee, 1998, 2001; Yan & Zhang, 2009; Yuksel, 2015) which posit that short-horizon institutions trade on information about the short-term value. Therefore, the impact of their trading on long-term returns seems irrelevant to argue about their informativeness.

We saw in the previous section that short-horizon institutions buy and sell independent of intangible information. This suggests that they do not add to the mispricing caused by market overreaction to intangible information. However, we see here that the short-horizon institutional selling in response to negative intangible news mitigates the mispricing. This suggests that short-horizon institutions trade not in a way to exploit the mispricing caused by market overreaction, however, their selling in the same direction to intangible information is informed. Furthermore, the stabilizing impact does not go beyond two quarters suggesting short-term private information. Once again our findings regarding the informativeness of short-horizon institutions side with Yan & Zhang (2009).

Coefficients of other control variables show expected signs. High long-horizon institutional buy herding ($BHerd_{i,t}^{LHI}$) predicts low eight-quarter returns in the full sample suggesting a price destabilization. However, it loses its significance while explaining short-term returns. The coefficient of herding by short-horizon institutions ($BHerd_{i,t}^{SHI}$) is positive and significant for two-quarter returns. These results are similar to Yuksel (2015). Short-horizon institutions have an informational advantage as suggested by the coefficients of ΔIO_t^{SHI}. Furthermore, ΔIO_t^{LHI} and IO_{t-1}^{LHI} are insignificant in predicting returns.

4.5 The Same- and Opposite-Side Trading

We show that institutions with different horizons trade together in the same direction as well as against each other in the opposite direction. Moreover, intangible information significantly impacts same- and opposite-side long-horizon institutional trading whereas it is insignificantly related to same- and opposite-side short-horizon institutional trading. Therefore, we hypothesize that same- and opposite-side long-horizon institutional trading destabilize stock prices and contribute to the book-to-market effect.

A competing scenario is that since long-horizon institutional trading coincides with that of relatively informed trading of short-horizon institutions, they may have correlated private information. Or, long-horizon institutions follow their short-horizon counterpart due to the better informativeness of the later. Under this scenario, their same-side trading represents informational herding rather than behavioral. Lakonishok et al. (1992) argue that the herding due to informational reasons stabilizes stock price. If we interpret same-side trading this way, we can expect to get an insignificant or a positive price impact in the same-side trading.

The results show that long-horizon institutional buying exacerbates the market-overreaction to intangible information in the same- and opposite-direction subsample. $CEI_{i,t-1} * BHerd_{i,t}^{LHI}$ negatively significantly predicts two-quarter returns in the same-direction subsample and eight-quarter returns in the opposite-direction subsamples. One standard deviation increase in CEI followed by one standard deviation increase in long-horizon institutional buying in quarter t results in 0.36% (0.355×0.089×0.113) lower two-quarters returns, compared to the return reversals associated with CEI alone in the same-direction sub-sample. Moreover, the enhanced return reversals are not observed for eight-quarter returns.

The exacerbated long-term return reversals are also observed in the opposite direction subsample (column 6) although the short-term reversals are not significant. $CEI_{i,t-1} * BHerd_{i,t}^{LHI}$ predicts long-term return reversals in the opposite-direction subsample. These results suggest that when short- and long-horizon institutions coincide in there trading behavior the returns get back to their equilibrium level quicker than when they trade in the opposite direction. Overall, the same-direction trading of long-horizon institutions in the direction of intangible information exacerbate short-term return reversals, and the opposite-side trading of these institutions magnify long-term return reversals. $CEI_{i,t-1} * SHerd_{i,t}^{LHI}$ is insignificant in both subsamples as before.

Unlike long-horizon institutions, short-horizon institutions do not add to the mispricing. $CEI_{i,t-1} * SHerd_{i,t}^{SHI}$ insignificantly predicts two- and eight-quarter returns in the same- and opposite-direction subsample. However, the $CEI_{i,t-1} * SHerd_{i,t}^{LHI}$ is only significant in predicting two-quarter returns in the same-direction subsample. One standard deviation decrease in CEI followed by one standard deviation increase in short-horizon institutional selling in quarter t reduces the return reversals by 0.31% (0.355×0.091×0.097). These results are in line with our previous findings regarding the informativeness of short-horizon institutions.

In summary, as long-horizon institutions trade in the direction of intangible information regardless of whether they are trading in the same- or opposite-direction to short-horizon institutions, their trading negatively affects the stock price discovery process. However, this is true only for their buy-side trading. And, even though short-horizon institutions trade independent of intangible information, we see a mitigating effect of their same-side selling on short-term return reversals associated with intangible information. We do not see any results supporting informational herding on the part of long-horizon institutions.

4.6 Conclusion

In this study, we show that only institutions with longer investment horizons trade in the direction of intangible information and contribute to market overreaction. Besides, the price destabilization is seen on the buy-side only. Short-horizon institutions do not seem to follow intangible information and magnify the mispricing caused by market overreaction.

Furthermore, we find that long-horizon institutions' same- and opposite-side trading contribute to the book-to-market effect whereas the same- and opposite-side trading of short-horizon institutions do not drive the book-to-market effect by magnifying the market overreaction.

This evidence is in sharp contrast to that in the previous studies which find institutions as unsophisticated altogether. Our findings support and complement those of Yan & Zhang (2009) that short-horizon institutions are better informed than long-horizon institutions. Our findings do not support the efficient markets view in the case of long-horizon institutions. They might have reputational concerns, as in Scharfstein & Stein (1990), which lead them to follow their peers and move stock prices away from their fundamental values. Conversely, we fail to reject the sophisticated institutions hypothesis in favor of short-horizon institutions.

Our findings have implications for identifying informed and skilled investors. We also highlight the importance of coinciding and differing strategies for understanding the behavior of institutions and the price discovery process. Our study also identifies new areas of investigation. First, we do not know when institutions with different investment horizons trade together in the same direction and trade in the opposite direction. Second, we see price destabilization only on the buy-side (long-horizon institutional buying) and price stabilization only on the sell-side (short-horizon institutional selling).

CHAPTER V

CONCLUSIONS

Financial institutions hold almost 63% of the market in 2018. Their large presence in the market can have consequences for the stock price formation, especially when they herd. A popular belief is that they are rational traders and improve the market efficiency. However, a large portion of the literature conclude against their roles as price stabilizers. It is important to understand their behavior well enough. To add to the existing body of knowledge about institutional behavior, we investigate the same- and opposite-side herding by institutions with different investment horizons. Institutions' trading, if behaviorally motivated, can exacerbate the market overreaction to intangible information that the literature documents as a driver of the book-to-market effect. To further enhance the understanding of institutional behavior and the value effect, we do an in-depth analysis of institutional trades and their role in driving the value effects.

First, we investigate the price impact of same- and opposite-side herding of short- and long-horizon institutions. The same-side herding happens when both types of institutions herd together in the same direction, and the opposite-side herding occurs when both types of institutions herd on the opposite side, i.e., one type of institution herds on the buy side while the other type sells or vice versa. We obtain the same- and opposite-direction subsamples of stocks that represent same- and opposite-side herding, respectively. Then, in each subsample, we regress stock returns on short- and long-horizon institutional herding measures (the measure proposed by Dasgupta et al. (2011a)) and other control variables using regression methodology of Fama & Macbeth (1973). We find that the previously documented negative impact of long-horizon institutional herding does not hold in the same-direction subsample. Although we do not rule out alternative explanations, we associate these findings to long-horizon institutions' tendency to follow short-horizon institutions and forming an informational cascade with in the framework of Bikhchandani et al. (1992). We further find that the long-horizon institutions destabilize stock prices in the opposite-direction subsample. Thus, the previous findings regarding the role of long-horizon institutional herding in price destabilization are specific to the opposite-direction subsample.

Moreover, short-horizon institutional herding does not destabilize stock prices in both sub-samples. These findings are consistent with earlier results suggesting that the short-horizon institutions are relatively informed.

Second, we investigate the contribution of each type of institution in value effect. There is considerable evidence in the literature that high book-to-market stocks earn high future returns. Many explanations are put forwarded in the literature including the institutional role in driving the value effect. That is, institutional trading in the direction of intangible information (i.e., they buy high intangible-return stocks and sell low intangible return stocks) leads to the magnified reversals of intangible returns. Since high book-to-market stocks tend to have poor past intangible returns, they earn higher future returns. We associate the value effect to investment horizon of institutions. We show that the institutional contribution to the book-to-market effect is conditional on the investment horizon of institutions.

Using panel regressions, we show that short-horizon institutional trading is insignificantly related to past intangible information proxied by composite equity issuance whereas long-horizon institutional trading is positively significantly related to past intangible information. Then, we show that short-horizon institutional trading in the direction of intangible information does not magnify the intangible return reversals. However, long-horizon institutional trading in the direction of intangible information exacerbate the intangible return reversals. These results suggest that only long-horizon institutions buy or sell in response to intangible information which enhances the market overreaction, and thus result in the future return reversals.

Our results highlight the role of investment horizon of institutions in book-to-market effect which was previously associated with all institutions as a group. These results further confirm the informativeness of short-horizon institutions compared to long-horizon institutions whose trades could be behaviorally motivated.

Overall, our results further confirm the previous findings regarding the informativeness of short-horizon institutions. For long-horizon institutions, we find that they do not always affect the price stability, negatively. Specifically, when they trade in tandem with short-horizon institutions they do not destabilize the stock prices. Similarly, the role of long-horizon institutions in driving the market overreaction and the value effect also confirms these findings. All these findings increase our understanding of the role of these institutions in improving the market efficiency.

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APPENDIX A

SUPPLEMENTARY MATERIAL FOR "THE PRICE IMPACT OF SAME- AND OPPOSING-DIRECTION HERDING BY INSTITUTIONS WITH DIFFERENT INVESTMENT HORIZONS"

This document reports the descriptive statistics and robustness tests on the price impact of short- and long-horizon institutional trade persistence. Section A.1 reports the descriptive statistics for all institutions, short-horizon institutions, and long-horizon institutions. Section A.2 presents robustness checks. First, we keep all institutions including those that change their investment horizon. The results are similar to those of the main analysis. Second, we control for the alternative measure of past returns. In summary, our main findings are robust to aforementioned methodological concerns.

A.1 Institutional Data Description

Table A.1 reports number of managers (N), managers' Mean equity holdings (Mean), value of holdings in aggregate institutional portfolio (Aggregate), and institutions' share of market (Share) for all institutions, SHIs, and LHIs in the last quarter of every even year from 1980 to 2018. This table includes all institutions with share holdings available for the previous five quarters to estimate average turnover. Furthermore, only shares with SHRCD 10 or 11 are considered to estimate the churn rate.

The total number of managers increases over the years from 450 in 1982 to 3,887 in 2018. SHIs and LHIs represent 1/3 of the total number of institutions as they belong to the top and bottom terciles. The average value managed by all institutions, SHIs, and LHIs has increased over the years. Besides, average holdings (in $s) exhibit major setbacks from an increasing trend in 2002 and 2008. Value managed by an average LHI is considerably higher than that of an average SHI in all years. Aggregate institutional holdings for all institutions grew from approximately $398.68 billion in December 1982 to $15,658 billion in December 2018. For SHIs, aggregate holdings grew from approximately $125 billion to approximately $2,517 billion during the same period. Finally, LHIs held $126 billion in December 1982 that grew to $6,435 billion in December 2018. To put the value of the aggregate institutional portfolio in perspective, we also report it as a percentage of the market value of all the stocks in CRSP (Share). The proportions of the market controlled by all institutions, SHIs, and LHIs in 1982 were 32.2%, 10.06%, and 10.18%, respectively. The fraction grows to 62.78% for all institutions and 25.8% for LHIs. In contrast, the proportion managed by SHIs in 2018 has remained almost same in 2018. SHIs do not hold a big share of the market compared to LHIs.

Table A.1: Descriptive Statistics: Institutions

Year	All				SHI				LHI			
	N	Mean ($mill.)	Aggregate ($bill.)	Share (%)	N	Mean ($mill.)	Aggregate ($bill.)	Share (%)	N	Mean ($mill.)	Aggregate ($bill.)	Share (%)
1982	450	885.96	398.68	32.13	150	832	124.8	10.06	150	842.61	126.39	10.18
1984	511	992.53	507.18	33.41	171	875.27	149.67	9.86	171	1078.17	184.37	12.14
1986	593	1252.42	742.68	34.95	198	939.87	186.09	8.76	198	1464.7	290.01	13.65
1988	685	1241.22	850.23	37.61	229	948.01	217.09	9.6	229	1506.26	344.93	15.26
1990	785	1293.45	1015.36	40.66	262	928.52	243.27	9.74	262	1631.04	427.33	17.11
1992	851	1943.84	1654.21	44.17	284	1542.41	438.04	11.7	284	2565.84	728.7	19.46
1994	834	2022.06	1686.4	39.69	278	1795.65	499.19	11.75	278	2148.86	597.38	14.06
1996	923	3625.02	3345.9	46.54	308	1983.7	610.98	8.5	308	3584.65	1104.07	15.36
1998	1139	4828.6	5499.77	47.39	380	3232.33	1228.29	10.58	380	4280.68	1626.66	14.02
2000	1383	5309.6	7343.18	53.82	461	2606.36	1201.53	8.81	461	5463.42	2518.64	18.46
2002	1390	3578.19	4973.68	53.1	464	1478.82	686.17	7.33	464	3545.5	1645.11	17.57
2004	1769	4276.35	7564.86	55.74	590	1863.3	1099.35	8.1	590	4777.75	2818.87	20.77
2006	2135	4795.08	10237.49	65.27	712	1692.18	1204.83	7.68	712	6040.03	4300.5	27.42
2008	2440	2564.73	6257.93	64.78	814	1013.07	824.64	8.54	814	2858.23	2326.6	24.09
2010	2420	3602.05	8716.96	62.11	807	1409.13	1137.17	8.1	807	3751.11	3027.15	21.57
2012	2805	3719.08	10432.02	68.12	935	1399.22	1308.27	8.54	935	4589.58	4291.25	28.02
2014	3242	4802.98	15571.25	69.81	1081	1724.71	1864.41	8.36	1081	6344.44	6858.34	30.75
2016	3509	4625.25	16230.01	70.34	1170	1714.11	2005.5	8.69	1170	6106.91	7145.09	30.97
2018	3887	4028.35	15658.18	62.78	1296	1942.02	2516.85	10.09	1296	4965.25	6434.96	25.8

Note: This table reports number (N) of managers, mean value of equity holdings (Mean), the value of holdings in aggregate institutional portfolio (Aggregate), and market share (Share), for all institutions, short- and long-horizon institutions, in the last quarter of every 2 years. Institutions are classified using a similar methodology to Yan & Zhang (2009). Only managers with data available in last five quarters (including current quarter) are included. Mean represents the mean value of equity managed by institutions. Aggregate represents the aggregate value of equity managed by institutions. Market share is calculated as $\frac{\text{Market value of institutional portfolio}}{\text{Market value of all stocks in CRSP}}$.

A.2 Robustness Checks

A.2.1 Keeping All Institutions

Table A.2 reports predictive regressions of two- and eight-quarter returns on TP^{SHI}, TP^{LHI}, and other control variables similar to panel B of Table 3 (excluding stocks with minimum trade persistence). More importantly, we include 1,545 institutions that changed their horizon status in our analysis here. Our results do not change except that the SHIs are positively predicting the short-term stock returns. The findings of non-destabilizing impact of SHIs' herding and the destabilizing impact of LHIs' herding are robust to the inclusion of all institutions.

A.2.2 Alternative Return Reversals

Fama & French (1996) suggest skipping one year after the formation period for better contrarian results. Secondly, short-term continuation and long-term reversals might offset each other. Skipping one year avoids this phenomenon. Lastly, in Bondt & Thaler (1985), the first 12 months of the holding period do not result in significant abnormal returns. $R_{i,t-15:t-4}$ is the cumulative return from quarter t-15 to t. In Table A.3, we control for past returns cumulated over quarters t-15 to t-4. We exclude institutions that change their horizon at least once during the sample period. Besides, we remove stocks with minimum trade persistence, that are the stocks having $ABS(TP^{SHI}) = ABS(TP^{LHI}) = 1$. Our main findings do not change after making these adjustments.

Table A.2: Robustness Check (Keeping All Institutions)

	Market-Adjusted Returns					
	Ret_{t+1}			$Ret_{t+1,t+8}$		
	(SD)	(OD)	(FULL)	(SD)	(OD)	(FULL)
TP^{SHI}	0.001**	−0.0001	0.001**	−0.002	−0.004	−0.002
	(0.0005)	(0.001)	(0.0003)	(0.002)	(0.003)	(0.002)
TP^{LHI}	−0.001	−0.002***	−0.001**	−0.004*	−0.009***	−0.005***
	(0.001)	(0.001)	(0.0003)	(0.002)	(0.003)	(0.001)
IO^{LHI}	−0.004	0.010	0.004	−0.032	−0.001	0.003
	(0.012)	(0.010)	(0.009)	(0.043)	(0.042)	(0.041)
IO^{SHI}	0.024*	0.048***	0.040***	0.136***	0.118**	0.142***
	(0.014)	(0.013)	(0.011)	(0.049)	(0.058)	(0.047)
CF/P	0.011	0.008	0.008	0.077	0.104*	0.101*
	(0.009)	(0.009)	(0.007)	(0.055)	(0.057)	(0.055)
Sale/P	0.001	0.001*	0.001	0.010***	0.010***	0.008**
	(0.001)	(0.001)	(0.0005)	(0.004)	(0.004)	(0.003)
E/P	−0.006	0.004	0.004	−0.094	−0.080	−0.145
	(0.017)	(0.016)	(0.013)	(0.105)	(0.111)	(0.116)
EG	0.00003	0.001	0.001	0.033	0.011	0.049
	(0.008)	(0.007)	(0.004)	(0.040)	(0.030)	(0.034)
B/M	−0.005*	−0.002	−0.003*	−0.012	−0.012	−0.010
	(0.003)	(0.002)	(0.002)	(0.011)	(0.017)	(0.011)
CAP	−0.0003	−0.001	−0.001	−0.007	−0.008	−0.008
	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)	(0.007)
TURN	−0.012	−0.036**	−0.026	−0.094	−0.086	−0.071
	(0.019)	(0.018)	(0.016)	(0.091)	(0.119)	(0.094)
$Ret_{t-15,t}$	−0.001	−0.0002	−0.001	−0.007	−0.008	−0.007
	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.006)
CSI	−0.013***	−0.015***	−0.015***	−0.099***	−0.089***	−0.098***
	(0.003)	(0.004)	(0.003)	(0.018)	(0.016)	(0.017)
Constant	0.004	0.003	0.004	0.060	0.061	0.062
	(0.010)	(0.011)	(0.010)	(0.064)	(0.065)	(0.062)
Avg. N	767	771	2065	939	706	1889
Observations	106,583	107,188	287,095	123,893	93,128	249,309
R^2	0.112	0.121	0.099	0.108	0.106	0.092

Note: This table reports coefficients and standard errors corrected for autocorrelation (in brackets) from the regression of one- and eight-quarter cumulative market-adjusted returns on TP^{SHI}, TP^{LHI}, and other control variables following Fama & Macbeth (1973), in each of the same direction sub-sample (SD), opposite-direction sub-sample (OD) and full sample (FULL). The data covers the period 1980Q1 to 2018Q4. *, **, and *** represent the statistical significance of coefficients at 10%, 5%, and 1%, respectively.

Table A.3: Robustness Check (Alternative Return Reversals)

	Market-Adjusted Returns					
	Ret_{t+1}			$Ret_{t+1,t+8}$		
	(SD)	(OD)	(FULL)	(SD)	(OD)	(FULL)
TP^{SHI}	0.0004	0.0002	0.001^{***}	-0.002	-0.006^{**}	-0.001
	(0.001)	(0.0004)	(0.0003)	(0.003)	(0.003)	(0.002)
TP^{LHI}	0.00004	-0.002^{***}	-0.001^{**}	-0.002	-0.009^{***}	-0.004^{***}
	(0.0005)	(0.001)	(0.0003)	(0.002)	(0.003)	(0.002)
IO^{LHI}	-0.002	0.010	0.005	-0.003	0.054	0.031
	(0.013)	(0.014)	(0.011)	(0.055)	(0.057)	(0.050)
IO^{SHI}	0.037^{**}	0.047^{***}	0.044^{***}	0.126^{*}	0.074	0.095
	(0.017)	(0.017)	(0.015)	(0.068)	(0.078)	(0.064)
CF/P	0.008	0.011	0.008	0.066	0.107^{*}	0.097^{*}
	(0.010)	(0.009)	(0.008)	(0.062)	(0.060)	(0.055)
Sale/P	0.001	0.002^{**}	0.001	0.011^{***}	0.012^{***}	0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
E/P	0.003	0.008	0.004	-0.128	-0.043	-0.138
	(0.017)	(0.016)	(0.014)	(0.137)	(0.109)	(0.125)
EG	-0.001	0.007	0.004	0.036	0.053	0.042
	(0.008)	(0.008)	(0.005)	(0.053)	(0.032)	(0.044)
B/M	-0.004^{*}	-0.004	-0.003	-0.007	-0.017	-0.011
	(0.002)	(0.003)	(0.002)	(0.014)	(0.017)	(0.013)
CAP	-0.001	-0.001	-0.001	-0.006	-0.011	-0.008
	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)	(0.007)
TURN	-0.031	-0.012	-0.024	-0.071	-0.100	-0.077
	(0.019)	(0.021)	(0.017)	(0.110)	(0.118)	(0.107)
$Ret_{t-15,t-4}$	-0.002	-0.001	-0.001	-0.006	-0.0004	-0.004
	(0.001)	(0.001)	(0.001)	(0.004)	(0.006)	(0.004)
CSI	-0.011^{***}	-0.017^{***}	-0.014^{***}	-0.098^{***}	-0.098^{***}	-0.100^{***}
	(0.003)	(0.004)	(0.003)	(0.017)	(0.020)	(0.018)
Constant	0.009	0.008	0.008	0.055	0.079	0.067
	(0.010)	(0.012)	(0.011)	(0.066)	(0.067)	(0.066)
Avg. N	753	749	1502	687	683	1370
Observations	104,691	104,090	208,781	90,649	90,154	180,803
R^2	0.112	0.118	0.100	0.131	0.106	0.103

Note:This table reports coefficients and standard errors corrected for autocorrelation (in brackets) from the regression of one- and eight-quarter cumulative market-adjusted returns on TP^{SHI}, TP^{LHI}, and other control variables following Fama & Macbeth (1973), in the same- (SD) and opposite-direction sub-samples. The data covers the period 1980Q1 to 2018Q4. *, **, and *** represent the statistical significance of coefficients at 10%, 5%, and 1%, respectively.

APPENDIX B

DEFINITIONS OF VARIABLES

1. *Sale/Price (S/P)* is the revenues from the end of the fiscal year ending in last calendar year divided by the market equity at the end of last calendar year. It is employed from June of the current year through May of next year.

2. *Earnings/Price (EP)* is the income from the extraordinary items divided by the market equity. Like sale/price, the numerator is from the end of the fiscal year, and the denominator is the end of the calendar year value. It is employed from June of the current year through May of next year.

3. *Earnings Growth (EG)*, employed starting from June of the current year, is the yearly change in the income before extraordinary items last year divided by the calendar year-end market equity.

4. *Size (CAP)* is the natural log of market capitalization at the end of the current quarter.

5. *Share Turnover (Turn)*, in the current quarter, is equal to the volume of shares traded divided by the number of outstanding shares.

6. $Ret_{t-15,t}$ is equal to the returns cumulated over past four years.

7. $Ret_{t-3,t-1}$ is the cumulative return from quarter *t-3* to quarter *t-1*.

8. $Ret_{t-16,t-5}$ $\mathrm{Ret}_{\mathrm{i,t\text{-}16:t\text{-}5}}$ is the cumulative return from quarter t-16 to quarter t-5.

9. *Age* is the number of months since the stock first appears in monthly CRSP data divided by 12.