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Three Essays on Institutional Investing

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To my family

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Resumen

Esta tesis estudia las transacciones de una muestra grande de inversores institucionales de EE.UU. y examina el rol de este sub-grupo de inversores en el fomento de mercados más eficientes. El primer capítulo estudia la existencia de un vínculo directo entre los inversores institucionales y los co-movimientos de la liquidez observados en los mercados bursátiles. A diferencia de otros estudios que emplean diferentes proxies para el comercio agregado institucional, este trabajo utiliza una base de datos distribuida por ANcerno Ltda. que provee datos de alta frecuencia de transacciones institucionales. La evidencia empírica sugiere que los co-movimientos de la liquidez aumentan con la actividad comercial institucional a nivel agregado. Los resultados de las negociaciones bursátiles institucionales para pares de acciones sugieren que esta relación es una consecuencia de la correlación en las transacciones. Los resultados son robustos a diferentes especificaciones, formas funcionales y sub-muestras basadas en características de las acciones y periodos de tiempo. Además, utilizando el escándalo de los fondos mutuos de 2003, se observa alguna evidencia de un vínculo causal entre la co-variación de la liquidez y las operaciones comerciales institucionales a nivel agregado. El segundo capítulo investiga las fuentes de la relación contemporánea entre los cambios de propiedad institucional y los retornos trimestrales, examinando la relación transversal diaria e intradiaria entre retornos y desequilibrios institucionales de oferta-demanda. Los hallazgos empíricos sugieren que la relación contemporánea trimestral (diaria) está determinada principalmente por inversores institucionales siguiendo los movimientos intra-trimestrales (intra-diarios). No se encuentra evidencia que apoye la habilidad de los inversores institucionales para predecir retornos intra-trimestrales (intra-diarios). De otro lado, el comercio institucional de momentum de corto plazo no parece tener un efecto desestabilizador en los precios de los activos. El tercer capítulo brinda evidencia sobre el comportamiento institucional de manada en el corto plazo. En el estudio se encuentra una evidencia débil de comportamiento de manada, lo cual es consistente con los resultados trimestrales encontrados en otros artículos. Además, en concordancia con la literatura previa, los resultados sugieren que el comportamiento de manada desde el lado de la demanda tiene un efecto estabilizador sobre los precios, mientras que, desde el lado de la oferta, tiene un efecto desestabilizador. Finalmente, la persistencia en el comportamiento institucional de manada es un predictor fuerte de la reversión de los retornos.

Abstract

This thesis studies the trading activities for a large sample of the U.S. institutional investors and examines the role played by this sub-group of investors in promoting more efficient markets. The first chapter addresses the question of whether there is a direct link between institutional trading activities and liquidity co-movement observed in equity markets. Unlike the previous studies that employ different proxies for the aggregate institutional trading, I use a proprietary database distributed by ANcerno Ltd., that provides high-frequency institutional transaction data. The empirical evidence suggests that commonality in liquidity increases with the aggregate institutional trading activity. The results of common institutional trading for pairs of stocks suggest that this relationship is a consequence of correlated trading . The findings are robust to different specifications, functional forms and sub-samples based on stock characteristics and time periods. Furthermore, using the mutual fund scandal of 2003, I find some evidence of causal link between commonality in liquidity and institutional trading activity. The second chapter investigates the sources of the contemporaneous relation between the changes in institutional ownership and returns found at quarterly intervals by examining the daily and intradaily cross-sectional relation between institutional buy-sell imbalances and returns. The empirical findings suggest that the quarterly (daily) contemporaneous relation is mainly driven by institutional investors following the intra-quarter (intradaily) price movements. I do not find any evidence to support the institutional investors' ability to predict intra-quarter (intradaily) returns. Additionally, the short-term institutional momentum trading doesn't does not seem to have a destabilizing effect on prices. The third chapter provides empirical evidence on the short-term institutional herding. I document a weak evidence of weekly institutional herding, which is consistent with the quarterly results found in the previous studies. Moreover, in accordance to the the extant literature, I find that buy-side herding has a stabilizing effect on prices, while the sell-side herding affects the prices in a destabilizing manner. Finally, I find that the persistence in institutional herding is a strong predictor of return reversals.

Chapter 1

Introduction

1.1 Introduction and Summary

The key role of the modern capital markets is to facilitate the transfer of funds between firms seeking for financing and fund savers. This main function is carried out by the ease of trading different asset classes, thus helping to share and diversify risk among different market participants. Another key feature of the modern financial markets is the interaction between companies rising capital and institutional investors that manage a growing pool of assets. Most household investors choose to invest in mutual funds, pension funds, or retirement products as their main investment vehicle to minimize the cost of information search and other market frictions. In the United States, for example, traditional institutional investors such as, mutual funds, pension funds, insurance companies, and hedge funds account for over 50% of equity ownership for firms listed on Nyse, Nasdaq, and the Amex exchanges (Federal Reserve Board, 2011). The fact that institutional investments account for such a substantial amount of the U.S. equities and that institutional trading constitutes the main part of the daily trading volume may have a crucial impact on the quality of financial markets. Both the importance of market quality for regulators and other market participants and the growing role of institutional investments motivate this dissertation. In particular, it uses actual institutional transaction data to empirically investigate whether institutional trading activity can explain commonality in liquidity, examine the short-term institutional herding and the impact of short-term herding as well as the persistence in institutional herding on asset prices, and to investigate the daily and intradaily relation between institutional imbalances and returns.

There is a vast literature in finance devoted to examining the growth of institutional shareholdings, the increasingly influential role of institutional investors in financial markets and their impact on firm policies. Khorana, Servaes, and Tufano (2005) investigate the growth of equity ownership in mutual fund industry in 57 countries. Institutional preference for certain stock characteristics and the impact of these preferences on prices are studied in (e.g., Lakonishok et al., 1992; Falkenstein, 1996; Gompers and Metrick, 2001; Dahlquist and Robertsson, 2001; Bennett et al., 2003; Ferreira and Matos, 2008). Moreover, there is an extensive work devoted to analyzing the performance of mutual funds and pension funds (e.g., Grinblatt and Titman, 1992, 1993; Grinblatt, Titman, and Wermers, 1995; Carhart, 1997; Blake, Lehmann, and Timmermann, 1999; Wermers, 2000; Barras, Scaillet, and Wermers, 2010). Institutional investors also have a strong influence on firm policies through corporate governance by monitoring the managers through direct actions or "voting with their feet." A series of studies investigate the impact of institutional investors on firms' corporate governance (e.g., Smith (1996), Wahal (1996), Bushee (2001), Abarbanell, Bushee, and Raedy (2003), Gillan and Starks (2003), Hartzell and Starks (2003), Parrino, Sias, and Starks (2003), Almazan, Hartzell, and Starks (2005), Chen, Harford, and Li (2007))

The main objective of this thesis is to investigate the impact of institutional investments on market efficiency. The thesis employs a unique database of high frequency institutional transactional data. The data, obtained from ANcerno Ltd. a transaction costs analyst, provide a unique opportunity to examine various hypotheses regarding the influence of institutional investors on market quality. The ANcerno data contains detailed information about 1142 institutional clients including money managers, pension plan sponsors and brokerage companies, they identify exact date and execution price of each transaction, number of traded shares, an indicator whether the transaction is buy or sell, a unique identifier for each institution, and a unique stock identifier. The data allow us to provide empirical evidence on the impact of institutional trading activity on market-wide liquidity shocks, short-term institutional herding and its impact on prices, and the daily relation between institutional trading activity and returns.

The second chapter investigates the role of institutional trading activity in explaining liquidity comovements observed in equity markets, a direct link between institutional activity and commonality in liquidity. Commonality in liquidity refers to the existence of common underlying factors affecting the liquidity of individual stocks. Chordia, Roll, and Subrahmanyam (2000) are the first to provide empirical evidence on the existence of stock liquidity covariation with the market- and industry-wide liquidity. Following the work of Chordia et al. (2000), there have been a large number of empirical studies providing evidence on the existence of liquidity commonality not only in the U.S. markets, but also around the world as well as across different samples and time periods. However, the sources and the economic mechanism behind the commonality in liquidity has received less attention. Although the literature investigates two main sources of commonality in liquidity, that is, supply-side of and demand-side for liquidity, the primary goal of this chapter is to shed more light on the demand-side explanation of the liquidity commonality. In particular, the chapter examines whether there is a direct link between institutional trading activity and liquidity comovements using actual institutional transactional data. The chapter derives implications from the herding literature and explains the main results in the context of correlated trading by institutional investors due to their tendency to trade on common information, liquidity shocks, or herding behavior. We find strong evidence that institutional trading is an important source of commonality in liquidity, and that commonality in liquidity increases with institutional trading activity. These results are not specific to stock characteristics (i.e. firm size and liquidity level) or driven by the endogeneity of institutional stock holdings and are robust to different sub-samples based on firm size, liquidity level, and time periods. To examine whether the association between liquidity covariation and institutional trading is due to the correlated trading among institutional investors, we also connect pairs of stocks through the number of common institutions trading the pair. The result of this analysis indicates that the mechanism of liquidity covariation is the correlated trading across institutions. Finally, results from the natural experiment of the mutual fund scandal in 2003 are suggestive of a causal effect of institutional activity on commonality in liquidity, although for the largest and most liquid securities.

The third chapter investigates the relation between institutional trading activity and returns, both at daily and intradaily horizons. In the United States, institutional investors are only required to report their equity shareholdings at quarterly frequency, hence, most of the previous studies use changes in institutional ownership to proxy for institutional trading activity. Using quarterly data the previous studies show that changes in institutional ownership are strongly autocorrelated, positively correlated with next period returns, and the changes in institutional ownership appear to be positively correlated with past returns. These findings are interpreted as follows: (1) institutions trade persistently; (2) on average, institutional trades are profitable: (3) institutional investors are momentum traders. Furthermore, there is a strong positive relation between changes in institutional shareholdings and same period returns (quarterly or yearly). However, it is hard to interpret this relation because institutions can move prices in the direction of their trades, react to price movements within the quarter, and can predict short term stock returns. The ideal way to get a clear understanding of institutional trading patterns is by using changes in institutional ownership as they occur. Using high frequency institutional transaction data, chapter 3 investigates the potential sources of the contemporaneous relation documented at quarterly level and examines the short-term relationship between returns and institutional imbalances. I find a strong positive contemporaneous relationship between institutional imbalances and returns at a daily level. Institutional imbalances follow prior day's returns, a one standard deviation increase in daily returns are associated with 0.04 increase in institutional buy-sell imbalances in the following day. I find no evidence that institutional imbalances predict short-term future returns. Contemporaneously, institutions tend to sell loser stocks more often than the winners, however, they buy prior day's winners more than selling prior day's losers. The intradaily analysis shows that the primary sources of the daily contemporaneous relation between changes in institutional ownership and returns is the institutional feedback trading, but not the intradaily returns predictability.

Institutional investors are also accused of focusing excessively on the short-term trading strategies, and that they tend to take positions on the same side of the market for the same stocks in a given period in a way that is unrelated to fundamentals. These actions may have a destabilizing impact by increasing the volatility of financial markets and force firms to focus on short-term more than long-term strategies. However, if institutions form the herd by trading on information will enhance the efficiency of market prices by accelerating the adjustment of new information into prices.

Therefore, the fourth chapter is devoted to exploring short-term institutional herding and the impact of institutional herding as well as the persistence in institutional herding on security prices. Although there is a rich theoretical literature providing various explanation for why institutional investors might engage in herding behavior, the empirical evidence on herding behavior by institutions is at best mixed. The main goal of this chapter is to provide empirical evidence and to shed more light on short-term institutional herding and its impact on prices. Consistent with the results found at quarterly horizon in Lakonishok et al. (1992) and Wermers (1999), I find weak evidence of institutional herding at weekly frequency. The overall level of weekly institutional herding of 2.5% suggests that out of 100 institutions, there are roughly two more institutions on the same side of the market more than what would be expected if they trade randomly and independently. Both institutional buy and sell herding affect returns differently. While returns continuation is followed institutional buy herding, reversals are observed following institutional sell herding. Consistent with the long-term findings in Dasgupta et al. (2011), I find that persistence in institutional herding over multiple weeks is associated to return reversals after a period of about eight weeks.

The thesis uses a high-frequency proprietary database of institutional transactions to examine the influence of institutional investments on market efficiency. The thesis contributes to the extant literature on institutional investments in three ways. First, it provides direct link between institutional trading activity and commonality in liquidity; the empirical findings suggest that liquidity comovement increases with the trading activity of institutional investors. Second, it provides empirical evidence on the short-term institutional herding and its impact on prices. Although I find weak evidence of short-term institutional herding, I find strong evidence on the price impact of institutional herding. Third, the thesis also provides empirical evidence on the daily and intradaily relation between the aggregate institutional trading and returns.

Chapter 2

Institutional Investment and Commonality in Liquidity: Evidence from Transaction Data

Contents

2.1 Introduction

In 1965, institutional investors held 16.2% of U.S. equities. That percentage increased to 50.2% in 2010, according to the Board of Governors of the Federal Reserve System (2011). The fact that institutional investors are managing such a substantial share of the U.S. equity market has important potential consequences for price formation and liquidity. In this chapter, we use institutional investors' transaction data to investigate whether institutional investors' trading activities can explain observed market-wide liquidity shocks.

Asset liquidity, that is, the ability to trade large quantities rapidly, at a low cost, and with little price impact, is of paramount importance to market participants. A number of studies document empirical evidence suggesting that investors require a compensation to invest in less liquid assets (see, e.g., Amihud and Mendelson, 1986; Amihud, 2002). But investors also care about how an asset's liquidity moves together with the liquidity of other stocks, i.e., commonality in liquidity. To the extent that liquidity risk cannot be fully diversified, investors require a risk premium for investing in a stock whose liquidity decreases precisely when liquidity is most needed, that is, in periods of liquidity dry-ups (Acharya and Pedersen, 2005; Pastor and Stambaugh, 2003; Korajczyk and Sadka, 2008). The recent financial crisis has evidenced the potential effects of market-wide liquidity dry-ups on the ability of financial intermediaries to provide liquidity to the real sector (Cornett et al., 2011). Although time-variation in market liquidity is well documented in the literature (Chordia et al., 2000; Hasbrouck and Seppi, 2001), the mechanism through which commonality in liquidity arises in stock markets is still not fully understood. Understanding how commonality in liquidity arises in financial markets could help investors better manage liquidity risk. Moreover, it would help market designers and regulators set rules that minimize the probability of liquidity dry-ups.

Two main sources of commonality in liquidity have been investigated in the literature. Coughenour and Saad (2004), Hameed et al. (2010), Comerton-Forde et al. (2010) and Brunnermeier and Pedersen (2009) posit that market-wide liquidity fluctuations are the consequence of the existence of market participants who provide liquidity to many assets. For instance, access to capital by market makers, hedge funds, and investment banks, may vary through time. Such variations affect their ability to provide liquidity and, to the extent that financial intermediaries operate in many assets simultaneously, they could cause liquidity comovement. As opposed to the supply-side explanation, other authors have argued in favor of a demand-side explanation. Institutional investors trade as a response to liquidity shocks or to the arrival of new information. For example, when open-end mutual funds experience net outflows of money, they are often forced to liquidate their positions to meet redemptions. To the extent that these motives for trading affect a large number of institutional investors at the same time, there will be an increase in the demand for liquidity for the assets traded by those institutions, which will in turn affect the liquidity of the traded assets (Chordia et al., 2000). Correlated trading across assets will be strengthened if different institutions concentrate their trades on the same assets due, for instance, to these institutions sharing similar investment styles. Karolyi et al. (2012) exploit the heterogeneity in market characteristics across stock exchanges to disentangle the plausibility of these competing views on the origin of commonality in liquidity and conclude that the empirical evidence is more consistent with the demand-side explanation: While commonality in liquidity is greater in countries with more correlated trading activity, as proxied by stock turnover, it does not increase in times when financial intermediaries are more likely to hit their capital constraints.

The purpose of this chapter is to investigate the relationship between institutional investors' trading and commonality in liquidity using data on actual institutional investors' trades. Previous attempts to establish a link between institutional investors' trading activity and commonality in liquidity have suffered from lack of publicly available institutional trading data and have relied on various proxies for institutional trading activity. Kamara et al. (2008) use institutional ownership and index inclusion to proxy for institutional trading. Karolyi et al. (2012) use stock turnover to proxy for institutional trades. These proxies for institutional trading suffer from a number of limitations. Turnover does not distinguish between trading by institutions and trading by retail investors. While index inclusion (or exclusion) could be a good proxy for institutional trading, changes in the composition of an index are sparse and do not measure appropriately the volume of institutional investor trading activity or the correlation in trading across institutions.

Our work builds on the study of Koch et al. (2012), who use a stock's mutual fund ownership, defined as the percentage of a firm's shares outstanding held by mutual funds, as well as quarterly changes in mutual fund ownership, to proxy for the amount of institutional investors' trading in the stock. Mutual fund ownership overcomes the limitations of the proxies described above, but it is also an imperfect proxy for institutional trading. Two firms with similar fractions of their shares held by institutional investors could experience very different trading activity if the institutions that invest in those companies differ in the frequency and size of their trades. Moreover, mutual fund ownership is likely to be associated with stock characteristics reflecting the portfolio choices of institutional investors, which may bias the results of the analysis if those characteristics are correlated with the outcome variable. Although changes in mutual funds' holdings come closest to actual institutional trading activity, this proxy does not capture round trip trades between two consecutive portfolio disclosure dates. The problem becomes more severe if holdings are reported only at the quarterly frequency. The dangers of using low-frequency holdings data to proxy for mutual funds' trading activity are best illustrated in a recent study by Elton et al. (2010), who revisit some well known hypotheses, such as momentum trading, tax-motivated trading, window dressing, and tournament behavior, using holdings data observed at the monthly frequency instead of quarterly or semi-annual holdings data.

The database we employ in this dissertation, distributed by ANcerno Ltd., a private transaction costs analyst, contains detailed information on institutional transactions that are responsible for nearly 8% of the total volume in CRSP in each year of our sample period.[1] This dataset overcomes many of the limitations of previously employed proxies: It distinguishes between institutional and retail investors' trades; It enables us to measure the degree of correlated trading across institutions; And it does not ignore round-trip transactions.

We replicate the study of Koch et al. (2012) using institutional investors' trades data instead of holdings data. However, we control for institutional ownership to account for potential portfolio choice effects. We also control for total trading volume in order to distinguish institutional trading activity from that of retail investors. As mentioned above, commonality in liquidity should be stronger when different institutional investors trade the same assets. To account for correlated trading across institutional investors, we follow the approach of Antón and Polk (2014), who find that stocks that are held by a larger number of common funds ("connected" stocks) exhibit higher excess comovement in returns. Analogously, we study whether the degree of liquidity comovement between two stocks is associated with the number of common institutions trading in both stocks. Finally, although we deal with the potential endogeneity of institutional portfolio choices by explicitly controlling for institutional ownership, the decision of which stocks to trade is also endogenous. Again, building on Antón and Polk (2014), we propose to exploit the mutual fund late trading and market timing scandal of 2003, which forced some families of funds to liquidate their positions, as an exogenous source of variation in institutional trading to study its effect on commonality in liquidity.

Our results suggest that institutional investor trading explains commonality in liquidity. The empirical evidence reveals a significant positive relationship between commonality in liquidity and institutional investor trading activity. Our findings are not driven by the endogeneity of institutional ownership or other observable stock characteristics and are robust to different empirical specifications. Moreover, the results of the analysis of connected stocks are consistent with the idea that the mechanism for commonality in liquidity is correlated trading across institutions. Finally, the evidence from the 2003 mutual fund scandal is suggestive of a causal effect of institutional trading

[1] The ANcerno trade data have been used by academic researcher and produced various studies including Goldstein, Irvine, Kandel, and Wiener (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2012), and Hu, McLean, Pontiff, and Wang (2010).

on liquidity comovement, although only for the largest and the most liquid stocks.

The remainder of this chapter is organized as follows. In Section 2.2, we develop our main hypotheses and explain the methodology used to test the hypotheses. The data are described in Section 2.3. Section 2.4 presents evidence of the relationship between commonality in liquidity and institutional trading activity. In Section 2.5, we study the relationship between common institutional trading and liquidity co-variation. Section 2.6 presents the results of our identification analysis. Robustness tests are included in Section 2.7. We conclude the chapter in Section 2.8.

2.2 Hypotheses and Methodology

2.2.1 Hypotheses

Correlated trading across assets can arise if institutions' information-based strategies are correlated, as institutional investors react to the same information or as institutional investors infer information from the observed trading activity of others. Also, correlated trading can be the consequence of institutions responding to common liquidity shocks. In either case, if institutional investors trade at the same time and in the same direction, the increase in the demand for liquidity could result in liquidity comovement (Chordia et al., 2000). Consistently with this reasoning, our first hypothesis captures the idea that commonality in liquidity should be more prevalent among stocks with a higher level of institutional trading activity.

Hypothesis 1: ***Stocks that are highly traded by institutional investors exhibit commonality in liquidity***.

For institutional trading to cause liquidity commonality, institutions must demand liquidity at the same time across assets. When the shocks that motivate institutions' trades affect a larger number of institutions, we would expect an increase in the correlation of trading across institutions and therefore, more liquidity commonality among assets. For example, the mutual fund sector often experiences large market-wide inflows or outflows of money, which result in many funds demanding liquidity at the same time. This is so because mutual funds experiencing large outflows are often forced to liquidate positions in assets to meet redemptions as a consequence of the institutional constraints they face (Coval and Stafford, 2007; Jotikasthira et al., 2012; Zhang, 2010). Similarly, a mutual fund experiencing large inflows often must increase its existing positions to avoid large cash balances (Pollet and Wilson, 2008). In either case, many institutions will be forced to demand liquidity at the same time and this will affect market-wide asset liquidity. Therefore, we would expect the association between institutional trading and commonality in liquidity to be higher in periods of extreme aggregate flows of money into and out of mutual funds.

Hypothesis 2a: ***The effect of institutional investors' trading activity on commonality in liquidity is stronger in periods of large aggregate flows into/out of mutual funds***.

It could be argued that mutual funds are better able to cope with money inflows than outflows. After all, increasing cash holdings as a response to inflows may be detrimental to fund performance but is feasible, whereas failing to redeem shares or borrowing is not an option for mutual funds facing outflows. While mutual funds could split their purchases and distribute them through time when facing money inflows, they will often be forced to liquidate positions when experiencing outflows. Therefore, we also consider the following variant of Hypothesis 2:

Hypothesis 2b: ***The effect of institutional investors' trading activity on commonality***

in liquidity is stronger in periods of flows of money out of mutual funds.

While we expect all assets traded by institutions to experience correlated trading, this correlation will be higher if assets are traded by the same institutions. Antón and Polk (2014) document a positive association between comovement of stock returns and the degree of connectedness between stocks through common mutual fund ownership. In particular, they forecast the cross-sectional variation in return correlation using the degree of shared ownership or the number of funds that hold a pair of stocks i and j in their portfolios: Pairs of stocks that are connected in this fashion exhibit more price comovement controlling for stock characteristics. Following the same reasoning and using the same approach, we hypothesize that stock connectedness through institutional trading explains commonality in liquidity.

Hypothesis 3: ***Commonality in liquidity is stronger among stocks that are connected through common institutional trading***.

2.2.2 Variable Definitions

Our primary measure of stock-level institutional trading is based on the fraction of firm i's shares traded by all institutions in our sample on day d. Specifically, for each stock, we construct a daily measure of aggregate institutional investor trading

$$Daily\_ITrade_{i,d} = \frac{\sum_{j=1}^{J} sharestraded_{i,j,d}}{shrout_{i,d}} \tag{2.1}$$

where $sharestraded_{i,j,d}$ is the number of shares traded (buy and sell) in stock i by institution j on day d, $shrout_{i,d}$ is the total number of shares outstanding of stock i on day d. In our analysis we use the mean value of $Daily\_ITrade_{i,d}$ in quarter t, which we denote by $ITrade_{i,t}$.

We follow the literature and use Amihud (2002) illiquidity measure to proxy for stock daily illiquidity. The Amihud (2002) illiquidity measure is computed as the absolute value of stock i's return on day d divided by the dollar volume of trading in stock i on that day.[2]

$$illiq_{i,d} = \frac{\mid r_{i,d} \mid}{\mid dvol_{i,d} \mid} \tag{2.2}$$

We use Amihud illiquidity measure in our study in two ways. First, we employ the change in Amihud (2002) illiquidity measure to estimate loadings of stock liquidity on market-wide liquidity as well as pair-wise liquidity comovement. Second, we add the level of Amihud illiquidity measure as an additional control in many specifications to account for the possible effect of liquidity level on commonality in liquidity. In particular, changes in Amihud illiquidity are computed as

$$\triangle illiq_{i,d} = ln\left[\frac{illiq_{i,d}}{illiq_{i,d-1}}\right] \tag{2.3}$$

where $r_{i,d}$ is the return for stock i in day d and $dvol_{i,d}$ is the dollar volume for stock i in day d.

[2]See e.g., Hasbrouck (2009) and Goyenko et al. (2009) for a summary of the literature on the performance of Amihud (2002) measure.

2.2.3 Testing Methodology

To test whether stocks with high institutional trading activity exhibit commonality in liquidity, we follow a two-step approach similar to that used by Coughenour and Saad (2004) and Koch et al. (2012). In the first step, we estimate the individual stock liquidity co-variation with the liquidity of a portfolio of stocks with high institutional trading activity (value of $ITrade$ in the top quartile of the cross-sectional distribution). In the second step, we test whether liquidity co-variation between individual stocks and the high $ITrade$ portfolio is stronger among firms with high institutional trading.

More specifically, for each firm i and quarter t in our sample, we run a time series regression of daily changes in the Amihud illiquidity measure on the illiquidity of two portfolios, a high institutional trading portfolio containing all stocks in the top quartile of institutional trading activity as sorted at the end of the prior quarter and a market portfolio containing all stocks:

$$\triangle illiq_{i,d} = \alpha_{i,t} + \beta_{HI,i,t} \triangle illiq_{ITrade,d} + \beta_{mkt,i,t} \triangle illiq_{mkt,d} + \delta controls + \varepsilon_{i,d} \tag{2.4}$$

We follow Chordia et al. (2000) and include as controls one lead and one lag changes in the two portfolio illiquidity variables, contemporaneous firm return squared, and lead, lag, and contemporaneous market returns. The squared stock return is included to proxy for volatility, which could be associated with liquidity. As in Chordia et al. (2000), for each regression we exclude firm i from the market portfolio as well as from the high institutional trading portfolio. To minimize the effect of outliers, we winsorize observations that are in the top and bottom 1% of the stock's liquidity distribution.

Our first hypothesis is that the liquidity of stocks with high levels of institutional investor trading activity covaries more with that of other highly traded stocks. To test this hypothesis, we study whether estimated loadings on the high institutional trading portfolio are positively related to the level of institutional investors' trading in the cross section of stocks. Moreover, we regress β_{HI} against the previous quarter institutional investors level of correlated trading measure, $ITrade_{i,t-1}$, controlling for total market trading activity, $MTrade_{i,t-1}$ computed as the total CRSP volume for stock i divided by total shares outstanding, firm size and average illiquidity:

$$\beta_{HI,i,t} = \alpha + b_1 ITrade_{i,t-1} + b_2 MTrade_{i,t-1} + b_3 ln(size_{i,t-1}) + b_4 illiq(avg)_{i,t-1} + \varepsilon_{i,t} \tag{2.5}$$

Hypothesis 2a predicts that the impact of institutional investors' trades will be greater in periods of high absolute flows. We follow Koch et al. (2012) and compute aggregate mutual fund flows for each quarter using data from CRSP Mutual Fund Survivorship Bias Database. In particular, we calculate net fund flows into equity mutual funds, and then divided this amount by the total market value at the beginning of the quarter. From the resulting time series, we calculate a dummy variable, $extremeflow$, that equals one if aggregate flows in a quarter are in the top or bottom 10% of the distribution of quarterly flows in our sample period, and zero otherwise. Net flows are signed, so the bottom (top) 10% is comprised of the largest net outflow (inflow) quarters. To test Hypothesis 2b, we create another dummy variable, $negflow$, that equals one if aggregate flows are negative, and zero otherwise. Each of these dummy variables is interacted with $ITrade_{i,t-1}$ and $MTrade_{i,t-1}$ and included in the regression specifications.

To test our third Hypothesis, we follow the approach proposed by Antón and Polk (2014) and look at pairs of stocks connected through common institutional trading. More specifically, we study whether the number of institutional investors trading simultaneously in two stocks predicts the pair-wise liquidity co-variation between the stocks, controlling for similarity in industry, size, book-to-market ratio, and momentum characteristics. In particular, we estimate

$$\begin{aligned}\triangle illiq_{i,t+1} \triangle illiq_{j,t+1} = \alpha &+ \beta_f F^*_{ij,t} + \beta_s DIFF\_SIZE^*_{ij,t} + \beta_b DIFF\_BEME^*_{ij,t} \\ &+ \beta_m DIFF\_MOM^*_{ij,t} + \beta_k NUM\_SIC^*_{ij,t} + \beta_{s1} SIZE1^*_{ij,t} \\ &+ \beta_{s2} SIZE2^*_{ij,t} + \beta_{s12} SIZE1SIZE2^*_{ij,t} + \varepsilon_{ij,t}\end{aligned} \tag{2.6}$$

where $F_{ij,t}$ is the number of institutions that trade both stock i and j on month t. As in Antón and Polk (2014) for each cross section, we calculate the normalized rank transformation of $F_{ij,t}$ (so the variable has zero mean and unit standard deviation), which we denote as $F^*_{ij,t}$. To control for commonality in liquidity induced by similar stock characteristics, we follow Antón and Polk (2014) and for each month we first calculate every stock's percentile ranking on a particular characteristic. The measures of similarity, $DIFF\_SIZE$, $DIFF\_BEME$, and $DIFF\_MOM$, are just the negative of the absolute difference in percentile ranking across a pair for a particular characteristic: size, book-to-market, and momentum, respectively. To capture similarity in industry, we use the same approach as Antón and Polk (2014) and compute the number of consecutive SIC digits that are equal for a given pair, NUM_SIC. Similar to our main measure of institutional connectedness, the normalized rank transformation of these variables is used, which we denote with an asterisk superscript. As institutional trading is correlated with size, we add the normalized rank transformation of the percentile firm size as an additional controls, SIZE1 and SIZE2 (where the larger firm in the pair is labeled as the first stock), and the interaction between the two market capitalization percentile rankings.

We estimate these loadings using Fama and McBeth (1973) approach. We demean and normalize all the independent variables in the cross-section to have a unit standard deviation to facilitate the interpretation and that the intercept α measures the average cross-sectional effect. We compute the Newey-West standard errors so that the Fama-MacBeth estimates account for the autocorrelation up to four lags.

2.3 Data

Institutional transaction order-level data are obtained from ANcerno Limited for the period from January 1, 1999 through September 30, 2011. ANcerno is a leading consulting firm that provides institutional investors with transaction cost analysis and trading technology services. ANcerno data cover the equity transactions of ANcerno' clients, a large number of institutional investors including pension plan sponsors as well as institutional money managers. The dataset offers potential advantages in comparison to other high-frequency trading data that make them perfectly suitable for examining institutional investor trading and commonality in liquidity relationship. Each observation in the dataset provides a unique ANcerno client identification code, a unique stock identification code, *stockkey* as well as cusip, and ticker, execution price, the transaction price, number of shares executed, date and time stamps for the order, and whether the trade is a buy or sell. According to ANcerno's specialists, the database captures the entire history of all trades of ANcerno's clients as long as they remain in the sample. Since ANcerno is proprietary database, survivorship and selection bias issues are potential concerns. While the data may suffer from selection bias, the survivorship bias is not a concern according to Puckett and Yan (2011).

Summary statistics for ANcerno's trade data and stock characteristics are reported in Table 2.1. Panel A presents the full sample statistics. In aggregate, the sample incudes 1,142 institutions that execute nearly 205 million trades associated with approximately 33 trillion dollars in trading volume.

Table 2.1: Descriptive Statistics for ANcerno Institutional Trading Data and Stock Characteristics

This table reports summary statistics of institutional trading data obtained from ANcerno Ltd. The sample contains the trades of 1,142 institutions during the period from January 1, 1999 to September 30, 2011. The sample includes stocks where ANcerno volume is less than or equal to the total daily trading volume as reported in CRSP. Panel A shows descriptive statistics for the full sample of institutional trading data. Panel B reports yearly sub-sample descriptive statistics. Panel C reports descriptive statistics for stocks traded by ANcerno institutions. Our sample includes only common stocks (those with a share-code of 10 or 11 in CRSP). Amihud illiquidity measure is calculated as the average of daily ratios between absolute return and dollar trading volume. We compute stock characteristics each quarter. Market capitalization is as of the end of the previous quarter. All other stock characteristics are measured based on the 12-month period until the end of the previous quarter. Firm-size quintile breakpoints are computed for the stocks in our sample. We report the quarterly cross sectional averages for all stock characteristics in each size-quantile.

	No. Inst.	No. Stocks	No. Trades (mill.)	Shares Vol. (bill.)	Dollar Vol. (bill.)	Ave. Shares Vol. per Tr.	Med. Shares Vol. per Tr.	Ave. Dollar Vol. per Tr.	Med. Dollar Vol. per Tr.
Panel A:									
Full Sample	1142	7800	205.68	1110	32950	5395.65	300	160165.1	9396
Panel B:									
By year									
1999	379	4855	4.00	35	1550	8739	1600	388,477	58025
2000	370	4761	5.42	52	2320	9612	1500	427,977	54500
2001	398	4176	6.82	75	2270	11052	1400	332,664	38523
2002	424	3942	9.17	100	2390	10905	1300	260,799	30132
2003	401	3993	7.92	71	1750	8907	1020	220,640	27103
2004	404	4202	16.39	117	3320	7113	700	202,353	20361
2005	376	4050	14.75	94	2930	6399	400	198,372	13338
2006	399	4062	24.63	103	3270	4185	200	132,652	6526
2007	377	4114	31.02	103	3590	3323	100	115,614	4206
2008	333	3817	26.20	122	3450	4672	200	131,796	5961
2009	322	3693	21.00	102	2230	4839	255	106,310	5739
2010	308	3468	22.19	85	2310	3826	160	104,261	4605
2011	259	3331	16.18	51	1570	3142	145	96,935	4844

Panel C: Stock Characteristics

	Turnover (%)	Market Capitalization ($billions)	Amihud Illiquidity (in millions)	No. Shares Traded (millions)	Return (%)
Firm Size (quantile)					
Small	211	0.37	0.0182	2.15	2
2	255	0.80	0.0043	3.60	3
3	275	1.54	0.0019	5.90	4
4	269	3.45	0.0008	10.40	3
Large	218	28.00	0.0002	33.70	3
Full Sample	245.6	6.83	0.0051	11.15	3

On average, ANcerno's clients are responsible for almost 8% of CRSP dollar value of trading volume throughout 1999 to 2011 of our sample period.[3] Since total institutional investor trading accounts for 80% of CRSP trading volume, we estimate that ANcerno clients are responsible for 10% of all institutional trading volume. Panel B reveals several notable time series patterns in the trading of institutional investors in our sample. The number of institutions in the database peaks in 2002 and declines towards the end of sample period. The overall number of stocks that ANcerno clients trade declines from 4,855 in 1999 to 3,331 in 2011. The average dollar volume varies between a maximum of $427,977 in 2000 and a minimum of $96,935 in 2011. The median dollar volume ranges from $58,025 in 1999 to $4,206 in 2007.

To complement ANcerno trade data, we collect stock data, such as trading volume, prices, returns, and number of shares outstanding from CRSP. Panel C of Table 2.1 reports the descriptive statistics for the sample of stocks traded by ANcerno clients. We report the cross-sectional average of stock characteristics for the full sample and by firm size quintile. The average market capitalization of securities traded by ANcerno institutions is $6.83 billion, while the mean illiquidity is 0.0051. Moreover, we report that our sample of stocks have average turnover of 245.6% per year. In addition, we find that the average illiquidity of stocks in the bottom size quintile is 0.0182, while

[3]We follow Puckett and Yan (2011) and compute the fraction of trading volume by ANcerno's clients to the trading volume as reported by CRSP at the daily basis. Only common stocks (share code equal to 10 or 11) are included. Moreover, all ANcerno trades are divided by two because every ANcerno client represent only one side of a trade.

the corresponding number for stocks in the top size quintile is only 0.0002. Small stocks experience an average trading volume of 2.15 (million) shares, while the large stocks' average trading volume is 33.7 (million) shares.

Finally, for some of our tests, we use data on mutual fund total net assets from CRSP Survivorship Bias-Free mutual fund database and equity holdings from Thomson Reuters.

To obtain the required data for our empirical analysis and minimize observations with errors, we choose the following filtering criteria: (1) We delete all transactions if the order volume is greater than the total volume as reported by CRSP on each of the execution date; (2) We follow Chordia et al. (2000) and keep class A securities and exclude other categories such as shares of beneficial interest, derivatives, closed-end investment companies, preferred stocks, warrants, American depositary receipts, units, holdings and realty trusts, rights, and trusts; (3) We eliminate those shares where the average stock price over the year is less than $2 and higher than $200. This is relevant for our analysis because daily fluctuation in stock liquidity outside these price levels can be very high either because these stocks are rarely traded, ticking size constraints, or price discreteness. To estimate liquidity betas, we require a minimum of 40 observations per quarter. Finally, because some stocks are traded only one quarter we also require a stock to be traded at least 4 consecutive quarters. Our filtering criteria result in 3,297 firms in the sample.

2.4 Empirical Results

2.4.1 Institutional Investor Trading and Commonality in Liquidity

To test Hypothesis 1, we need to estimate liquidity betas from time series regressions of daily changes in stock liquidity on the changes in liquidity of a portfolio of highly-traded stocks and the market portfolio. Table 2.2 reports yearly average sample statistics for both the market and the high-institutional-trading portfolios as well as the estimated coefficients of interest. The left-hand side of Table 2.2 shows the yearly average of the liquidity beta coefficients with respect to the portfolio of highly traded stocks, the percentage of beta coefficients that are positive, the percentage of coefficients that are significant (at the 5% level), as well as a t-statistic on the sample of beta coefficients that are significant in that year. The table also presents the average firm size, average illiquidity and the number of stocks in both portfolios.

Time-series regression estimates reveal that an individual stock's liquidity co-varies with the liquidity of a portfolio of stocks that are highly traded by institutional investors, controlling for information inducing commonality with market liquidity. However, the institutional-liquidity beta is roughly one-half the size of the market-liquidity beta. We find that the magnitude and percentage of positive institutional liquidity betas are lowest at the beginning of our sample and increase toward the end of sample period, the opposite patterns are observed for market liquidity betas. It is interesting to compare our results with those of Koch et al. (2012), who use the change in the Amihud (2002) illiquidity measure (same as in our study) and the fraction of shares outstanding held by mutual funds to proxy for correlated trading (we use actual institutional trades). As in Koch et al. (2012), Table 2.2 shows that relatively few of the liquidity betas are significantly different from zero at the 5% level. This is probably due to short sample length of our time-series regressions.[4] The signs and significance of the commonality coefficients are also similar to those obtained in Koch et al. (2012). While the full sample average of β_{HI} in our sample is smaller, the degree of individual liquidity

[4]Both our estimates of the liquidity betas and those of Koch et al. (2012) differ from the estimates of Chordia et al. (2000) and Coughenour and Saad (2004), who find larger fractions of statistically significant coefficients. The fact that those studies use the full sample period rather than quarterly periods for the time-series regressions accounts for the differences. In unreported results, for each stock we run the full sample time series regression and find that 63% of institutional investors liquidity beta are positive and 20% of these coefficients significantly different from zero at the 5% level. On the other hand, 80% of market liquidity betas are positive with 33% being significantly different from zero at the 5% level.

variation explained is higher. As in Koch et al. (2012), on average, the firm size in the institutional investor portfolio is smaller than that in the market portfolio, consistent with the findings of Bennett et al. (2003), who document that in the recent years institutional investors have tended to increase the weight of smaller and riskier stocks in their portfolios. Institutional trading on average has increased over the whole sample of stocks through time. For the stocks in the top quartile of institutional trading activity has increased from 0.14% in 1999 to 0.22% in the 2009. Stocks were more illiquid in 1999 in comparison to 2011. The increase in liquidity is most notable among stocks highly traded by institutional investors with average illiquidity lower than that of stocks in the market portfolio in all years. This result indicates that institutional investors are attracted to liquid stocks, consistent with findings of earlier studies (Falkenstein, 1996).

Table 2.2: Time Series Estimates of Liquidity Betas

This table reports summary statistics on liquidity betas with respect to a high institutional trading portfolio and a market portfolio of NYSE, Amex and Nasdaq stocks. The high institutional trading portfolio is comprised of the stocks in the top quartile of institutional trading activity, $ITrade$, as ranked at the end of the previous quarter. $ITrade$ is the number of shares traded by all institutions divided by number of shares outstanding. Liquidity betas are estimated by regressing for each quarter and each firm, the daily change in the firm's illiquidity (Amihud measure) on the daily changes in the value weighted illiquidity measure for a portfolio of high institutional trading stocks and the market portfolio, as well as control variables. In each time series regression the stock's individual measure is removed from the market portfolio and the high $ITrade$ portfolio. The left (right) columns summarize the coefficient estimates for the high $ITrade$ portfolio liquidity (market portfolio liquidity). In each year, we record the average beta, the percentage of positive coefficients and the percentage of coefficients that are significant at the 5% level, and we compute a t-statistic on the sample of beta estimates that are positive and significant in that year. In addition, we report the average firm size and the number of stocks in each portfolio.

	HI ITrade Portfolio									MKT Portfolio							
	R^2	β_{HI}	%pos	%sig	tstat	ITrade	illiq	Size	#stocks	β_{mkt}	%pos	%sig	tstat	ITrade	illiq	Size	#stocks
1999	0.32	-0.06	47	6	2.46	0.014	0.58	3.92	336	0.77	68	8	2.57	0.0076	0.65	11.40	810
2000	0.34	0.05	51	5	2.39	0.018	0.44	4.73	411	0.53	61	6	2.46	0.0100	0.53	12.00	914
2001	0.32	0.12	53	8	2.49	0.029	0.38	3.63	469	0.47	61	8	2.45	0.0137	0.48	8.89	1114
2002	0.34	0.11	52	7	2.53	0.029	0.44	2.61	573	0.59	61	7	2.50	0.0149	0.56	6.43	1356
2003	0.34	0.20	53	6	2.43	0.020	0.26	2.65	548	0.61	63	7	2.45	0.0103	0.35	6.87	1296
2004	0.32	0.07	52	7	2.40	0.028	0.19	2.49	738	0.70	65	8	2.45	0.0154	0.26	6.54	1628
2005	0.31	0.11	52	5	2.41	0.023	0.16	2.39	802	0.69	63	7	2.45	0.0127	0.22	6.71	1714
2006	0.32	0.18	53	5	2.40	0.021	0.13	2.57	858	0.62	60	6	2.43	0.0122	0.19	6.72	1845
2007	0.33	0.45	58	6	2.40	0.021	0.11	2.94	950	0.37	56	6	2.42	0.0125	0.17	6.83	1998
2008	0.37	0.09	52	5	2.33	0.024	0.25	2.53	861	0.57	61	6	2.40	0.0144	0.39	5.95	1829
2009	0.37	0.55	61	8	2.47	0.022	0.26	2.33	855	0.20	54	7	2.41	0.0130	0.49	4.65	1845
2010	0.36	0.36	59	8	2.50	0.018	0.16	2.79	909	0.47	60	8	2.50	0.0108	0.28	5.48	1949
2011	0.37	0.53	61	8	2.46	0.015	0.16	2.76	775	0.25	55	6	2.49	0.0091	0.25	6.28	1930
Full Sample	0.34	0.21	54	6	2.44	0.022	0.27	2.95	699	0.53	60.6	7	2.46	0.0120	0.37	7.29	1556

To test Hypothesis 1, we regress estimated β_{HI}, our measure of commonality in liquidity, against the prior quarter's institutional trading $ITrade_{i,t-1}$ controlling for firm characteristics, such as size and average illiquidity. In addition, we add time dummies and cluster the standard errors at the stock level. Estimation results are reported in Panel A of Table 2.3. Column (1) of this table reports the results of the full sample pooled OLS regression of β_{HI} against institutional trading, time dummies and total market trade. The coefficient on β_{HI} is positive and statistically significant at conventional significance levels, which suggests that stocks with high institutional trading activity exhibit strong liquidity covariation.

Prior studies find that institutional investors select stocks based on characteristics that are correlated with future liquidity (Del Guercio, 1996; Falkenstein, 1996). In column (2) we add firm size and average illiquidity as additional controls. The coefficient on institutional investors' correlated trading remains positive and highly significant and the magnitude is slightly higher than the estimated coefficient without controls. This result is also economically significant: A one standard deviation increase (0.10) in institutional investor trading is associated with a 0.08 increase in β_{HI}, which equals a 33% increase relative to its mean value. These findings are similar to those obtained by Koch et al. (2012), who document that a one standard deviation increase in mutual fund ownership is associated with a 0.08 increase in their liquidity beta, a 27% increase from its mean.

One possible concern is whether our findings are driven by institutional investors' preferences for stock characteristics other than size and liquidity that could be correlated to commonality in liquidity. To control for time-invariant unobserved heterogeneity, we include firm fixed effects in Column (3). Columns (4) and (5) of Table 2.3 use different assumptions on the structure of the error term: Column (4) employs standard errors clustered at firm level and time level; and Column (5) reports the results of Fama-MacBeth (1973) regressions. Under all specifications, we find a positive relationship between liquidity beta with respect to the high institutional investor portfolio and trading by institutional investors. The relationship is both economically and statistically significant.

Koch, Ruenzi, and Starks (2012) provide empirical evidence that stocks with high mutual fund ownership exhibit strong liquidity comovements. Institutional trading correlates with institutional ownership which, in turn, captures endogenous institutional portfolio choices that could be related to commonality in liquidity. To account for that possibility, we control for institutional ownership in column (6). The results indicate that institutional ownership has explanatory power with respect to commonality in liquidity even when our proxy for institutional trading is included among the regressors. However, the association between our measure of institutional trading and liquidity commonality is still large and highly significant, suggesting that both variables capture different determinants of commonality in liquidity. A possible interpretation of this result is that institutional ownership correlates with some institutions' portfolio choice determinants that are associated with liquidity commonality.

In Panel B of Table 2.3, we replace $ITrade_{i,t-1}$ with D_{ITrade}, a dummy variable that equals one if institutional trading is in the top quartile in the prior quarter, and zero otherwise. The results of Column (2) in Panel B indicate that stocks in the top quartile of institutional investor trading in the previous quarter have a β_{HI} in the following quarter that is 0.17 greater than those outside the top quartile. This is a significant economic effect given the unconditional average of β_{HI} is 0.24. The estimated coefficient on this indicator variable is positive and statistically significant in all other specifications, too.[5]

[5]In unreported results, we include the squared values of ITrade and MTrade as regressors. Our conclusions remain unaltered

Table 2.3: Relationship between Commonality in Liquidity and Institutional Trading

This table reports results from pooled OLS regressions of estimates of on selected stock characteristics measured at the end of the previous quarter. β_{HI} is estimated from time-series regressions of daily changes in liquidity on changes in liquidity of a portfolio of stocks highly traded by institutions. $ITrade$ is the number of shares traded by institutions divided by number of shares outstanding, $MTrade$ is the total volume for as reported in CRSP, divided by the number of shares outstanding. $illiq(avg)$ is the firm's average Amihud (2002) illiquidity measure over the previous quarter. $instown$ is the number of shares held by all institutional investors divided by number of shares outstanding. $ln(size)$ is the natural logarithm of market capitalization. Panel A uses the standard measure of $ITrade$ and Panel B uses a dummy equal to 1 if $ITrade$ is in the top quartile in a given quarter, and zero otherwise. Time dummies are included in columns (1) to (3). Standard errors are clustered by firm in columns (1) to (4). Column (3) includes firm fixed effects. In column (4) standard errors are clustered by quarters. Column (5) reports results from Fama-MacBeth (1973) regressions.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
ITrade	54.66***	60.75***	32.25***	45.06***	68.56***	106.8***
	(5.98)	(6.39)	(4.26)	(4.38)	(6.61)	(7.83)
instown						0.407***
						(6.47)
MTrade	29.15***	28.08***	16.89***	30.03***	25.36***	28.99***
	(20.44)	(19.27)	(11.26)	(12.81)	(13.66)	(16.47)
illiq(avg)		−285**	−129*	−206*	422	−200***
		(−2.23)	(−1.67)	(−1.75)	(0.22)	(−1.67)
ln(size)		0.05***	0.09***	0.05**	0.04*	0.06***
		(6.41)	(4.39)	(2.06)	(1.87)	(6.91)
Observations	74875	74875	74875	74875	74875	60835
R^2	0.035	0.04	0.03	0.02	0.02	0.04
Panel B						
D_{ITrade}	0.1494***	0.1730***	0.0640***	0.1601***	0.1476***	0.147***
	(7.16)	(8.32)	(2.92)	(5.51)	(6.52)	(6.09)
instown						0.472***
						(7.55)
MTrade	29.42***	28.22***	17.43***	9.60***	26.03***	31.41***
	(20.83)	(19.65)	(11.45)	(11.86)	(13.92)	(18.11)
illiq(avg)		−288**	133*	−201*	38	−213*
		(−2.25)	(−1.72)	(−1.72)	(0.19)	(−1.74)
ln(size)		0.06***	0.09***	0.05**	0.04*	0.06***
		(6.45)	(4.52)	(2.10)	(1.86)	(6.55)
Observations	74875	74875	74875	74875	74875	60835
R^2	0.04	0.04	0.03	0.02	0.02	0.04
Time effects	Y	Y	Y			Y
Firm effects			Y			
Time cluster				Y		
Firm cluster	Y	Y	Y	Y		Y
Fama MacBeth					Y	

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

In Table 2.4, we reexamine the relationship between commonality in liquidity and institutional trading activity for sub-samples obtained by dividing the sample by size quartiles, average illiquidity quartiles, positive and negative market-return quarters, and sub-periods. The results are presented in Panels A and C of Table 2.4. The first four columns show a significant positive relationship between institutional trading and commonality in liquidity in all size sub-samples. Also, there exists a strong positive relationship between institutional trading and commonality in liquidity in all liquidity sub-samples, except for the most illiquid stocks (last column).

Panels B and D report the results for different sub-periods and for up- and down-markets. The first three columns show that the association between institutional trading and liquidity commonality is present in all sub-periods. However the magnitude of the coefficient of this relationship varies over time. In the last two columns we split the sample in up- and down-market quarters and find a strong association in both market regimes. The coefficient on $ITrade$ is larger in quarters with positive market returns, 132.2 with a t-statistic of 6.10, as opposed to 97.35 with a t-statistic of 6.03 in quarters with negative market returns. Nevertheless, the difference between the coefficients is not statistically significant.

Overall, these findings provide clear evidence that stocks with high institutional investor trading activity are characterized by strong liquidity comovement. This finding is not driven by institutions' portfolio choices, which gives further credence to the interpretation of the findings of Koch et al. (2012). Also the association can not be attributed to retail investors' trading. The relation is robust to different assumptions with respect to functional forms, unobserved heterogeneity, observations' independence, as well as a variety of sub-samples based on size, illiquidity and market conditions.

Table 2.4: Relationship between Commonality in Liquidity and Institutional Trading: Sub-sample Analysis

This table reports results from pooled OLS regressions of estimates of on selected stock characteristics measured at the end of the previous quarter for different subsamples. β_{HI} is estimated from time-series regressions of daily changes in liquidity on changes in liquidity of a portfolio of stocks highly traded by institutions. $ITrade$ is the number of shares traded by institutions divided by number of shares outstanding, $MTrade$ is the total volume for as reported in CRSP, divided by the number of shares outstanding. $illiq(avg)$ is the firm's average Amihud (2002) illiquidity measure over the previous quarter. $instown$ is the number of shares held by all institutional investors divided by number of shares outstanding. $ln(size)$ is the natural logarithm of market capitalization. Panels A and C report results of regressions for size and illiquidity quartile-based subsamples. Panels B and D report results of regressions for two subperiods and for up- and down-markets separately, where up (down) market periods are quarters in which the market return was positive (negative). Panels A and B use the standard measure of $ITrade$, and Panels C and D use a dummy equal to 1 if $ITrade$ is in the top quartile in a given quarter, and zero otherwise. Time dummies are included in all regressions. Standard errors are clustered by firm.

	Size				Illiq(avg)			
Panel A	Low	2	3	High	Low	2	3	High
ITrade	66.99***	93.79***	110.4***	100.5***	93.83***	90.59***	107.6***	35.15
	(3.04)	(4.22)	(3.58)	(3.29)	(3.58)	(3.33)	(4.80)	(1.39)
instown	0.342***	0.241**	0.369***	0.365**	0.400***	0.400***	0.256**	0.329***
	(3.12)	(2.15)	(3.29)	(2.43)	(2.60)	(3.06)	(2.37)	(3.19)
MTrade	31.46***	28.15***	22.31***	27.95***	26.04***	27.06***	36.74***	53.25***
	(9.40)	(9.85)	(8.19)	(6.71)	(8.79)	(7.84)	(9.36)	(10.51)
illiq(avg)	−51.30	−222.70	949.10	14383.8**	38960.3**	9584.8**	1581.8**	54.40
	(−0.52)	(−0.68)	(0.93)	(2.77)	(3.03)	(3.27)	(3.04)	(0.69)
ln(size)	0.0314	0.0383	0.0869	0.0478*	0.102**	0.254**	0.154**	0.0842
	(0.62)	(0.59)	(1.50)	(1.92)	(3.27)	(4.50)	(3.12)	(1.95)
Observations	14940	14186	14934	16775	16339	14406	14643	15447
R^2	0.04	0.04	0.06	0.09	0.04	0.04	0.06	0.08
Panel B	1999-2003		2004-2007		2008-2011		Down Mkt	Up Mkt
ITrade	108.1***		88.55***		95.79***		97.35***	132.2***
	(5.17)		(3.77)		(4.50)		(6.03)	(6.10)
instown	−0.112		0.358***		0.636***		0.436***	0.314***
	(−1.11)		(3.70)		(6.76)		(6.04)	(3.41)
MTrade	30.77***		28.98***		23.80***		29.14***	28.06***
	(11.65)		(9.53)		(8.66)		(14.73)	(12.20)
illiq(avg)	224.7***		383.9		−308.9***		−329.5*	−139.2
	(3.55)		(1.35)		(−3.35)		(−2.42)	(−1.15)
ln(size)	−0.0450**		−0.0022		0.1810***		0.0542***	0.0692***
	(−3.15)		(−0.16)		(16.30)		(5.65)	(5.77)
Observations	15470		21968		23397		42811	18024
R^2	0.04		0.03		0.08		0.05	0.04
		Size					Illiq(avg)	
Panel C	Low	2	3	High	Low	2	3	High
D_{ITrade}	0.0712	0.164***	0.214***	0.0265	0.0633	0.200***	0.143**	0.0221
	(1.50)	(3.57)	(4.71)	(0.51)	(1.32)	(4.37)	(3.25)	(0.42)
instown	0.377***	0.283**	0.420***	0.468**	0.491***	0.430***	0.320***	0.344***
	(3.46)	(2.55)	(3.81)	(3.14)	(3.22)	(3.35)	(3.00)	(3.37)
MTrade	33.90***	29.83***	23.39***	31.21***	28.21***	27.87***	40.03***	55.62***
	(10.39)	(10.46)	(9.38)	(7.45)	(9.67)	(8.42)	(10.45)	(11.37)
illiq(avg)	−61	−275.7	747.7	13625.5**	38261.8**	9767.9***	1572.0**	52.2
	(−0.61)	(−0.83)	(0.73)	(2.71)	(2.97)	(3.30)	(3.03)	-0.67
ln(size)	0.0204	0.0336	0.0827	0.0398	0.0953**	0.257***	0.151**	0.0794
	(0.40)	(0.52)	(1.43)	(1.60)	(3.02)	(4.53)	(3.06)	(1.84)
Observations	14940	14186	14934	16775	16339	14406	14643	15447
R^2	0.04	0.04	0.06	0.08	0.04	0.04	0.06	0.08
Panel D	1999-2003		2004-2007		2008-2011		Down Mkt	Up Mkt
D_{ITrade}	0.183***		0.142***		0.102**		0.150***	0.141***
	(4.04)		(3.36)		(2.85)		(5.21)	(3.40)
instown	−0.0739		0.411***		0.708***		0.493***	0.403***
	(−0.74)		(4.32)		(7.60)		(6.90)	(4.42)
MTrade	32.61***		31.01***		26.20***		31.08***	31.64***
	(12.26)		(10.62)		(9.87)		(16.23)	(13.87)
illiq(avg)	223.4***		383.3		−328.1***		−345.0*	−154.9
	(3.45)		(1.35)		(−3.49)		(−2.52)	(−1.24)
ln(size)	−0.0478***		−0.0043		0.178***		0.0518***	0.0647***
	(−3.34)		(−0.31)		(16.08)		(5.40)	(5.38)
Observations	15470		21968		23397		42811	18024
R^2	0.04		0.03		0.08		0.05	0.04

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

2.4.2 Aggregate Fund Flows

In the previous subsection, we provide evidence that stock liquidity comovement is associated with institutional trading activity. As argued in Section 2.2, we expect more correlated trading when a large number of institutions are forced to demand liquidity. To test Hypotheses 2a and 2b, we follow Koch et al. (2012) and use aggregate fund flows as a proxy for market-wide shocks to the institutions' demand for liquidity. More specifically, we calculate the quarterly net dollar flow variable by aggregating the flow of money into or out of equity mutual funds industry each quarter. We compute the dollar net money flow into fund i in month t as:

$$DOLLAR\_FLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) \tag{2.7}$$

where $TNA_{i,t}$ is the Total Net Assets of fund i in month t and $R_{i,t}$ is the fund return over the period $t-1$ to t, as reported in the CRSP Mutual Fund Database. To compute the quarterly flows, we sum the dollar flows and divide them by TNA at the end of the previous quarter.

In Table 2.5, we report the results of estimating (2.5) with interactions of $ITrade$ and $MTrade$ with two dummies: an extreme-flow dummy that equals one if the quarter is in the top and bottom 10% of the time series distribution of flows respectively; and a negative-flow dummy that equals one for quarters with negative net flows. Column (1) shows that the impact of institutional trading on commonality in liquidity is much stronger during periods of extreme net flows than in normal periods. Specifically, the coefficient on $ITrade$ is 54.15 in quarters without extreme flows compared to 54.15 + 40.27 = 94.42 in quarters with extreme flows. In column (2) we include the interaction of $MTrade$ with extreme-flow dummy as an additional control. Although the estimated coefficient on the interaction term is small and not statistically significant, the coefficient on the interaction of extreme-flow with $ITrade$ becomes smaller and only significant at the 10% level.

Columns (3) and (4) report the results when $ITrade$ and $MTrade$ are interacted with the negative-flow dummy. In contrast to the results of Koch et al. (2012), our findings are not consistent with the impact of institutional trading on commonality in liquidity being more pronounced when mutual funds experience outflows.

In column (5), we include both institutional ownership and an interaction term of institutional ownership with the extreme-flow dummy. The coefficient on the interaction term between $ITrade$ and the extreme-flow dummy is no longer significant. Moreover, the interaction term between institutional ownership and the extreme-flow dummy is not significant either. In column (6), we include an interaction term between institutional ownership and the negative-flow dummy. Interestingly, institutional ownership and the interaction term between institutional ownership and the negative-flow dummy are highly significant. However, the coefficient on the interaction term is more than twice as large as the coefficient on institutional ownership, suggesting that the explanatory power of institutional ownership with respect to commonality in liquidity detected in Table 2.3 is largely due to quarters with negative flows.

Therefore, in contrast to Koch et al. (2012), we do not find evidence that the link between institutional trading activity and commonality in liquidity is stronger in periods of extreme flows or negative flows. One possible interpretation of these results is that in periods of extreme flows or negative flows, the level of trading by institutions increases, but not the degree of correlation in trading activity across institutions. Consistently with this explanation, the reason why Koch et al. (2012) find a stronger association between institutional ownership and commonality in liquidity in periods of extreme and negative flows is because institutional trading activity increases in those periods and not because trading becomes more correlated across institutions. Since the fluctuations in the level of trading are already captured by our proxy for institutional trading activity, the interaction term with mutual fund flows is not significant.

Table 2.5: Relation Between Liquidity Commonality and Institutional Trading Conditional on Aggregate Mutual Fund Flows

This table reports results from pooled OLS regressions of estimates of on selected stock characteristics measured at the end of the previous quarter, conditional on aggregate mutual fund flows. β_{HI} is estimated from time-series regressions of daily changes in liquidity on changes in liquidity of a portfolio of stocks highly traded by institutions. $ITrade$ is the number of shares traded by institutions divided by number of shares outstanding, $MTrade$ is the total volume for as reported in CRSP, divided by the number of shares outstanding. $illiq(avg)$ is the firm's average Amihud (2002) illiquidity measure over the previous quarter. $instown$ is the number of shares held by all institutional investors divided by number of shares outstanding. $ln(size)$ is the natural logarithm of market capitalization. In columns (1) to (4) we interact $ITrade$ and $MTrade$ with dummies based on aggregate net flows. All aggregate flows are scaled by total US market capitalization and flows are measured contemporaneously with β_{HI} . In columns (1) and (2) we interact $ITrade$ with a dummy variable $extremflow$ that equals one if aggregate net flows are in either the highest 10% or lowest 10% for that quarter, and zero otherwise. In column (2) and(4) we interact $ITrade$ and $MTrade$ with a dummy variable $negflow$ that equals one if aggregate net flows are negative for that quarter, and zero otherwise. In column (5) and (6) we control for $instown$. Time dummies are included but not reported. Standard errors are clustered by firm.

	(1)	(2)	(3)	(4)	(5)	(6)
ITrade	54.15***	56.23***	58.45***	58.44***	104.6***	110.3***
	(5.49)	(5.59)	(5.17)	(4.98)	(7.11)	(6.03)
ITrade ∗ extremflow	40.27***	29.49*			15.95	
	(2.72)	(1.77)			(0.54)	
ITrade ∗ negflow			6.046	6.065		−10.43
			(0.45)	(0.40)		(−0.43)
instown					0.439***	0.192**
					(6.50)	(2.50)
instown ∗ extremflow					−0.159	
					(−1.33)	
instown ∗ negflow						0.448***
						(4.33)
MTrade	27.98***	27.20***	28.05***	28.05***	27.63***	30.81***
	(19.26)	(18.42)	(19.35)	(16.98)	(16.21)	(15.10)
MTrade ∗ extremflow		3.371			5.301*	
		(1.39)			(1.70)	
MTrade ∗ negflow				−0.0066		−3.591
				(−0.00)		(−1.46)
illiq(avg)	−284**	−285**	−284**	−284**	−201.9*	−195.7*
	(−2.23)	(−2.23)	(−2.23)	(−2.23)	(−1.68)	(1.65)
ln(size)	0.0550***	0.0549***	0.0549***	0.0549***	0.0603***	0.0599***
	(6.42)	(6.40)	(6.41)	(6.42)	(6.87)	(6.88)
Observations	74875	74875	74875	74875	60835	60835
R^2	0.04	0.04	0.04	0.04	0.04	0.04

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

2.5 Common Trading

To test our third hypothesis, pairs of stocks connected through common institutional trading exhibit higher commonality in liquidity, we follow an approach analogous to that proposed by Antón and Polk (2014). In particular, we form pairs of common stocks (share codes 10 and 11) from NYSE, Amex and Nasdaq whose market capitalization is above one billion and we require firms to have at least 200 observation per year. We choose this filtering criteria to limit the number of pairs. Table 2.6 reports the number of stocks, pairs of stocks, and trading institutions, as defined by ANcerno client codes. Table 2.7 reports the extent of institutional trading. For the entire sample period, the median number of institutions per traded stock is 121, while the median number of stocks traded by each institution is 566.

We report the number of common institutions for a pair of stocks in Table 2.8. All stock pairs have at least one active institutional trading in common and the median pair has 14 institutional investors in common. The table also shows that the number of common institutional trading-based connections between stocks in our sample has increased over the period we study. In 1999, the median number of common institutional trading connections was 6. In 2009, the median number of trading connections was 24, although this figure is only 14 in the last year of our sample period.

Table 2.9 reports estimation results. In column (1), we estimate a specification with the number of institutions trading in both stocks as a regressor and find a positive and statistically significant link between that variable and liquidity comovement between two stocks. A change of one standard deviation in the degree of common trading results is associated with a 7.3% increase in the expected product of liquidity changes relative to the average degree of covariation.

The ability to forecast differences in liquidity comovement using institutional connectedness would be expected if the predictability simply reflects the fact that the institutions choose to trade stocks that are similar even if institutional trading is not associated with liquidity commonality. Therefore, we include four variables to control for stock similarity. The results of this analysis are reported in columns (2)-(4) of Table 2.9. Control variables are normalized to have a standard deviation of one and transformed (in the case of size, book-to-market, and momentum) so that higher values indicate greater style similarity. The coefficient on our measure of common institutions is similar to that found in column (1), although comovement in stock liquidity also seems to be strongly associated with stock similarity. The coefficient on common institutional trading has the second strongest economic significance among all variables under consideration.

Table 2.6: Number of Stocks, Pairs and Institutions Per Year

This table lists the total number of stocks, pairs of stocks, and institutions for every year of the sample period. The sample consists of all NYSE-Amex-Nasdaq stocks that are above NYSE median capitalization as of the end of each month. The fourth column lists the number of institutions that trade at least one of the stocks in the sample.

Year	Stocks	Pairs	Institutions
1999	737	271216	379
2000	839	351541	370
2001	837	349866	398
2002	813	330078	424
2003	817	333336	401
2004	988	487578	404
2005	1081	583740	376
2006	1170	683865	399
2007	1185	701520	377
2008	1027	526851	333
2009	845	356590	322
2010	1003	502503	308
2011	1070	571915	259

Table 2.7: Number of Institutions and Stocks Summary Statistics

This table reports summary statistics for the sample defined in Table 6 over the following variables: number of institutions that trade each stock and number of stocks traded by each institution.

Panel A: 1999-2011					
	Mean	Median	SD	Min	Max
Institutions per stock	129.74	121	61.79	1	361
Stocks per Institution	612.76	566	341.90	1	1508
Panel B: 1999-2002					
	Mean	Median	SD	Min	Max
Institutions per stock	142.84	130	74.35	1	361
Stocks per Institution	509.30	454	296.55	1	1468
Panel C: 2003-2007					
	Mean	Median	SD	Min	Max
Institutions per stock	123.89	116	56.69	1	348
Stocks per Institution	652.83	599	361.25	1	1508
Panel D: 2008-2011					
	Mean	Median	SD	Min	Max
Institutions per stock	124.32	119	51.60	1	276
Stocks per Institution	663.41	641	335.75	1	1324

Table 2.8: The Cross-sectional Distribution of Common Institutions

This table reports the distribution of the variable $F_{ij,t}$ measuring the number of Institutions trading both stocks in a pair during the previous month. The distribution is shown for the average of full sample and for each year in the sample.

	Common Institutions($F_{ij.t}$)		Percentiles							
	mean	sd	0%	25%	50%	75%	90%	95%	99%	100%
Full Sample	15.93	10.77	1	9	14	21	29	36	53	185
1999	8.34	7.12	1	4	6	11	16	21	36	132
2000	10.59	8.86	1	5	8	13	21	27	44	158
2001	14.00	10.58	1	7	11	18	26	33	54	170
2002	17.27	12.05	1	9	15	22	32	40	61	185
2003	15.62	11.01	1	8	13	21	30	36	53	167
2004	15.18	9.30	1	9	13	19	27	33	47	170
2005	13.45	8.52	1	8	12	17	24	30	43	117
2006	14.60	9.54	1	8	13	18	26	33	49	124
2007	15.66	9.29	1	9	14	20	27	33	48	131
2008	20.20	11.28	1	13	18	25	34	41	58	164
2009	26.00	12.81	1	17	24	32	42	50	68	161
2010	20.98	10.86	1	14	19	26	35	42	58	140
2011	16.28	9.05	1	10	14	20	28	34	48	118

Table 2.9: Liquidity Commonality in a Pair of Stocks

This table reports Fama-McBeth estimate of monthly cross-sectional regressions forecasting the realized cross-product of changes in stock illiquidity for a sample of stocks. The predictive variables are updated monthly and include our main measure of institutional connectedness, the number of institutions trading in both stocks $F_{ij,t}$, and a series of controls at time t. We measure similarity of the two stocks in the pair as the negative of the absolute value of the difference in size, BE/ME and momentum percentile ranking across the two stocks in the pair ($DIFF\_SIZE_{ij,t}$, $DIFF\_BEME_{ij,t}$, $DIFF\_MOM_{ij,t}$ respectively). We also measure the number of similar SIC digits, $NUM\_SIC_{ij,t}$ for the two stocks in a pair as well as size percentile of each stock in the pair and an interaction ($SIZE1_{ij,t}$, $SIZE2_{ij,t}$, $SIZE1SIZE2_{ij,t}$). All independent variables are then rank transformed and normalized to have a unit standard deviation, which we denote with an asterisk superscript. We calculate Newey-West standard errors (four lags) of the Fama-MacBeth estimates that take into account autocorrelation in the cross-sectional slopes.

	(1)	(2)	(3)	(4)
F^*	0.0123***	0.0119***	0.0115***	0.0117***
	(5.76)	(5.5)	(7.72)	(7.99)
Constant	0.1601***	0.1601***	0.1602***	0.1601***
	(7.46)	(7.46)	(7.47)	(7.47)
$DIFF\_SIZE^*$		0.0037***		0.0033***
		(7.22)		(7.15)
$DIFF\_BEME^*$		0.0044***		0.0044***
		(6.29)		(6.54)
$DIFF\_MOM^*$		0.0088***		0.0088***
		(6.01)		(6.05)
NUM_SIC^*		0.0178***		0.0178***
		(16.84)		(16.74)
$SIZE1^*$			0.0008	0.0003
			(0.46)	(0.17)
$SIZE2^*$			−0.0000	−0.0005
			(−0.01)	(−0.3)
$SIZE1SIZE2^*$			0.0050***	0.0045***
			(12.51)	(12.5)

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

2.6 The Mutual Fund Scandal of 2003

Thus far, our results indicate that commonality in liquidity is higher for stocks that are highly traded by institutional investors. We also show that our results are robust to different specifications. As we estimate these effects using lagged $ITrade$ at the quarterly frequency, an important issue is the extent to which we can make statements about the causal nature of the relationship between $ITrade$ and β_{HI}. Two concerns are in order. First, a third variable, such as a specific stock characteristic, could be causing both institutional trading in a certain group of stocks and commonality in liquidity. Controlling for observable stock characteristics and time-invariant unobservable characteristics is not enough if the third variable is not observable and varies through time. Second, a positive relation between $ITrade$ and β_{HI} is consistent with commonality in liquidity causing institutional trading. For instance, a market-wide deterioration of liquidity risk could lead investors to unwind their positions to reduce future liquidity risk. To address this concern, this section deals with the potential consequences of endogeneity.

Building on Antón and Polk (2014), we propose to exploit a natural experiment based on the mutual fund scandal that occurred in September 2003. In the last quarter of 2003, 25 fund families faced allegations of illegal trading that included market timing and late trading. Affected funds experienced significant outflows as a consequence of the scandal. Kisin (2011) documents that the funds of affected families continued to experience outflow until 2006. The estimated losses of assets for the affected funds are 14.1% within a year and 24.3% in two years since the scandal broke. McCabe (2009) estimates the losses 36 months after the scandal to be 37% of the assets under management for the involved fund families. We argue that capital flows arising from this scandal are exogenous to funds' trading activities, and so is the excess trading experienced by stocks more widely held by mutual funds.

More specifically, we instrument institutional trading on a given stock with the fraction of shares of that stock owned by all scandal-affected institutions divided by the fraction of shares owned by all institutions as the time scandal broke or one quarter before the scandal. We then use two-stage least-squares estimation, where the natural experiment takes place (from December 2003 to December 2006). Column (1) of Table 2.10 shows the results of the first-stage regression, $ITrade$ on $fraction_0$ and various controls used in regression (2.5). The coefficient on $fraction_0$ is positive and highly significant. Column (2) of Table 2.10 presents the results of the second-stage regression, where the dependent variable is $\beta_{HI,it+1}$. The coefficient on $ITrade$ is positive and large in magnitude, but statistically insignificant. While the scandal-affected families experienced outflows in the 36 months following the scandal, the effect of their trades on illiquidity movements could have faded through time as the market anticipated abnormal trading in the stocks held by those families. In columns (3) and (4), we estimate the 2SLS regressions excluding 2006. The coefficient on $ITrade$ for the second stage is statistically significant but only at the 10% level. Therefore, we find no evidence of a causal effect of institutional trading–as a response to the scandal–on commonality in liquidity for the market as a whole, except for, perhaps, the first two years following the fraud allegations.

In Table 2.4, we show the association between institutional trading and commonality in liquidity is stronger for the most liquid stocks and stocks with the largest market capitalization. Building on those results, in columns (5)-(6) we report regression results for stocks in the top quintile of the market capitalization and liquidity distribution. In contrast to the results for all stocks, in both subsamples, the coefficient on $ITrade$ for the second stage regression is not only positive but also statistically significant at the 5% level.

Table 2.10: Mutual fund Scandal of 2003

This table reports results from a 2SLS instrumental variables regression based on mutual funds scandal 2003, using data from December 2003 to December 2006. In the first stage, we predict the variable $ITrade_{it}$ with the fraction of shares owned by all scandal funds divided by the fraction of shares owned by all funds as the time scandal broke or one quarter before the scandal $fraction_{i0}$ column (1). The second stage of the regression uses the fitted $ITrade$ to forecast the $\beta_{HI,it+1}$ column (2). In columns (3) and (4) we report the results excluding 2006. Columns (5) and (6) report estimation results for the sub-sample of stocks in the top quintile of the market capitalization distribution. In columns (7) and (8), we report results for the sub-sample of stocks in the top quintile of the liquidity distribution. Time dummies are included, but not reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ITrade		847.18		1239.22*		1531.3**		801.53**
		(1.46)		(1.89)		(2.04)		(1.96)
instown	0.0011***	−0.7018	0.0011***	−1.158	0.0009***	−0.8960	0.0012***	−0.4981
	(21.83)	(−1.04)	(17.09)	(−1.55)	(12.72)	(−1.16)	(15.85)	(−0.90)
fraction0	0.0008***		0.0008***		0.0013***		0.0016***	
	(4.68)		(3.96)		(5.26)		(6.37)	
MTrade	0.0661***	−8.274	0.0728***	−39.279	0.0534***	−16.17	0.0530	2.8984
	(50.22)	(−0.21)	(43.03)	(−0.82)	(27.94)	(−0.39)	(31.40)	(0.13)
ln(size)	−0.00004***	0.01054	−0.00004***	0.0121	−0.00004***	0.180***	−.0001***	0.1036**
	(−7.49)	(0.34)	(−6.52)	(0.32)	(−3.54)	(3.54)	(−8.18)	(2.33)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	11004	11004	7772	7772	3486	3486	6109	6109
R^2	0.31		0.31		0.33		0.30	
$F-$stat	21.92		15.67		27.67		40.61	

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

2.7 Robustness Tests

The empirical evidence thus far suggests that stocks that are highly traded by institutional investors exhibit strong commonality in liquidity. The relation between β_{HI} and $ITrade$ is robust to various model specifications. In this section, we show that our main findings are not affected by the the first-step liquidity beta estimation. In particular, we address the concerns that arise from using Amihud illiquidity measure as a proxy for stock liquidity. For instance, the liquidity co-variation that we document could be induced by commonality in (absolute) returns, not necessarily by comovements in the ratio of absolute returns to dollar volume. We first show that our results are not driven by returns or volatility comovement, and then demonstrate that our findings are not particular to the structure of our first step time-series regression.

We follow Koch et al. (2012) and address the impact of return comovements and volatility comovements in three different ways. First, we estimate the covariance between individual stock return and the value-weighted return of the high institutional trading portfolio and add it as an additional control in the regression equation (2.5). We refer to this variable as institutional return beta. The results of these regressions are presented in Panel A Table 2.11. Column (1) reports the results of equation (2.5) after adding institutional return beta as an additional control, consistent with Koch et al. (2012) we find that institutional return beta has a strong positive impact on β_{HI}. This shows that commonality in return (information affecting return on high institutional trading stocks) has an impact on commonality in liquidity among these stocks. Nevertheless, the positive impact of institutional trading activity on β_{HI} still remains highly significant. Second, we run our base regression (2.5) on sub-samples based on institutional return beta quartiles to capture any potential non-linear relationship between liquidity beta and institutional return beta. The results of these regression are reported in column (2) through column (5). We find that our main findings hold in all sub-samples as indicated by highly significant and positive estimate for the impact of $ITrade$ on β_{HI}. Third, we alter the first step time series regression (2.4) by adding the return of high institutional trading stocks portfolio to account for the potential impact of covariation between stock liquidity and the return of highly trade stocks portfolio. Column (6) reports the result of equation (2.5) using β_{HI} from the modified first step specification as dependent variable. We still find a positive significant impact of $ITrade$ on β_{HI}.

Table 2.11: Robustness Tests: Controlling for Return and Volatility Comovement

This table reports results from pooled OLS regressions of estimates of on selected stock characteristics measured at the end of the previous quarter, conditional on aggregate mutual fund flows. β_{HI} is estimated from time-series regressions of daily changes in liquidity on changes in liquidity of a portfolio of stocks highly traded by institutions. $ITrade$ is the number of shares traded by institutions divided by number of shares outstanding, $MTrade$ is the total volume for as reported in CRSP, divided by the number of shares outstanding. $illiq(avg)$ is the firm's average Amihud (2002) illiquidity measure over the previous quarter. $instown$ is the number of shares held by all institutional investors divided by number of shares outstanding. $ln(size)$ is the natural logarithm of market capitalization. The first column repeats the standard regression of β_{HI} on $ITrade$ and includes as an additional control variable the beta estimate between the firm return and the value-weighted return on the high institutional trading portfolio estimated contemporaneously with the liquidity beta. columns (2) to (5) run the above regression on cross-sectional sub-samples sorted by the return beta. Model (6) runs the same regression, but controls for return covariation in the first stage. Specifically, the dependent variable is a liquidity beta estimated in a time series regression that controls for firm returns and the return on the high institutional trading portfolio. We repeat this analysis in Panel B, substituting squared returns, $return^2$, for returns, as a proxy for volatility.

Panel A: Controlling for Comovement in Return

		Return Beta				
		Low	2	3	High	
	(1)	(2)	(3)	(4)	(5)	(6)
ITrade	100.7***	99.03***	60.76**	97.02***	97.89***	102.6***
	(7.76)	(2.82)	(2.21)	(4.18)	(5.11)	(7.44)
instown	0.442***	0.358***	0.599***	0.465***	0.240**	0.431***
	(7.21)	(3.25)	(5.33)	(4.28)	(2.19)	(6.71)
MTrade	19.53***	13.32***	21.07***	25.86***	17.62***	28.91***
	(12.14)	(3.22)	(5.40)	(8.39)	(8.96)	(16.40)
Ret_beta	0.0001***					
	(20.90)					
illiq(avg)	−253.5*	31.88	−433.2**	−357.1***	−507.6***	−190.5
	(−1.81)	(0.26)	(−2.29)	(−2.96)	(−2.68)	(−1.56)
ln(size)	0.0962***	0.0542***	0.0881***	0.111***	0.123***	0.0619***
	(10.90)	(4.30)	(6.08)	(8.19)	(7.08)	(6.93)
Observations	60835	15492	15406	15204	14733	60525
R^2	0.05	0.03	0.04	0.05	0.07	0.04

Panel B: Controlling for Volatility Comovement

		Volatility Beta				
		Low	2	3	High	
	(1)	(2)	(3)	(4)	(5)	(6)
ITrade	102.1***	116.1***	75.11**	103.0***	84.97***	93.79***
	(7.67)	(4.60)	(2.18)	(4.30)	(4.44)	(6.91)
instown	0.429***	0.332***	0.690***	0.451***	0.15	0.388***
	(6.93)	(3.22)	(6.32)	(4.14)	(1.37)	(6.16)
MTrade	25.43***	20.33***	20.59***	27.96***	19.82***	27.04***
	(15.18)	(6.08)	(6.06)	(8.76)	(9.64)	(16.01)
Vol_beta	0.0079***					
	(15.01)					
illiq(avg)	−223.4*	−88.83	−51.83	−539.3***	−524.9***	−198.7*
	(−1.75)	(−0.49)	(−0.47)	(−3.08)	(−3.72)	(−1.69)
ln(size)	0.0745***	0.0373***	0.0934***	0.0967***	0.0930***	0.0519***
	(8.49)	(2.80)	(6.96)	(6.65)	(5.95)	(5.84)
Observations	60835	15097	15537	15377	14824	60525
R^2	0.05	0.03	0.05	0.05	0.06	0.04

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

Furthermore, we address the concern that our findings could be driven by the fact that common movements in volatility of stocks traded to a high degree by institutional investors lead to higher liquidity commonality. We conduct a test similar to that described above, replacing returns in the time-series regressions with return squared to proxy for stock volatility. We report the result of this additional analysis in Panel B of Table 2.11. We find that results obtained from the standard second stage regression do not change: We still find positive significant impact of $ITrade$ on β_{HI}.

Table 2.12 varies the definition of common trading for our benchmark specification of Table 2.9. We first replace the number of common institutions, $F_{ij,t}$, with the total dollar volume by all common institutions of the two stocks scaled by number of shares outstanding of the two stocks, $F^{T}_{ij,t}$. Our next alternative is to measure the common trading by the the total cross product of dollar volume by all common institutions of the two stocks scaled by number of shares outstanding of the two stocks, $F^{CT}_{ij,t}$. Both alternative measures of common trading forecast the cross-sectional variation in realized changes in liquidity cross-products.

Table 2.12: Robustness Tests: Liquidity Commonality in a Pair of Stocks

This table reports Fama-McBeth estimate of monthly cross-sectional regressions forecasting the realized cross-product of changes in stock illiquidity for a sample of stocks. The predictive variables are updated monthly and include different measures of institutional connectedness and a series of controls at time t. As measures of connectedness, we use the number of institutions trading in both stocks, $F_{ij,t}$; the total trading volume by all common institutions in dollars of the two stocks scaled by number of shares outstanding of the two stocks, $F^{T}_{ij,t}$; the total cross product of trading volume by all common institutions in dollars of the two stocks scaled by number of shares outstanding of the two stocks, $F^{CT}_{ij,t}$. We measure the negative of the absolute value of the difference in size, BE/ME and momentum percentile ranking across the two stocks in the pair ($DIFF\_SIZE_{ij,t}$, $DIFF\_BEME_{ij,t}$, $DIFF\_MOM_{ij,t}$ respectively). We also measure the number of similar SIC digits, $NUM\_SIC_{ij,t}$ for the two stocks in a pair as well as size percentile of each stock in the pair and an interaction ($SIZE1_{ij,t}$, $SIZE2_{ij,t}$, $SIZE1SIZE2_{ij,t}$). All independent variables are rank-transformed and normalized to have a unit standard deviation, which we denote with an asterisk superscript. We calculate Newey-West standard errors (four lags) of the Fama-MacBeth estimates that take into account autocorrelation in the cross-sectional slopes.

	(1)	(2)	(3)
F^*	0.0117^{***}		
	(7.99)		
$F^{T*}_{ij,t}$		0.0028^{***}	
		(2.44)	
$F^{CT*}_{ij,t}$			0.0026^{**}
			(2.14)
Constant	0.1602^{***}	0.1611^{***}	0.1611^{***}
	(7.47)	(7.52)	(7.52)
$DIFF\_SIZE^*$	0.0033^{***}	0.0032^{***}	0.0032^{***}
	(7.15)	(7.04)	(7.07)
$DIFF\_BEME^*$	0.0044^{***}	0.004344	0.0043^{***}
	(6.54)	(6.48)	(6.5)
$DIFF\_MOM^*$	0.0088^{***}	0.0087^{***}	0.0087^{***}
	(6.05)	(6.09)	(6.09)
NUM_SIC^*	0.0178^{***}	0.0179^{***}	0.0179^{***}
	(16.74)	(16.7)	(16.69)
$SIZE1^*$	0.0003	0.0053^{***}	0.0056^{***}
	(0.17)	(2.81)	(2.97)
$SIZE2^*$	-0.0005	0.0045^{**}	0.0048^{***}
	(-0.3)	(2.55)	(2.7)
$SIZE1SIZE2^*$	0.0045^{***}	0.0051^{***}	0.0052^{***}
	(12.5)	(12.03)	(12.74)

***, **, and * denote statistical significant at 1, 5, and 10 percent level, respectively.

2.8 Conclusions

In this chapter, we reevaluate the empirical evidence that institutional investors' trading activity induces the liquidity of stocks to move together. We overcome the limitations of previously employed proxies and establish a direct link between institutional trading activity and liquidity commonality by using data on actual institutional investor trades obtained from ANcerno Ltd for the 1999-2011 period. Consistent with the interpretation of the findings of Koch et al. (2012), our results suggest that the trading activity of institutional investors is an important factor in explaining commonality in liquidity. However, by controlling for institutional ownership we can be confident that these results are not driven by institutional investors' portfolio selection effects.

Contrary to our expectation, we do not find evidence that the association between institutional trading and commonality in liquidity strengthens in periods of extreme or negative flows of money into and out of mutual funds. A possible interpretation of this result is that in periods of extreme flows or negative flows, the level of trading by institutions increases, but not the degree of correlation in trading activity across institutions. Since our variable of interest is institutional trading, the effect of flows on commonality in liquidity is already taken into account.

We also find evidence that the impact of institutional trading on commonality in liquidity is due to correlated trading across institutional investors. In particular, the liquidity of pairs of stocks that are connected through their common active institutional trading covary more together, controlling for stock characteristics.

Finally, when we instrument trading with the fraction of a stock's share owned by institutions affected by the 2003 scandal and focus on the months following the scandal, we find weak evidence of a causal link from institutional trading to commonality in liquidity for the market as a whole. However, our results are suggestive of a causal link from institutional trading to commonality in liquidity for large and liquid firms.

The results of our study are interesting both for market participants and regulators. First, we document that an increase in institutional investors' trading activity is associated with higher commonality in liquidity. This has implications for portfolio managers following active strategies, who might consider avoiding stocks whose trading is dominated by institutional investors. Second, our results should be taken as a warning against the large-scale effects of regulations that force financial institutions to demand liquidity at the same time as a response to a common deterioration of capital and liquidity levels.

Chapter 3

Short-Term Institutional Herding: Evidence from Transaction Data

Contents

3.1 Introduction

A growing body of literature on the trading behavior of institutional investors shows that institutions engage in herding behavior, that is, institutional investors have a tendency to flock together on the same side of the market for a given stock and a given period. Theoretical literature provides various potential explanations for institutional herding. Broadly speaking these theories fall into two major groups, intentional and unintentional herding (Kremer and Nautz, 2013). The intentional herding may arise due to reputational risk or because institutions infer information from the previous trades of better-informed managers (Scharfstein and Stein, 1990; Bikhchandani et al., 1992; Sias, 2004). Alternatively, the unintentional herding may occur when institutional investors trade on common public information or because they share common aversion or attraction to certain stock characteristics (Froot et al., 1992; Hirshleifer et al., 1994; Falkenstein, 1996). Despite of the rich theoretical literature on institutional herding, the empirical evidence is at best mixed. Lakonishok et al. (1992) find a weak evidence of herding behavior among a sample of U.S. pension funds. Grinblatt et al. (1995) find no evidence of herding among mutual funds. Wermers (1999) finds little evidence of mutual funds engaging in herding behavior, with slightly stronger evidence in small stocks. More recently Sias (2004) examines the time-series properties of institutional demand for a security and find a strong evidence of institutional herding.

The weak connection between the theory and evidence could result from the fact that herding behavior is a high frequency phenomenon. On one hand, the theoretical models provide various explanations and conditions under which herding may arise in financial markets in a high-frequency trading context. On the other hand, due to data limitations, the empirical studies rely on the low frequency data, quarterly holding, to investigate the predictions of these theoretical models. However, for example, if herding behavior arises because investors infer information from the previous trades of better-informed investors, we would expect them to update their beliefs more quickly and trade in the same direction. Furthermore, if herding occurs due to the correlated signals about the firm, such information can only be exploited at short-term horizons. Therefore, measuring institutional herding at quarterly frequency may bias the results and fail to detect the short-term institutional herding. Moreover, the low-frequent data impede the analysis of the price impact of institutional herding; since we cannot examine the intra-quarter relation between institutional trading and returns, it is unclear whether institutions react to or lead stock price movements. The current study addresses these data limitations and employ a proprietary database of daily institutional transaction data to test whether institutions herd at weekly level, investigate the determinant of short-term institutional herding, and the consequences of institutional herding on security prices. Understanding the different drivers and types of institutional herding is important for regulatory purposes and whether institutional herding leads to market inefficiencies. Because we only observe the trade of each institution and not the motives behind these trades, identifying whether the herding is intentional or unintentional is a difficult task. However, I follow the previous empirical studies and link herding behavior to information environment of the firm by using variables such as firm size and daily turnover to proxy for the quality and available information about the firm.

Several other empirical studies address these data limitations and use higher frequency data to investigate herding behavior in financial markets. For example, Barber et al. (2009a) address the issues of the low frequency data using Trade and Quotes (TAQ) and Institute for the Study of Security Markets (ISSM) transaction data. Although the data they employ are anonymous, not investor specific, their results suggest that individual investors engage in short-term herding behavior and that the small trade order imbalance can reliably predict weekly returns. Venezia et al. (2011) investigate the monthly herding behavior among professional and amateur investors using transaction data provided by a large bank in Israel. They find a herding tendency among both types of investors, however, the herding behavior is lower among professionals, herding depends on stock characteristics such as size and systematic risk, and that their results are consistent with the theory of information-based herding. Kremer and Nautz (2013) study the herding behavior at daily level among the German institutional investors using a comprehensive database of all transactions made by all German institutions. These authors distinguish between the intentional and unintentional herding behavior and find that institutional herding depends on stock characteristics such as past returns and volatility, and that their results are consistent with the unintentional herding hypothesis.

The current study contributes to the empirical literature on institutional herding by employing daily transactional data for a large sample of U.S. institutional investors. The data distributed by ANcerno Ltd., a private transaction costs analyst, provide a unique opportunity to investigate the short-term institutional herding as they contain detailed information on the trade-by-trade transactions made by all institutions in the sample. This database overcomes many of the data limitations inherent in the previous studies and provides new evidence on the weekly herding behavior of institutional investors and its impact on prices for a broad cross-section of stocks on the U.S. markets.

I investigate the weekly institutional herding behavior using Lakonishok, Shleifer, and Vishny (1992) measure (LSV) and compute the sample average over all the stocks and time periods. A positive and significant herding measure would be in favor of herding behavior. Next, I follow Kremer and Nautz (2013) and study whether institutional herding is intentional or unintentional. To examine the type and the determinants of institutional herding, I use two different approaches. First, I follow Wermers (1999) and use a portfolio sort method based on firm size and prior week returns. Second, in a multivariate setting I estimate a cross-sectional regressions using Fama and MacBeth (1973) approach. Finally, I examine whether institutional herding has a stabilizing or destabilizing impact on prices by regressing a set of future cumulative returns against the buy and sell herding measures. Moreover, I follow Dasgupta et al. (2011) and study the impact of the persistence in the investment decisions of institutional investors on security prices using Fama and MacBeth (1973) approach.

The results can be summarized as follow. First, there is little evidence of institutional herding at weekly horizon. The overall (LSV) herding measure of 2.5% suggests that among 100 institutions trading a stock during the week, there are two more institutions on the same side of the market than what would be expected if they trade randomly and independently. Second, there is more herding on the buy side than on the sell side of the market. In addition, a sub-period analysis shows that the level of herding before 2007 (before the financial crisis) is stronger than the herding intensity in the most recent years (the crisis and the post-crisis period). Third, institutional buy and sell herding affect asset prices differently. While the buy herding is positively associated with the future returns, the sell herding is related to return reversals. Finally, the persistence of institutional herding over multiple weeks is a strong predictor of return reversals, that is, stocks consistently sold by institutions over three to six weeks outperform the stocks bought by them over the next eight to twenty-four weeks.

The weak evidence of institutional herding at weekly horizons is consistent with quarterly findings in the previous studies. Lakonishok et al. (1992) find a weak evidence of herding behavior among pension funds and Wermers (1999) document a weak evidence of mutual fund herding. The price impact results are similar to that for the German institutions documented in Kremer and Nautz (2013) who find an asymmetric impact of buy and sell herding on prices. While the buy herding has a stabilizing effect, the sell herding affect prices in a destabilizing manner. Furthermore, the findings on the short-term persistence of institutional herding are consistent with the long-term results found in Dasgupta et al. (2011), such that the persistence in institutional herding leads to return reversals.

The rest of this chapter is organized as follow. In Section 3.2 I develop the main hypotheses. Section 3.3 presents the applied herding measure and the testing methodology. Section 3.4 discusses the main empirical results. Section 3.5 provides some conclusions remarks.

3.2 Hypotheses

According to the economic theory, herding behavior in financial markets could arise when investors intentionally disregard their prior beliefs and follow the trades of other market participants or when investors unintentionally react to common signals by analysing the same sources of information. The unintentional herding may occur when institutions receive correlated signals about the firm or follow the same indicators, leading them to deduce similar conclusions about the future payoffs of a given security (Hirshleifer et al., 1994). It may also arise if institutional traders share common preferences or aversion to certain stock characteristics (Falkenstein, 1996). Additionally, fund managers can be seen as a relatively homogenous group sharing similar education as well as professional skills, therefore, they tend to interpret the information in a similar fashion. Alternatively, the institutional herding my arise when fund managers intentionally ignore their own private information and follow the trades of other investors (Scharfstein and Stein, 1990; Bikhchandani et al., 1992). Based on the predictions of the theoretical models and the empirical findings found at quarterly level, the first hypothesis captures the idea of whether institutional investors engage in herding behavior at weekly level.

Hypothesis 1: ***Institutional investors tend to be net buyers or sellers for a given stock and during a given period***.

Fund managers having low quality information about the future earnings for the stocks compromising their portfolio holdings have greater motives to ignore their noisy private information and follow the crowd if the market consensus is different Wermers (1999). This type of herding is especially common in markets where little public information is available. Previous studies suggest that large firms experience greater predisclosure information production and propagation than the small ones (Atiase, 1985). This is because large firms usually release more information and there are more security analysts following large firms than small firms. Therefore, firm size is used as a proxy reflecting the amount and the quality of information available. Since less information is produced about small firms, institutional herding in this subgroup of stocks would be evidence in favor of intentional herding. It should also be noted that higher institutional herding on the sell side for the small stocks is consistent with the notion that institutional traders share common aversion to small stocks (Falkenstein, 1996). Alternatively, the unintentional herding would be more prevalent among large stocks as institutions have more commonality in information. The empirical evidence found at quarterly horizon support the intentional herding hypothesis as there is higher institutional herding among small firms (Lakonishok et al., 1992; Wermers, 1999; Choi and Sias, 2009). Thus, the second hypothesis captures the relationship between institutional herding and firm size to distinguish between the intentional and unintentional herding.

Hypothesis 2: ***There is greater institutional herding among small capitalization firms than the large firms***.

Grinblatt et al. (1995) show that the majority of mutual funds engage in positive feedback trading strategies to pick stocks. Moreover, Wermers (1999) shows that the intensity of institutional herding is higher among stocks with extreme prior returns, in particular, mutual funds tend to buy past winners more frequently than selling past losers. Sias (2004) shows that institutional herding is in part due to institutional positive feedback trading. Building on the previous empirical findings, institutional herding arising as a consequence of simultaneous reaction to past price movements is consistent with the unintentional herding. That is, institutions may follow each other into and out of the same securities because they share common attraction (aversion) to stocks with high positive (negative) past returns. Thus, the third hypothesis captures the relation between institutional herding and past stock returns to distinguish between the intentional and unintentional herding. A positive relation between the past returns and LSV herding measure would be evidence in favor of the unintentional herding.

Hypothesis 3: ***Institutional herding arises as a consequence of institutions following feedback trading strategies.***

Institutional herding, whether it is intentional or unintentional, may induce price pressure and affect asset prices in a stabilizing or destabilizing manner. For instance, if institutions trade together based on informational motives, such herding may lead to more efficient markets by enhancing the adjustment of fundamental information into prices and promoting price discovery (Froot et al., 1992). Conversely, if institutions systematically disregard their own private information and follow the crowd, prices may move away from their fundamental values (Scharfstein and Stein, 1990). The conclusions of the empirical studies regarding the impact of institutional herding on prices is found to be that stabilizing and destabilizing depends on the time interval considered. For example, studies examining the relation between institutional herding and returns at quarterly level find that herding has a stabilizing effect (Wermers, 1999; Sias, 2004). In contrast, studies considering long time horizons find that institutional herding is associated with reversals in returns (Dasgupta et al., 2011). Thus, the last hypothesis captures the relation between short-term institutional herding and returns. A positive (negative) relation between the buy (sell) herding and future returns would suggest that short-term institutional herding has a stabilizing effect on market prices.

Hypothesis 4: ***Short-term institutional herding has a stabilizing impact on asset prices.***

3.3 Methodology and Variable Definitions

3.3.1 Herding Measure

The primary herding measure used in this study is the Lakonishok, Shleifer, and Vishny (1992) (LSV) that detects the empirical herding behavior among market participants. This metric that has been widely used in the empirical studies (e.g., Grinblatt et al., 1995; Wermers, 1999) captures the tendency of investors to trade a specific stock together and in the same direction over the same period, for whatever reason, more often than what would be expected if they trade independently and randomly. The LSV herding measure for stock i and week t (HM_{it}) is given by

$$HM_{it} = |br_{it} - \overline{br_t}| - E[|br_{it} - \overline{br_t}|] \tag{3.1}$$

where br_{it} is the ratio of all institutional investors trading the stock i during week t that are net buyers and $\overline{br_t}$ is the average of the buyer ratio across all stocks in week t. The LSV measure in equation (3.1) is a simple "count" of the number of institutions that are net-buyers in stock i during week t relative to the total number institutions trading stock i during week t, minus the expected proportion of buyers. This statistic assumes under the null hypothesis of no herding, the trading decision whether it is buy or sell has a bernoulli distribution with equal success probability. The first term of equation 3.1 captures the deviation of the buyer ratio for stock i in week t from the overall buy probability at week t. Therefore, HM_{it} measures the similarity in the trading patterns of institutions in excess of market-wide herding. The second term $E[|br_{it} - \overline{br_t}|]$ is an adjustment factor allowing for random variation around the expected ratio of buyers which ensures that HM_{it} is zero if the trading decisions are independent (see., Lakonishok et al., 1992).

To investigate the magnitude and the direction of institutional herding as well as its impact on asset prices I follow Wermers (1999) and use a modified herding measure that distinguishes between buy-side and sell-side herding. The buy herding (sell herding) BHM_{it} (SHM_{it}) captures whether stocks experience a higher (lower) buyer ratio than the average stock during the same week. The two measures are given as

$$BHM_{it} = HM_{it}|br_{it} > \overline{br_t} \tag{3.2}$$

$$SHM_{it} = HM_{it}|br_{it} < \overline{br_t} \tag{3.3}$$

To examine the first hypothesis of whether institutional investors engage in herding behavior at weekly level, I follow Lakonishok et al. (1992) and compute the average LSV measure across all stocks and over all time periods to obtain the average herding measure $\overline{HM}$. A positive and significant value of $\overline{HM}$ would be evidence in favor of herding behavior, that is, institutions tend to accumulate on the same side of the market in their trading decisions. The higher the value of $\overline{HM}$ the stronger the herding. For instance, $\overline{HM} = 5\%$ suggests that out of 100 transactions, five more investors trade on the same side of the market than what would be expected if the trading decisions were random and independent.

3.3.2 Testing Methodology

Previous studies link institutional herding to the informational environment of the firm and employ several firm characteristics to proxy for the quality and quantity of available information. For example, Lakonishok et al. (1992) and Wermers (1999) find the intensity of institutional herding to be higher among small firms and Wermers (1999) show that the level of mutual funds herding to be higher among stock experiencing extreme prior-quarter returns. Moreover, Venezia et al. (2011) and Kremer and Nautz (2013) show that LSV herding measure is positively related to stock volatility and trading volume.

To examine the second and the third hypotheses, I apply two different approaches. First, I use a portfolio sort similar to that in Wermers (1999) and assign each stock to one of the five portfolios formed based on firm size and prior week returns, then I calculate the cross-sectional average of HM, BHM, and SHM for each quintile and compare these averages for small and large firms as well as between winners and losers. Second, in a multivariate setting I estimate the following Fama and MacBeth (1973) regression:

$$HM_{it} = \alpha + \beta_1 Size_{i,t-1} + \beta_2 Turn_{it} + \beta_3 Vol_{it} + \beta_4 |r_{i,t-1}| + \varepsilon_{it} \tag{3.4}$$

where HM_{it} is the LSV herding measure for stock i in week t, $Size_{i,t-1}$ is the logarithm of the prior week market capitalization of firm i, $Turn_{it}$ is the average stock turnover for firm i in week t, Vol_{it} captures return volatility, computed as the standard deviation of returns for the past 50 weeks, and $|r_{i,t-1}|$ is the absolute value of the prior week return, I use the absolute returns because the herding measure does not distinguish between buy side or sell side. While the second hypothesis implies a negative relation between firm size and LSV herding measure, the third hypothesis predicts a positive relation between prior week returns and institutional herding.

The set of variables included in equation (3.4) may influence institutional herding on the buy and sell side differently. Therefore, I estimate a separate regression for BHM_{it} and SHM_{it} to examine the impact of each of the variables on institutional buy-herding and sell-herding. Moreover, I replace the absolute return $|r|$ by the signed return r since the direction of the recent price movements will influence whether institutions follow positive feedback trading on the buy or the sell side:

$$\begin{aligned} BHM_{it} = \alpha &+ \beta_1 Size_{i,t-1} + \beta_2 Turn_{it} + \beta_3 Vol_{it} + \beta_4 r_{i,t-1} \\ &+ \beta_5^b Dummy_{it}^b + \varepsilon_{it} \end{aligned} \tag{3.5}$$

$$\begin{aligned} SHM_{it} = \alpha &+ \beta_1 Size_{i,t-1} + \beta_2 Turn_{it} + \beta_3 Vol_{it} + \beta_4 r_{i,t-1} \\ &+ \beta_5^s Dummy_{it}^s + \varepsilon_{it} \end{aligned} \tag{3.6}$$

I also add a dummy variable in both equations $Dummy_{it}^b$ ($Dummy_{it}^s$) to capture whether the institutions are on the buy-side (sell-side) herding on the prior week.

To test the forth hypothesis, I investigate the relationship between weekly institutional herding and future returns. Previous studies suggest that if institutions trade stocks in a destabilizing manner (e.g., Scharfstein and Stein, 1990), stock prices will experience significant reversals. Conversely, if institutions trade stocks in a stabilizing fashion (Hirshleifer et al., 1994), stock prices will experience significant continuation. To examine whether institutional herding has a stabilizing or destabilizing effect, I study the relation between institutional buy and sell herding and future cumulative returns by estimating the following fixed effect regression:

$$\begin{aligned} r_{i,t,t+n} = \alpha &+ \beta_1 BHM_{it} + \beta_2 SHM_{it} + \beta_3 Size_{i,t} + \beta_4 Vol_{it} \\ &+ \beta_5 r_{i,t,t-2} + \beta_6 r_{i,t,t-24} + \varepsilon_{it} \end{aligned} \tag{3.7}$$

where $r_{i,t,t+n}$ is the stock cumulative returns for $n = 1, 2, ..., 24$ weeks. The independent variables BHM_{it} and SHM_{it} are the buy and sell institutional herding, $Size_{i,t}$ is the firm size, Vol_{it} is the return volatility, computed as the standard deviation for the past 50 weeks returns, $r_{i,t,t-2}$ is the recent lagged returns from week $t-2$ to week t and $r_{i,t,t-24}$ is the lagged returns from week $t-24$ up to week t.

Dasgupta et al. (2011) study the impact of institutional trading on asset prices when institutions buy or sell the same stocks over multiple quarters. They document a strong long-term return predictability of institutional trading activity, after controlling for many of the stock characteristics. They show that persistence in institutional trading is related to return reversals. In particular, stocks that are sold over multiple quarters by institutional investors outperform stocks bought by them after a period of 2 years. Similarly, I examine the price impact of the persistence in institutional herding by following the same approach as in Dasgupta et al. (2011). While these authors examine the price effects of institutional buying or selling over multiple quarter, this paper focus on the price impact of the persistence in short-term institutional herding.

First, I follow Brown et al. (2013) and compute an adjusted herding measure to capture the case where the direction of herding in a given stock changes from one week to another. Specifically, for each week and each group of buy-herding (sell-herding) stocks, I subtract the minimum value of BHM (SHM) from each stock's BHM (SHM), then the adjusted herding measure is set to equal to the differenced value of BHM if the stock is buy-herding, and to the negative of the differenced SHM if the stock is sell herding for a given week. Second, I follow Dasgupta et al. (2011) and define persistence in institutional herding as the number of consecutive weeks in which we observe a buy-herding or sell herding for the stock. This variable is positive for buy-herding and negative for sell-herding. For instance, a stock experiencing buy-herding in week t and week $t-1$ but sell-herding at week $t-2$ has herding persistence of 2, while a stock experiencing sell-herding in week t and week $t-1$ but buy herding in week $t-2$ has herding persistence of -2. The maximum herding persistence assigned to a stock is 6 (-6). Persistence values of 1 and -1, a stock experiencing buy or sell herding only in week t, are assigned a value 0. Finally, to examine the link between persistence in weekly institutional herding and future returns, I follow Dasgupta et al. (2011) and estimate a cross-sectional regressions of cumulative weekly market adjusted returns on past herding persistence, past returns, and a variety of stock characteristics. The specification is as follows:

$$r_{i,t,t+n} = \alpha + \beta Persist_{it} + \delta r_{i,t,t-2} + \gamma r_{i,t,t-24} + \lambda X + \varepsilon_{it} \tag{3.8}$$

where $r_{i,t,t+n}$ is the stock cumulative returns over weeks $t+1$ to $t+n$ for $n = 1, 2, ..., 24$ weeks. The explanatory variable $Persist_{it}$ is persistence in institutional herding, measured as the number of consecutive weeks in which a stock experience buy or sell herding. The variable $r_{i,t,t-2}$ is the recent lagged returns from week $t-2$ up to week t and the $r_{i,t,t-24}$ captures the lagged returns up to 24 prior weeks. The other explanatory variables include stock turnover, firm size, standard deviation of the past 50 week returns, market return, and prior week log price. To simplify the interpretation of the coefficient estimates, all the explanatory variables are standardized (to have mean 0 and standard deviation of 1) using their cross-sectional moments. I estimate the above regression using Fama and MacBeth (1973) procedure. The t-statistics are calculated from Newey and West (1987) standard errors adjusting for autocorrelations up to 4 weeks.

3.4 Results

Panel A of Table 3.1 reports the overall level of herding revealed by our sample of institutional investors. The average herding measure ($\overline{HM}$) of 2.5 percent is computed over all stocks-weeks during the sample period, for stocks that were traded by at least 3 institutions. Panels B and C show similar level of institutional herding, although slightly higher, across all stocks-weeks traded by at least 5 and 10 institutions, respectively. The average institutional herding of 2.5 percent means that if there were 100 institutions trading a given stock in a particular week, then roughly two more institutions trade on the same side of the market than what would be expected if they traded randomly and independently. The overall average herding level (2.5 percent) is similar to that reported by Lakonishok et al. (1992) for their sample of pension funds (2.7 percent) and slightly less than overall mutual fund herding reported by Wermers (1999) (3.4 percent).

Table 3.1 also examines the overall level of institutional herding by partitioning the sample into two subperiods (2007 as the break point) as well as whether institutions tend to form the herd on either side of the market. I choose 2007 as a break point to examine the variations in institutional herding in the crisis and pre-crisis periods. The results reveal that institutions typically herd on the buy-side more often than on the sell-side. The overall institutional buy-herding is 2.9 percent, while the overall institutional sell-herding is 2 percent, and the difference of 0.9 percent is statistically significant at one percent level. The subperiod results show that institutional investors exhibit herding behavior in both sub-samples. However, the level of institutional herding is stronger in the pre-crisis period. The overall herding measure in the pre-crisis period is 3.2 percent, while in the crisis period is only 1.6 percent. The difference in the level of institutional herding between the two subperiods is 1.6 percent and is statistically significant at one percent level. These findings are counterintuitive. We would expect the level of herding to be higher in volatile markets, in particular on the sell side. However, these results are likely due to the fact that empirical herding measures represent only the excess trading relative to the overall trend.

Table 3.1: LSV Herding Measure

The herding measure HM_{it} for a given stock-week equals to $|br_{it} - \overline{br_t}| - E[|br_{it} - \overline{br_t}|]$, where br_{it} is the ratio of the total number buyer institutions for a given stock-week to overall number of institutions trading that stock-week. The herding measures HM_{it}, BHM_{it}, and SHM_{it} are computed for a sample of US institutional investors including 1,142 institutions from January 1, 1999 through September 30, 2011. The herding measure is calculate for a large sample of stocks listed on Nyse, Nasdaq, and Amex exchanges. Panels A, B, and C present the full sample average herding measure across all stocks and time periods as well as the average herding measure before and after 2007 with minimum number of institutions trading a stock-week of 3, 5, and 10, respectively. Standard errors are given in parentheses, number of observations are (x1000).

	Panel A			Panel B			Panel C		
	HM	BHM	SHM	HM	BHM	SHM	HM	BHM	SHM
Full	2.5%	2.9%	2.0%	2.7%	3.0%	2.3%	2.9%	3.2%	2.7%
	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
Obs	1,204	629	574	1,088	565	522	940	485	454
$Year < 2007$	3.2%	3.6%	2.7%	3.4%	3.7%	3.0%	3.7%	3.9%	3.4%
	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)	(0.09)	(0.10)	(0.09)
Obs	697	364	332	639	334	305	535	278	257
$Year >= 2007$	1.6%	2.1%	1.0%	1.7%	2.1%	1.2%	1.9%	2.2%	1.6%
	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)	(0.08)	(0.08)	(0.09)	(0.07)
Obs	506	265	241	449	232	217	404	207	197
Diff	1.6%	1.5%	1.7%	1.7%	1.5%	1.8%	1.7%	1.7%	1.8%
	(82.22)	(52.85)	(64.33)	(92.60)	(60.51)	(70.73)	(92.11)	(61.75)	(68.64)

The overall results show that there is little evidence of institutional herding at weekly level. These results are similar to the quarterly findings obtained in the previous studies. Institutions tend to form the herd more often on the buy-side of the market than the sell-side and the level of herding is stronger in the pre-crisis period compared to the crisis period.

3.4.1 Institutional Herding and Stock Characteristics

To test hypotheses 2 and 3, I examine the average level of institutional herding ($\overline{HM}$) as well as the average buy-side ($\overline{BHM}$) and sell-side ($\overline{SHM}$) using a portfolio approach similar to that in Wermers (1999). First, I independently rank all the stocks in the sample based on the firm size and prior week returns, then for each quintile I calculate the average institutional herding measures. Next, I examine the relation between institutional herding and stock characteristics in a multivariate setting by estimating a Fama and MacBeth (1973) regression of herding measures against firm size and prior week returns controlling for other firm characteristics such as turnover and stock volatility.

Panel A of Table 3.2 presents the average herding measures across all stock-weeks segregated by firm size. Size quintile breakpoints are determined by ranking all the stocks in the sample according to their market capitalization; these breakpoints are updated at the beginning of each week. Looking first at the results of the unsigned herding measure ($\overline{HM}$), Panel A shows that institutions tend to herd more often in the large firms than in the small firms. The average institutional herding in the large firms is 3.14 percent, while the average institutional herding in small firms is 2.36 percent; the difference of 0.78 percent is statistically significant at one percent level. Since the intentional herding hypothesis implies the herds to form more often in the small firms than in the large firms, these findings are in favor of the unintentional herding explanation. However, when looking at the signed herding measures, I find that the herd tend to form more often on the buy-side than on the sell side in trading the small firms. The institutional buy-herding ($\overline{BHM}$) in the small firms is 3.32 percent, while the institutional sell-herding ($\overline{SHM}$) in the small firms is only 1.17 percent; the difference of 2.15 percent is statistically significant at one percent level. On the other hand, institutional herding tends to form more often on the sell-side than on the buy-side in trading the large firms. The institutional buy-herding in the large firms is 2.23 percent, while the institutional sell-herding in the large firms is 3.82 percent, the difference is 1.59 percent statistically significant at one percent level. These weekly results show that institutional investors share preferences for buying (selling) the small (large) stocks as they tend to pile-up on the buy-side (sell-side) of the market in trading the small (large) stocks.

Panel B of Table 3.2 reports the average institutional herding across all stock-weeks for quintiles based on the prior week stock returns. The quintile breakpoints are determined by all stocks in the sample and update weekly. The presented results are for the overall institutional herding ($\overline{HM}$) as well as institutional buy ($\overline{BHM}$) and sell ($\overline{SHM}$) herding. The results show that the overall institutional herding is roughly the same among the loser and winner stocks. The average institutional herding among the losers is 2.53 percent, while the average institutional herding among the winners is 2.69 percent. In addition, the herd tends to form more often on the buy-side in trading the winners than the losers; the difference is statistically significant but small in magnitude. There is no significant difference in institutional sell herding in trading winner and loser stocks.

Table 3.2: Herding Measures Segregated By Firm Size and Prior Week Returns Quintile

The herding measure HM_{it} for a given stock-week equals to $|br_{it} - \overline{br_t}| - E[|br_{it} - \overline{br_t}|]$, where br_{it} is the ratio of the total number of buyer institutions for a given stock-week to overall number of institutions trading that stock-week. The herding measures HM_{it}, BHM_{it}, and SHM_{it} are computed for a sample of US institutional investors including 1,142 institutions from January 1, 1999 through September 30, 2011. The herding measure is calculate for a large sample of stocks listed on Nyse, Nasdaq, and Amex exchanges. Panel A reports the average herding measures across all stock-weeks belonging to different quintile formed by firms' market capitalization. Panel B reports these averages for quintile formed based on stocks' prior week. The last line of each panel provide the differences between BHM_{it} and SHM_{it} for each quintile and the corresponding t-statistic based on paired t-test. The last column of each panel provide the differences between BHM_{it} (SHM_{it}) for the top and bottom quintile and corresponding t-statistic based on paired t-test.

Panel A	S	2	3	4	L	Diff
HM	2.36%	2.30%	2.27%	2.38%	3.14%	0.78%
						(25.32)
BHM	3.32%	3.40%	3.02%	2.52%	2.23%	-1.09%
						(-23.66)
SHM	1.17%	0.85%	1.32%	2.24%	3.82%	2.65%
						(63.23)
$Diff$	2.15%	2.55%	1.69%	0.28%	-1.59%	
t-stat	(40.4)	(53.92)	(40.13)	(7.39)	(-49.63)	
Panel B	**L**	**2**	**3**	**4**	**W**	
HM	2.53%	2.39%	2.37%	2.46%	2.69%	0.16%
						(5.23)
BHM	2.97%	2.84%	2.74%	2.88%	3.26%	0.29%
						(6.61)
SHM	2.05%	1.89%	1.96%	2.02%	2.07%	0.02%
						(0.43)
$Diff$	0.92%	0.95%	0.78%	0.86%	1.19%	
t-stat	(20.88)	(22.46)	(18.61)	(20.36)	(26.97)	

While the previous analysis controls for firm size and prior week returns, institutional herding is likely to be influenced by other stock characteristics. Therefore, I further test hypotheses 2 and 3 in a multivariate setting by regressing the herding measures against firm size and prior week returns controlling for stock volatility and turnover as well as dummy variables to control for the persistence in herding measures and to identify the direction of herding in the prior week. Table 3.3 presents the weekly Fama and MacBeth (1973) regressions results for equations (3.4), (3.5), and (3.6). The first column reports regression results for the unsigned herding measure ($\overline{HM}$), while the second and third columns report regression estimates for buy-side ($\overline{BHM}$) and sell-side ($\overline{SHM}$) herding measures, respectively.

Looking first at the results of the unsigned herding measure, I find that the coefficient estimate for the firm size is positive and statistically significant at one percent level. The fact that institutional herding increases with the firm size is consistent with the unintentional herding hypothesis as the quantity and quality of information about large firms is higher. Moreover, the positive and significant loading for the stock turnover gives further evidence for the unintentional hypothesis since higher trading volume should be associated with higher information quality and lower asymmetric information. The parameter estimate for the absolute returns is positive and significant at one percent level indicating that institutions engage in feedback trading strategies, i.e., the herd is more likely to buy past winners and sell past losers which is consistent with the unintentional herding. Finally, the positive relation between institutional herding and stock volatility suggests that there is more herding among volatile stocks, which hints at intentional herding hypothesis. However, in the following I estimate the impact of volatility on buy and sell herding separately and provide different explanation.

Table 3.3: Institutional Herding and Stock Characteristics

The herding measure HM_{it} for a given stock-week equals to $|br_{it} - \overline{br_t}| - E[|br_{it} - \overline{br_t}|]$, where br_{it} is the ratio of the total number buyer institutions for a given stock-week to overall number of institutions trading that stock-week. The herding measures HM_{it}, BHM_{it}, and SHM_{it} are computed for a sample of US institutional investors including 1,142 institutions from January 1, 1999 through September 30, 2011. The herding measure is calculate for a large sample of stocks listed on Nyse, Nasdaq, and Amex exchanges. Stock turnover is calculated as the ratio of total trading volume to number of shares outstanding, Size is the log of market capitalization, σ is the standard deviation of weekly stock return in the past 50 weeks, $r_{i,t-2}$ is the cumulative two weeks lagged return, $Dummy_B$ ($Dummy_S$) is a dummy variable capturing whether the stock experience buy (sell) herding in the previous week. The dependent variable and all the independent variables are standardized to facilitate the interpretation. The coefficients are estimated using Fama and MacBeth (1973). t-statistics, in parentheses, are calculated from Newey and West (1987) standard errors adjusting for autocorrelations up to 4 weeks.

	HM	BHM	SHM
$Size$	0.0471	-0.0076	0.0848
	(23.28)	(-3.46)	(29.27)
$Turnover$	0.0273	0.0152	0.0584
	(18.4)	(10.07)	(29.63)
$\sigma_{i,t,t-50}$	0.0111	0.0107	-0.0053
	(6.12)	(5.7)	(-2.48)
$\lvert r_{i,t-1}\rvert$	0.0069		
	(5.11)		
$r_{i,t-1}$		0.0243	-0.0138
		(14.37)	(-6.85)
$Dummy_b$		0.2191	
		(32.48)	
$Dummy_s$			0.2444
			(81.85)
$Cons$	-0.0150	-0.1382	-0.1166
	(-9.08)	(-63.52)	(-55.09)

The second and third columns of Table 3.3 report the estimated coefficients for equation (3.5) and

(3.6). The negative and significant coefficient on firm size suggests that institutional buy-herding is significantly stronger among the small firms. In contrast, the degree of institutional sell-herding is significantly stronger among the large firms. These findings are consistent with the univariate analysis discussed previously. Consequently, there is an asymmetric effect of stock volatility on both buy and sell herding. On one hand, the impact of volatility on (BHM) is positive and statistically significant suggesting that the higher the volatility, the higher the institutional herding on the buy-side. On the other hand, the impact of volatility on (SHM) is significantly negative indicating that there is higher institutional sell-herding in the less volatile stocks. This asymmetric effect of volatility on institutional buy and sell herding is not compatible with the intentional herding such that the return volatility should affect both buy and sell herding in the same way. Apparently, institutions share common preferences for buying (selling) small (large) stocks and stocks have experienced high (low) volatility. This is a clear indication of the unintentional herding that could result from common risk management practices. Additionally, the impact of prior week returns on buy (sell) herding is positive (negative) and statistically significant at one percent level suggesting that the herd engages in feedback trading strategies which is also in favor of the unintentional herding behavior.

3.4.2 Price Impact of Institutional Herding

In this section, I investigate the impact of institutional buy and sell herding on asset prices. In particular, I estimate a fixed effect regression of the future cumulative returns against BHM and SHM controlling for various stock characteristics as well as time dummies. Table 3.4 summarizes the main estimation results of equation (3.7) for a set of cumulative returns computed up to 24 weeks in the future. The results show that there is asymmetric relation between institutional buy and sell herding and future returns. On one hand, the strong positive relation between institutional buy herding and cumulative returns suggests that institutions on the buy-side correctly predict the future price movements up to eight weeks. The strong positive relation fades away in week 12 and becomes negative but insignificant in week 24. Accordingly, there is no evidence of return reversals, therefore, there is no indication of a destabilizing effect. On the other hand, institutional sell herding is associated with significant return reversals. While the relation between institutional sell herding and cumulative returns is negative in the short-term, this relation changes its sign and becomes positive and significant starting from week 8. The fact that stocks heavily sold by the herd experience price reversals is consistent with the destabilizing hypothesis of institutional herding, such that, the herd on the sell-side pushes prices below their fundamental values, thus, experiencing price correction in the subsequent periods.

The price continuations (reversals) following the buy (sell) herding are consistent with the results of the previous studies regarding the asymmetric impact of institutional buy and sell trades on prices. The main conclusions of these studies are as follow: (i) institutional buy trades have a permanent impact on prices therefore stock prices continue to increase following the buy trades (ii) institutional sell trades have a temporary effect on prices and therefore price corrections over the following period take place. The interpretation of these finding is that institutional buy trades convey information thus more informative than the sell trades. The fact that institutional buy herding is more concentrated among the small stocks than the large stocks is consistent with information hypothesis. Therefore, stocks heavily bought by the herd experience price continuations. Conversely, institutional sell herding is concentrated among the large stocks which operate in less opaque environment, hence, the herd forms on the sell side for non-informational reasons and therefore stocks sold by the herd experience price reversals.

Table 3.4: The Impact of BHM and SHM on Asset Prices

The herding measure HM_{it} for a given stock-week equals to $|br_{it} - \overline{br_t}| - E[|br_{it} - \overline{br_t}|]$, where br_{it} is the ratio of the total number buyer institutions for a given stock-week to overall number of institutions trading that stock-week. The herding measures HM_{it}, BHM_{it}, and SHM_{it} are computed for a sample of US institutional investors including 1,142 institutions from January 1, 1999 through September 30, 2011. The herding measure is calculate for a large sample of stocks listed on Nyse, Nasdaq, and Amex exchanges. Stock turnover is the ratio of stock daily trading volume to number of shares outstanding, Size is the log of market capitalization, σ is the standard deviation of weekly stock return in the past 50 weeks, $r_{i,t,t-2}$ is the cumulative two weeks lagged return, $r_{i,t,t-24}$ is the cumulative returns for the past 24 weeks, $Ln(price)$ is the log price at the end of previous week. All regressions include firm fixed effects and time dummies. Standard errors are clustered by firm. t-statistics are given in parentheses.

	$r_{i,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+4}$	$r_{i,t,t+8}$	$r_{i,t,t+12}$	$r_{i,t,t+24}$
BHM	0.0088	0.0124	0.0121	0.0123	0.0092	0.0025	-0.0048
	(11.13)	(10.66)	(8.43)	(7.2)	(3.68)	(0.8)	(-1.04)
SHM	-0.0057	-0.0057	-0.0038	-0.0015	0.0110	0.0234	0.0413
	(-6.14)	(-3.97)	(-2.16)	(-0.73)	(3.5)	(6.00)	(7.14)
$Size$	-0.0065	-0.0120	-0.0171	-0.0227	-0.0407	-0.0560	-0.1080
	(-10.83)	(-10.87)	(-10.74)	(-10.86)	(-10.33)	(-9.84)	(-9.96)
$Turnover$	-0.0127	-0.0308	-0.0551	-0.1029	-0.2642	-0.3402	-0.6510
	(-1.23)	(-1.85)	(-2.37)	(-3.42)	(-3.62)	(-3.45)	(-3.56)
$\sigma_{i,t,t-50}$	0.0443	0.0862	0.1266	0.1701	0.3329	0.4648	0.8852
	(7.89)	(8.12)	(8.27)	(8.41)	(8.3)	(8.03)	(8.39)
$r_{i,t,t-2}$	-0.0233	-0.0338	-0.0410	-0.0453	-0.0919	-0.1229	-0.1775
	(-17.59)	(-15.42)	(-15.31)	(-15.12)	(-21.04)	(-22.75)	(-23.55)
$r_{i.t.t-24}$	-0.0006	-0.0010	-0.0011	-0.0018	-0.0031	0.0010	-0.0100
	(-1.78)	(-1.48)	(-1.09)	(-1.4)	(-1.23)	(0.3)	(-1.76)
$Ln(price)$	-0.0045	-0.0097	-0.0153	-0.0200	-0.0415	-0.0636	-0.1222
	(-7.06)	(-8.38)	(-9.17)	(-9.14)	(-10.02)	(-10.65)	(-10.84)
$cons$	0.1583	0.2895	0.4037	0.5200	0.9687	1.3525	2.7681
	(13.95)	(13.86)	(13.56)	(13.36)	(13.21)	(12.8)	(13.74)

Dasgupta et al. (2011) document that persistence in institutional herding is a strong predictor of the cross-sectional returns at long intervals. More specifically, institutional trade persistence is related to return reversals such that stocks persistently sold by institutions over 3 to 5 quarters outperform stocks bought by them after a period of about two years. The argument is based on the theoretical models of herding (e.g., Scharfstein and Stein (1990); Bikhchandani, Hirshleifer, and Welch (1992)). In this models, when investors decide to take a certain action over multiple periods, other investors mimic their actions, creating persistence in investment decisions over time. Based on the predictions of the theoretical models and empirical findings found at long-term horizon, I investigate the impact of persistence in the short-term institutional herding on asset prices. In particular, I examine the impact of institutional buy and sell herding over multiple weeks (three to six week) on a set of future cumulative returns.

Table 3.5 reports the Fama and MacBeth (1973) regression results of equation (3.8) for a set of future cumulative returns computed up to 24 weeks. The first two columns of Table 3.5 shows that persistence in institutional herding over 3 to 6 weeks significantly predicts the cumulative returns over the next two weeks. However, when looking at the last three columns, it can be seen that the persistence in institutional herding significantly predicts return reversals. Stocks that are sold by the herd over multiple weeks outperform the stocks bought by them over the next 8 to 24 weeks.

Table 3.5: The Relation between Herding Persistence and Returns

The herding measure HM_{it} for a given stock-week equals to $|br_{it} - \overline{br_t}| - E[|br_{it} - \overline{br_t}|]$, where br_{it} is the ratio of the total number buyer institutions for a given stock-week to overall number of institutions trading that stock-week. The herding measures HM_{it}, BHM_{it}, and SHM_{it} are computed for a sample of US institutional investors including 1,142 institutions from January 1, 1999 through September 30, 2011. The herding measure is calculate for a large sample of stocks listed on Nyse, Nasdaq, and Amex exchanges. Stock turnover is the ratio of stock daily trading volume to number of shares outstanding, Size is the log of market capitalization, σ is the standard deviation of weekly stock return in the past 50 weeks, $r_{i,t,t-2}$ is the cumulative two weeks lagged return, $r_{i,t,t-24}$ is the cumulative returns for the past 24 weeks, $Ln(price)$ is the log price at the end of previous week, and $mktRet$ is the market return. The coefficients are estimated using Fama and MacBeth (1973). t-statistics, in parentheses, are calculated from the Newey and West (1987) standard errors adjusting for autocorrelations up to 4 weeks.

	$r_{i,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+4}$	$r_{i,t,t+8}$	$r_{i,t,t+12}$	$r_{i,t,t+24}$
$Persist$	0.0006	0.0005	0.0003	0.0000	-0.0007	-0.0018	-0.0041
	(6.95)	(3.88)	(1.67)	(0.13)	(-2.23)	(-4.32)	(-6.22)
$Turnover$	0.0003	0.0003	0.0002	0.0000	-0.0013	-0.0024	-0.0071
	(1.67)	(1)	(0.62)	(-0.04)	(-1.74)	(-2.34)	(-4.25)
$Size$	0.0001	0.0002	0.0000	-0.0003	-0.0002	-0.0004	-0.0027
	(0.27)	(0.35)	(-0.04)	(-0.27)	(-0.13)	(-0.21)	(-0.88)
$\sigma_{i,t,t-50}$	0.0002	0.0007	0.0011	0.0018	0.0041	0.0070	0.0218
	(0.81)	(1.49)	(1.62)	(2.02)	(2.71)	(3.61)	(6.05)
$r_{i,t,t-2}$	-0.0010	-0.0013	-0.0014	-0.0014	-0.0022	-0.0034	-0.0025
	(-6.57)	(-5.02)	(-4.25)	(-3.33)	(-4.23)	(-5.5)	(-2.24)
$r_{i.t.t-24}$	-0.0002	-0.0004	-0.0006	-0.0010	-0.0027	-0.0037	-0.0122
	(-0.93)	(-0.78)	(-0.96)	(-1.19)	(-1.99)	(-2.37)	(-4.77)
$Ln(price)$	-0.0019	-0.0038	-0.0055	-0.0072	-0.0140	-0.0202	-0.0402
	(-9.93)	(-10.43)	(-10.21)	(-10.26)	(-11.17)	(-11.64)	(-13.7)
$mktRet$	-0.0547	-0.0353	-0.0783	-0.1261	-0.0544	-0.1789	0.1112
	(-3.62)	(-1.53)	(-3.34)	(-4.23)	(-1.44)	(-3.77)	(1.47)
$cons$	0.0021	0.0052	0.0078	0.0109	0.0210	0.0319	0.0697
	(4.27)	(5.38)	(5.48)	(5.66)	(6.79)	(7.83)	(10.41)

A one-standard deviation increase in herding persistence predicts in future returns of about 0.4%, net of the effects of all control variables. These results are in accordance with the findings found at long-term horizons. In particular, the persistence in institutional herding at weekly horizons is a significant predictor of return reversals.

In sum, the overall results suggest that whether institutional herding is intentional or unintentional has an impact on stock prices. While the buy herding is positively associated with the future returns, the sell herding is associated with return reversals. Moreover, institutional investors buying or selling a stock over multiple weeks leads to return reversals, that is, persistence in the investment decisions by institutional investors push prices away from their fundamental values, thus, price corrections occurs after a period of at least 8 weeks.

3.5 Conclusions

In this chapter I shed more light on the importance of the short-term institutional herding by using a database of institutional transactions from the U.S. market that include high-frequency and institutional investor-level data. The data covers a long period of time from January 1999 through September 2011. The chapter provides empirical evidence on the short-term institutional herding, the impact of institutional herding as well as herding persistence on asset prices. Consistent with the quarterly findings, I find weak evidence of institutional herding at weekly level. The overall level of institutional herding at weekly horizon is 2.5%. The overall results are consistent with the unintentional herding explanation. While institutions on the buy side share common preferences for small and volatile stocks, the sell side herding is common among large and less risky stocks. Institutional buy and sell herding affect prices differently. While the buy-side institutional herding has a stabilizing effect on prices, the sell-side affects prices in a destabilizing way. Finally, consistent with the long-term findings, the persistence of institutional herding at weekly levels is associated to return reversals.

Chapter 4

The Dynamics of Institutional Trading: Evidence from Transaction Data

Contents

4.1 Introduction

The institutional ownership of U.S. equities has grown considerably in the past decades. The fraction of equity shares held by institutions has increased from 16.2 % in 1965 to 50.2% in 2010 (Federal Reserve Board, 2011). The rapid growth of institutional shareholdings and sheer magnitude of institutional trading activity have induced numerous empirical and theoretical papers on the trading behavior of institutional investors. Because institutions are required to disclose their portfolio holdings only at a quarterly frequency, extant empirical studies rely on quarterly or annual data to examine the dynamic relation between changes in institutional ownership and same-period returns. The main findings of these studies can be summarized as follows: (i) institutional investors are momentum traders (Grinblatt, Titman, and Wermers, 1995; Bennett, Sias, and Starks, 2003; Sias, 2007), (ii) Institutional investors often allegedly follow each other and engage in herding behavior (Wermers, 1999), and (iii) there exists a strong positive contemporaneous relation between changes in institutional ownership and returns (Nofsinger and Sias, 1999; Wermers, 1999). Although the contemporaneous relation between changes in institutional ownership and returns is well documented in the literature, the economic mechanisms behind this relation have received less attention and require higher frequency data on institutional ownership to investigate them. In this chapter, I use detailed transaction data for a sample of U.S. institutional investors to investigate the sources of this contemporaneous relation found at quarterly and yearly intervals. In particular, I examine the daily and intradaily cross−sectional relationship between the trading activity of institutional investors and stock returns.

The contemporaneous relation between changes in institutional ownership and same-period returns is consistent with three main hypotheses (Nofsinger and Sias, 1999; Sias et al., 2006): (1) the aggregate institutional buying and selling activities have a contemporaneous impact on prices (price pressure); (2) institutional investors are short-term momentum traders; and (3) institutional investors possess superior information that allows them to time their trades (i.e., institutions are able to forecast short-term returns). Without higher frequency institutional ownership data, examining these competing explanations is a difficult task. However, with daily and intradaily institutional transaction data, testing each hypothesis is straightforward. For example, if the quarterly (daily) contemporaneous relation arises from institutional investors following momentum trading strategies at intra-quarterly (intradaily) horizon, we should observe institutional trades chasing the intra-quarterly (intradaily) asset prices. Alternatively, if the quarterly (daily) contemporaneous relation arises due to institutional investors' ability to predict intra-quarter (intradaily) returns, institutional trading activity would lead price movements. Finally, it is also possible that the contemporaneous relation at the quarterly (daily) intervals arises from the price impact of institutional trades, thus, a contemporaneous relation at daily or weekly (intradaily) frequency should be observed. The trade−to−trade institutional data allows us to examine the short-term relationship between stock returns and institutional investors' trades and provide empirical evidence on the relative importance of each hypothesis in inducing the contemporaneous relation between institutional ownership and returns found at quarterly and yearly intervals. Understanding the sources of the contemporaneous relation between the changes in institutional ownership and same-period returns is important because each of the competing explanations has different interpretations of whether aggregate institutional buying and selling activities affect asset prices and whether asset prices can affect aggregate institutional activity.

I first start analyzing the relationship between returns and institutional trading activity at daily frequency using portfolio sort and vector autoregression techniques. The results of the daily analysis suggest that the quarterly contemporaneous relationship is mainly driven by institutions following feedback trading strategies but not the institutional ability to predict returns. However, I also find a strong contemporaneous relationship between institutional trade imbalances and returns at daily horizon, which may hint at price impact of institutional trades. Therefore, I examine the relation between returns and institutional imbalances at intradaily level to identify the primary explanation for the contemporaneous relation found at daily level.

The contribution of this chapter is twofold. First, I find that the contemporaneous relation is primarily driven by the institutional investors following prices at daily and intradaily level. Second, I investigate the potential explanations of the contemporaneous relation by using actual transaction data for a sample of U.S. institutional investors for a period from 1999 through September 2011. This study overcomes the limitations of quarterly institutional ownership data used in the previous studies and employs a proprietary database of institutional trades obtained from ANcerno Ltd. The ANcerno data provides a unique opportunity to examine the daily and intradaily relation between institutional trading activity and returns, since the dataset contains a detailed information on institutional transaction that account for nearly 8% of the total trading volume of CRSP in each of the years of our study. There are several advantages of working with ANcerno's data; for example, we can distinguish between the trades of institutional and retail investors. It also provides information on the side of the transaction (whether it is buy or sell), number of shares traded by each institution, date and time stamps for each trade, and a unique numerical identification that serves to track the trades of each institution both in cross-section and over time. It is important to note that our analysis for the relationship between institutional imbalances and returns is cross-sectional as I remove market-wide effects from both variables.

The current study is not the first to examine the short−term relationship between returns and institutional trading activity. Griffin, Harris, and Topaloglu (2003) examine the daily and intradaily relation between returns and institutional trade imbalances, defined as the difference between institutional buying and selling activity divided by the number of shares outstanding, using transaction data for Nasdaq 100 securities. These authors employ portfolio sort, vector autoregression, and examine institutional imbalances and returns around extreme returns and institutional imbalances. They document a strong positive relationship between institutional imbalances and the contemporaneous and prior day's returns. However, there are two noteworthy differences between this paper and the one by Griffin et al. (2003). First, in this chapter I examine the trading behavior of a large sample of institutional investors, a comprehensive sample of stocks listed on NYSE, Amex, and Nasdaq, and a long period from 1999 through 2011, while the study by Griffin et al. (2003) covers only Nasdaq 100 stocks for 210 trading days (May 1, 2000 to February 28, 2001). Second, Griffin et al. (2003) study the trading behavior of institutional and retail investors; they classify each trade as initiated by individuals or institutional investors based on whether the market maker primarily deals with institutional or individual investors. While they show that their classification is robust, it is an imperfect proxy for institutional trading activity. On the other hand, I focus on the trading behavior of institutional investors using actual institutional transactional data. Therefore, the findings of this study are important because it covers a larger sample of firms underlying the potential differences in the characteristics of institutional trading across different exchanges, longer time period, and most importantly it uses a better proxy of institutional trading activity.

I summarize the main findings as follows. First, I find a strong positive relationship between institutional buy−sell imbalances and returns at daily level. Second, institutional investors follow past price movements. The difference in returns between the high institutional imbalance decile and low institutional imbalance decile is a statistically significant 0.884% on the day before portfolio formations and a significant 0.411% two days before portfolio formation. Results from vector autoregression analysis suggest that a one standard deviation increase in daily returns lead to a 0.04 standard deviation increase in institutional imbalance on the subsequent day, and institutional trading is highly autocorrelated at one-day lag. Third, there is a strong time variation in institutional momentum trading among loser and winner stocks. Forth, the results of the intradaily analysis suggest that the contemporaneous relation found at daily level between institutional imbalances and returns is primarily driven by institutional trades following the intradaily prices. Finally, there is no evidence on short−term institutional investors' ability to predict returns.

The remainder of the chapter proceeds as follow. Section 4.2 presents the related literature. Section 4.3 develop the main hypotheses, methodology used to investigate the relation between institutional trades and contemporaneous and past returns at the daily. Section 4.4 examine some alternative explanations and provide some robustness tests for the daily results. Section 4.5 provides an intradaily analysis. Reversals in Section 4.6. A brief conclusion in Section 4.7.

4.2 Related Literature

There is a growing body of literature on the trading behavior of institutional investors. Broadly speaking, this literature falls into three major groups: (1) papers studying the relation between institutional trading activity and past returns, (2) studies examining institutional investors' ability to predict future returns, and (3) those investigating the contemporaneous relationship between stock returns and changes in institutional ownership.

The first group of studies investigates the relation between institutional trading activity and past stock returns as well as the interaction between investors. Momentum trading arises when investors buy (sell) today in response to an increase (decrease) in recent prices. Theoretical models of investor behavior (e.g., DeLong et al. (1990); Hong and Stein (1999)) postulate that trading by one class of investors can lead to momentum in stock prices. These models allow explicitly for the presence of rational agents to follow prices. Empirical studies examining the trading behavior of institutional investors primarily use the changes in quarterly institutional holdings. Lakonishok et al. (1992) examine the quarterly holdings of a sample of pension funds and document a weak evidence of positive feedback trading or herding behavior. Grinblatt et al. (1995) analyze the trading behavior of 274 mutual funds and document a stronger evidence of momentum trading and Badrinath and Wahal (2002) show that the tendency of momentum trading varies considerably across institutional types and is mainly driven by new equity positions. Using daily data, Choe, Kho, and Stulz (1999) document a herding behavior and feedback trading by Korean and foreign institutional investors. Conversely, Grinblatt and Keloharju (2000) document a contrarian investing strategies by the Finnish institutional investors.

The second group of studies investigates whether managers possess superior skills and abilities to forecast future price movements. Chen, Jegadeesh, and Wermers (2000) document that stocks purchased by fund managers outperform stocks sold by them by approximately 2% per year after controlling for various stock characteristics. On the other hand, Griffin et al. (2003) find no evidence of return predictability at a daily level, but their findings indicate that institutional trades precedes stock price movements at intradaily level. However, this effect is economically small.

A third group of papers investigates the sources of the strong positive contemporaneous relationship between changes in institutional ownership and stock returns measured over the same period (quarterly and yearly). Sias, Starks, and Titman (2006) investigate the drivers of the contemporaneous relation by using a covariance decomposition methodology to estimate higher frequency correlations between unobservable monthly (weekly) changes in institutional holding and lead, lag, and contemporaneous monthly (weekly) returns. They conclude that the impact of institutional trades on prices is the primary explanation. However, Cai and Zheng (2004) conclude that stock returns Granger-cause quarterly changes of institutional ownership, but ownership changes do not predict stock returns. While both studies shed light on the relation between changes in institutional ownership and returns found at quarterly horizon, the exact nature of the intra-period relation cannot be known without higher frequency data. The higher frequency institutional transaction data permit us to examine these competing hypotheses and in the process, provide new evidence on the relation between daily institutional trades and past stock returns, price pressure, and the short-term forecasting ability of institutional trading activity.

4.3 Returns and Institutional Trading Relation

Empirical studies usually evaluate the relationship between institutional trading and returns using quarterly data. In this section, I develop the main hypotheses for the potential drivers of the strong positive contemporaneous relation between returns and changes in institutional ownership. Next, I explain the methodology used to examine the relation between institutional trading activity and returns at daily level. Finally, I present the empirical results.

4.3.1 Hypotheses

The contemporaneous relation between the changes in quarterly institutional ownership and quarterly returns is consistent with the institutional price pressure hypothesis. There are two possible explanations for why institutional trades may have a direct impact on asset prices. First, institutional investors are better informed than other investors, thus their trades reveal valuable information and consequently have a permanent effect on prices (Easley and O'Hara (1987)). Second, it is possible that the aggregate institutional trading requires price concession, therefore, driving away the liquidity suppliers from their optimal inventory positions which result in a temporary effect on prices (Stoll, 1978; Grossman and Miller, 1988). The empirical studies on the institutional price pressure show that institutional trading activities have both permanent and short-lived impacts on prices (e.g., Lakonishok et al., 1992; Chan and Lakonishok, 1993, 1995; Keim and Madhavan, 1997). Additionally, Edelen and Warner (2001) show that both the aggregate flow into U.S. equity funds and institutional trading activities affect security prices. They find that the price impact of aggregate institutional trades is similar in magnitude to that of the individual institutional trades. Since the price impact of institutional trading is well document in the literature the current study investigates the other two possible explanations for the strong positive contemporaneous relation between returns and changes in institutional ownership found at quarterly level, namely short-term momentum trading and returns predictability.

It is possible that the contemporaneous relation between quarterly returns and changes in institutional ownership is driven by institutional investors following short-term (intra-quarter) positive feedback trading strategies. This explanation is consistent with the theoretical models of investors' overreaction and/or investors' underreaction. These models suggest that sophisticated investors, such as hedge funds and mutual funds, may rationally engage in momentum trading strategies to exploit these overreaction and/or underreaction by other investors (DeLong et al., 1990; Hong and Stein, 1999). Furthermore, institutional feedback trading could also arise if institutions provide liquidity to other market participants who follow contrarian investment strategies (Barber et al., 2009b). Consistent with this reasoning, the first hypothesis captures the idea that institutional investors tend to buy stocks that performed well and sell the stocks that performed poorly in the recent past implying that returns will lead institutional trading activity.

Hypothesis 1: ***There is a positive relation between institutional trade imbalances and prior day returns***.

The second potential explanation for the positive contemporaneous relation between changes in institutional holding and same-quarter returns is also consistent with the hypothesis that institutional investors possess superior information and are able to predict the short-term returns. Therefore, stocks that institutional investors buy would outperform the stocks that they sell. The empirical evidence indicates that there is a weak positive relationship between aggregate institutional demand and future returns (Wermers, 1999, 2000; Bennett et al., 2003). These findings suggest that, at least in part, the quarterly contemporaneous relation between changes in institutional ownership and returns can be explained by the ability of institutional investors to predict short-term intraquarter returns. Thus, the second hypothesis captures the idea that institutional trade imbalances are positively associated with daily future returns. This hypothesis implies that the daily institutional imbalances would lead the returns.

Hypothesis 2: ***There is a positive relation between institutional trade imbalances and the following day returns***.

4.3.2 Variable Definition

The primary measure of stock−level institutional trading activity is calculated based on the daily institutional trading imbalance. In particular, for each firm i I compute the institutional buy−sell imbalance as the total daily volume of shares bought by institutions less the total daily volume of shares sold by institutions divided by the number of shares outstanding:

$$Imbal_{i,t} = \frac{InstitBuy_{i,t} - InstitSell_{i,t}}{Shareoutstand_{i,t}} \tag{4.1}$$

where $Imbal_{i,t}$ is institutional imbalance for stock i in day t, $InstitBuy_{i,t}$ is the total institutional buy volume for stock i in day t, $InstitSell_{i,t}$ is the total institutional sell volume for stock i in day t, and $Shareoutstand_{i,t}$ is the total number of shares outstanding of stock i on day t.

For each stock in the sample, I subtract from both daily stock returns and institutional imbalances an equally weighted average return and institutional imbalance, respectively to minimize market wide-effects.

4.3.3 Testing Methodology and Empirical Results

To investigate the daily relation between the trading activity of institutional investors and returns, I start the analysis by using a sorting method similar to that used by Nofsinger and Sias (1999) and Griffin et al. (2003) and assign stocks each day into one of the ten portfolios based on the intensity of the daily institutional buy−sell imbalances. Where the stocks assigned to the first decile are those experiencing the largest institutional selling activity and stocks in the top decile are those experiencing the largest institutional buying activity.

Table 4.1 reports the average stock characteristics across the ten portfolios sorted by their daily institutional buy−sell imbalance. I calculate the average volatility (standard deviation of daily returns during a quarter), firm size (market capitalization), turnover (total daily trading volume divided by number of shares outstanding), daily price level, daily raw returns, and daily institutional buy−sell imbalance. Each average is computed as the average of daily cross-sectional mean for stock characteristic in each decile. I start the analysis by examining price levels across the ten portfolios because big differences in prices may have a crucial influence on result inferences (Badrinath and Wahal, 2002). For instance, the formation of each portfolio based on institutional buy−sell imbalance gives each stock equal weight, therefore 10% increase in the trading of a stock traded at $10 per share is given the same weight as a 10% increase in the trading of a stock traded at $100 per share. Table 4.1 shows some differences in price level across institutional buy-sell portfolios, the average prices are higher for extreme groups ranging from $30.59 − $33.64. However, the variation in price levels across the ten groups is quite small, suggesting that giving equal weights to each stock when forming the ten portfolios is not likely to bias the results in decile formation. The typical stock size traded by ANcerno clients is approximately $4.5 billion with relatively higher volatility (smaller firms), suggesting that the largest fraction of institutional trading is not observed among the largest capitalization firms. This is in accordance with Bennett, Sias, and Starks (2003), who find that institutional investors increased their preferences for smaller and riskier securities. Moreover, institutional buying and selling activity is observed among stock with high turnover. Finally, while stocks that institutions tend to sell experience negative returns, the stocks institutions tend to buy experience positive returns.

Table 4.1: Stock Characteristics by Institutional Buy-Sell Imbalance

This table reports average security characteristics across 10 portfolios sorted by their daily institutional buy-sell imbalances. Stock returns are expressed in percentage per day. Market capitalization is reported in billions of dollars. Volatility is computed as the standard deviation of daily return during a quarter. Turnover is calculated as the total daily volume divided by number of shares outstanding (in percentage). Institutional imbalance is computed as the difference between daily institutional buy and sell and is expressed in percentage. Price is the daily market price.

	Return	Price	Turnover	Volatility	Cap	Inst.Imbal
D 1	-0.5581	33.23	0.0192	0.0297	4.67	-0.3328
D 2	-0.2849	33.03	0.0119	0.0266	8.25	-0.0792
D 3	-0.1521	33.51	0.0101	0.0255	11.81	-0.0319
D 4	-0.0639	32.63	0.0089	0.0249	13.34	-0.0109
D 5	0.0038	30.59	0.0080	0.0251	10.64	-0.0015
D 6	0.0645	31.14	0.0082	0.0250	10.76	0.0044
D 7	0.1271	32.52	0.0091	0.0251	12.11	0.0148
D 8	0.2343	32.87	0.0102	0.0258	10.27	0.0369
D 9	0.3967	32.37	0.0120	0.0270	7.24	0.0856
D 10	0.6967	33.64	0.0193	0.0301	4.20	0.3340

4.3.4 The Contemporaneous Relationship

Most of the existing empirical studies evaluate institutional trading behavior by examining the quarterly changes in institutional ownership. However, with the exception of the study by Griffin et al. (2003) and a short analysis in Nofsinger and Sias (1999), little is known about the short-term relation between institutional trading and returns in U.S. market.

Table 4.2 reports the time series average of the daily cross-sectional mean abnormal returns and institutional trading imbalances for firms within each institutional trading imbalance decile. In the formation day, stocks in the decile experiencing the largest institutional buying activity exhibit average excess return (relative to equally-weighted market return) of 0.626 percent, statistically different from zero at one percent level. Alternatively, stocks in the decile experiencing the largest institutional selling activity exhibit average excess return of -0.611 percent, again different from zero at one the percent level. The stocks experiencing strong institutional buying activity outperform the ones experiencing strong institutional selling activity by 1.24 percent per day, the difference is statistically significant at the one percent level. Griffin et al. (2003) report a difference of 7.98% for Nasdaq securities, while Nofsinger and Sias (1999) report a difference of 2.68% for 114 NYSE firms for a three months' period. Our finding is smaller in magnitude in comparison to both studies, likely because our sample covers longer time period, larger sample including firms listed on NYSE, Amex, and Nasdaq, smaller and less liquid firms. In unreported results, I find a considerable time variation in the returns differentials between stocks experiencing large institutional buying activity and stocks experiencing large institutional selling activity. While the return difference between top and bottom decile peaks in 2008 reaching 2% per day, the return differential is only 0.86% per day in 2004. I also estimate a daily cross-sectional regression of returns on institutional trading, firm size, turnover, and stock volatility and find that the strong contemporaneous relation between returns and institutional trading imbalances is not affected by controlling for these firm characteristics.

Table 4.2: Returns and Institutional Buy-Sell Imbalances for Portfolios Classified by Institutional Buy-Sell Imbalance

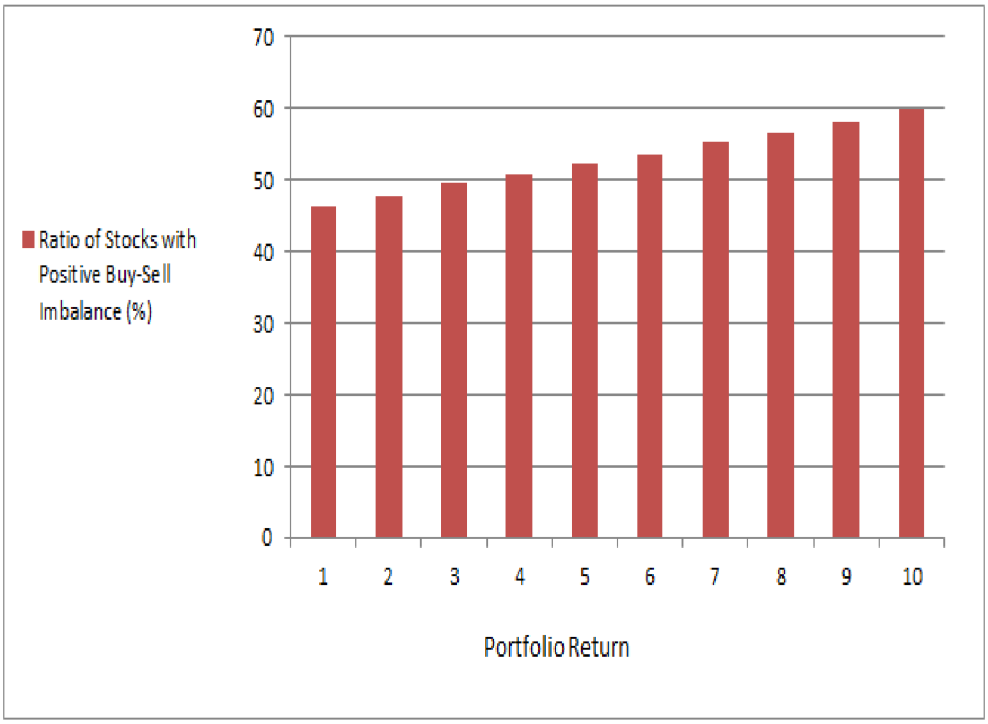
On each day the NASDAQ-AMEX-NYSE stocks are ranked by their daily institutional buy-sell imbalances and assigned to one of 10 portfolios. For each stock, institutional buy-sell imbalance (expressed in percent) is the difference between the institutional buy and sell volumes for that day scaled by the total number of outstanding shares. This table reports the time-series averages of lagged and contemporaneous institutional buy-sell imbalances and the difference between the return and the equal-weighted NASDAQ-AMEX-NYSE return (Return - EW Return) for each portfolio. The last row reports the mean difference between the high and low portfolios (H-L) for each variable.The statistical significance reported in the last row is computed from a paired t-test estimated from the time series of the difference between the high and the low institutional imbalance portfolios. The statistical significance reported in the first 10 rows are computed from a paired t-test estimated from the time series of the difference between the corresponding portfolio return and the mean across all 10 portfolios.

	-5	-4	-3	-2	-1	0	-5	-4	-3	-2	-1	0
Rank	Return − EW Return						Instit.Buy − Instit.Sell					
D1	−0.090[a]	−0.116[a]	−0.166[a]	−0.266[a]	−0.506[a]	−0.611[a]	−0.045[a]	−0.053[a]	−0.066[a]	−0.086[a]	−0.135[a]	−0.320[a]
D2	−0.019	−0.037	−0.058[a]	−0.118[a]	−0.248[a]	−0.373[a]	−0.015[a]	−0.017[a]	−0.021[a]	−0.026[a]	−0.038[a]	−0.074[a]
D3	−0.003	−0.003	−0.015	−0.059[a]	−0.129[a]	−0.240[a]	−0.006[a]	−0.008[a]	−0.009[a]	−0.012[a]	−0.016[a]	−0.030[a]
D4	0.006	−0.002	−0.001	−0.017	−0.063[a]	−0.135[a]	−0.002[a]	−0.003[a]	−0.004[a]	−0.004[a]	−0.006[a]	−0.010[a]
D5	0.004	0.002	0.000	−0.002	−0.023	−0.052[a]	−0.000[a]	−0.000[a]	−0.000[a]	−0.001[a]	−0.001[a]	−0.001[a]
D6	0.004	−0.010	0.009	0.001	0.028[b]	0.012[a]	0.001	0.001[a]	0.002	0.002	0.003[b]	0.004[a]
D7	−0.001	0.007	0.009	0.037[a]	0.075[a]	0.088[a]	0.005[a]	0.006[a]	0.006[a]	0.007[a]	0.009[a]	0.014[a]
D8	−0.002	0.019	0.024[b]	0.055[a]	0.139[a]	0.209[a]	0.010[a]	0.011[a]	0.013[a]	0.016[a]	0.021[a]	0.035[a]
D9	0.001	0.024[b]	0.048[a]	0.109[a]	0.239[a]	0.363[a]	0.020[a]	0.024[a]	0.027[a]	0.032[a]	0.045[a]	0.080[a]
D10	−0.021	0.001	0.036[b]	0.144[a]	0.378[a]	0.626[a]	0.053[a]	0.058[a]	0.070[a]	0.091[a]	0.138[a]	0.324[a]
H-L	0.069[a]	0.117[a]	0.202[a]	0.411[a]	0.884[a]	1.237[a]	0.098[a]	0.111[a]	0.136[a]	0.177[a]	0.273[a]	0.644[a]

a Significance at 1%.
b Significance at 5%.

4.3.5 Institutional Trading and Return Sort

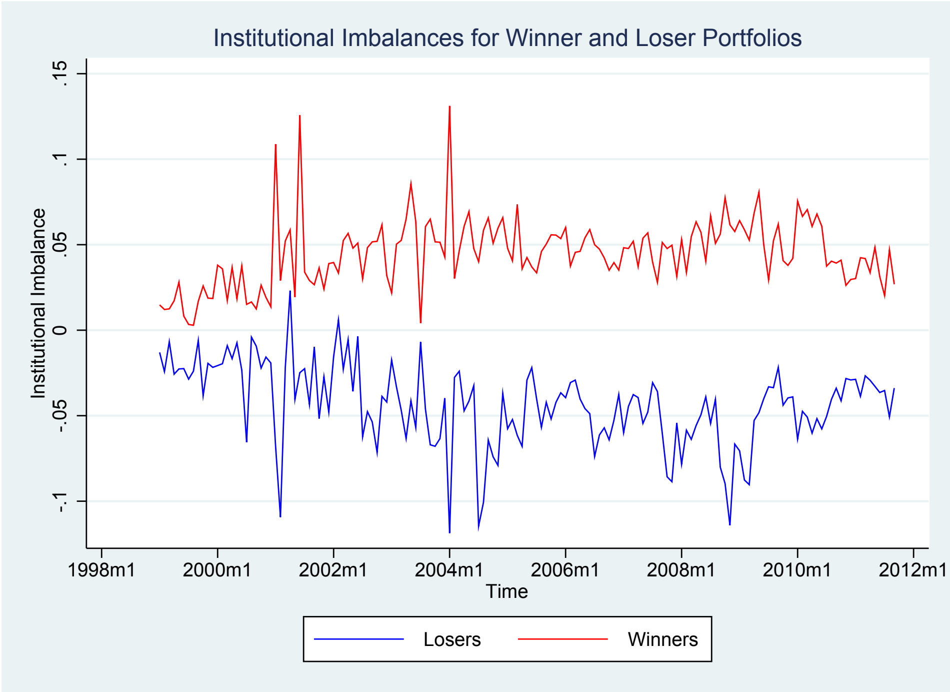
To investigate whether institutions trade on the prior day's returns, I follow Griffin et al. (2003) and sort firms into ten portfolios according to their daily return performance and then examine institutional buy-sell imbalances on the subsequent day. For each day−decile I compute the fraction of institutions that are net buyers in a stock which are displayed in Figure 4.1. Stocks in the decile experiencing the highest daily returns exhibit net buying by institutions more than net selling on the next day 59.8 percent of the time. On the other hand, stocks in the decile experiencing the lowest daily stock returns are bought by institutions in the following day for only 46.2 percent of the stocks. Figure 4.1 shows that institutional investors are 13.6 percent (59.8% − 46.2%) net buyers in stocks experiencing large prior day returns in comparison to those with low prior day returns. These findings are smaller than those documented by Griffin et al. (2003) who find that institutional investors are 23.9 percent more likely to be net buyers in Nasdaq 100 stocks that have experienced large prior day performance relative to those with low prior day performance. In unreported results, sub−sample analysis show that the fraction of institutions that are net buyers in top decile stocks relative to bottom decile stocks does not change neither over time nor in sub−samples based on firm characteristics such as size or liquidity. These findings suggest that the short−term institutional momentum trading is weaker than that documented in Griffin et al. (2003).



On each day, the sample of stocks are sorted by the prior day's return and assigned to one of ten deciles. For each decile, the proportion of stocks for which institutions are net buyers the following day is calculated. The time series average of these proportions is computed for each decile on the day following the ranking day.

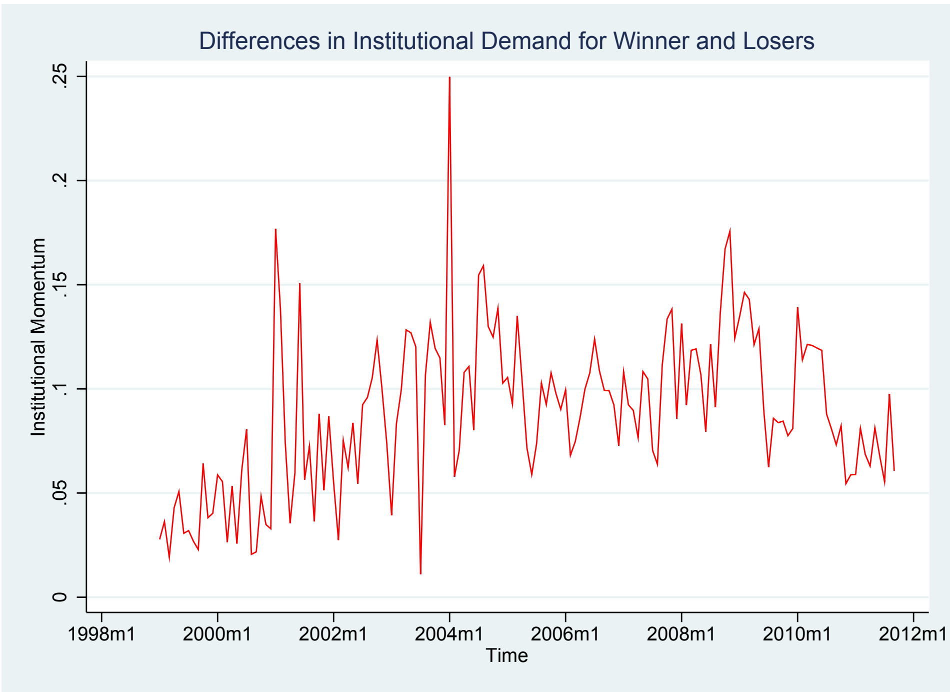
Figure 4.1: Institutional trading activity following ranking by daily returns

Prior studies document a considerable time variation in momentum profits due to either market state, investor sentiment, or the realized volatility of the market (e.g., Chordia and Shivakumar, 2002; Cooper et al., 2004; Wang and Xu, 2010). Therefore, I also examine how institutional trading following prior day's returns develops over time for both winner and loser portfolios. Figure 4.2 depicts the cross−sectional average of institutional imbalances for both winner and loser portfolios in the day following the portfolio formation. As can be seen, there is a notable time variation in institutional trading for both loser and winner portfolios, however, after 2004 the time variation in the loser stocks is stronger than that in the winners. Figure 4.3 displays the difference in institutional demand between winner and loser stocks over the sample period. There is a notable time variation in the degree of momentum trading by institutions, such that, it is positive during the whole sample period, we don't observe any considerable contrarian trading by institutions, and the institutional momentum trading has increased rapidly in the first half of the sample.



On each day, the sample of stocks are sorted by the prior day's return and assigned to one of ten deciles. The Figure displays the cross−sectional average of institutional imbalances for both winner and loser portfolios.

Figure 4.2: Institutional trading activity for winner and loser portfolios



On each day, the sample of stocks are sorted by the prior day's return and assigned to one of ten deciles. The Figure displays the differences in institutional imbalances for both winner and loser portfolios.

Figure 4.3: Difference in institutional demand for winner and loser portfolios

To further examine the relationship between institutional buy−sell imbalances and previous day's returns, extreme winner and loser portfolios (based on the prior day's return) are ranked into quintile based on the subsequent day institutional buy−sell imbalance. Panel A in Table 4.3 reports the time-series mean of the cross-sectional averages of the subsequent day institutional imbalances and abnormal returns for the stocks in the top daily return decile (winners). Results show a strong relationship between institutional imbalances and returns in the day following portfolio formation. The quintile of winners experiencing the largest next day institutional net selling activity exhibits strong return reversals− abnormal returns average −0.525 percent in the day following portfolio formation, statistically significant at one percent level. Alternatively, the quintile of winners experiencing the largest subsequent day institutional net buying exhibit strong momentum−abnormal returns average 0.733 percent in the day following the portfolio formation, again statistically significant at the one percent level. Panel B presents similar results for decile of losers divided into following institutional buy−sell imbalances quintile. In sum, these results suggest that institutions are short-term momentum traders and there is a strong positive relation between institutional trading activity and level of return momentum.

Table 4.3: Institutional Buy−Sell Imbalances and Return Sort

Each day a sample of NASDAQ-AMEX-NYSE stocks are sorted into ten portfolios based on daily raw return. Panel A presents the time-series average of the cross-sectional mean subsequent day institutional buy−sell imbalance and abnormal returns for stocks in the top daily return decile (winners) ranked into subsequent day institutional buy−sell imbalance quintiles. Similarly, Panel B presents the data for losers decile ranked into subsequent day institutional buy−sell imbalance quintile. $F-$statistic is based on the null hypothesis that the time-series averages of cross−sectional means do not differs across the portfolios. $t-$statistic between paracenteses.

	Subsequent Selling	2	3	4	Subsequent Buying	
	Panel A: Winners Ranked by Subsequent Institutional Imbalance					F-statistic
Subsequent Abnormal Returns	−0.525	−0.328	−0.149	0.189	0.733	2055***
	(−17.69)***	(−13.59)***	(−6.43)***	(7.62)***	(24.62)***	
Institutional Imbalance	−0.205	−0.015	0.010	0.058	0.333	2059***
	Panel B: Losers Ranked by Subsequent Institutional imbalances					
Subsequent Abnormal Returns	−0.702	−0.143	0.187	0.397	0.637	1748***
	(−21.17)***	(−5.41)***	(7.12)***	(13.88)***	(18.09)***	
Institutional Imbalance	−0.344	−0.050	−0.005	0.025	0.260	1759***

4.3.6 Vector Autoregression

The primary objective of the chapter is to investigate the relation between returns and institutional trading activity. Inferences about this relationship are potentially influenced by the time−series properties of each variable. Specifically, institutional imbalances are strongly related to past institutional imbalances (Sias and Starks, 1997; Griffin et al., 2003), and institutional trading is dependent on past returns (Grinblatt et al., 1995; Wermers, 1999; Griffin et al., 2003). Therefore, to examine whether institutional trades lead returns or returns lead institutional trades I follow Griffin et al. (2003) and use vector autoregression to investigate the time-series behavior of institutional trading activity and returns at daily level. For each stock in the sample, I compute the daily institutional imbalances and returns, and then deduct from both variables an equally weighted average institutional imbalance or return, respectively, to minimize market wide-effects. To simplify the interpretation of our results, the two variables are standardized (to have a zero mean and standard deviation of one) using their time series moments. Then, for each stock the following system of equations is estimated:

$$R_t = \alpha + \sum_{j=1}^{5} \beta_j R_{t-j} + \sum_{j=1}^{5} \gamma_j Iimbal_{t-j} + \varepsilon_{t,R} \tag{4.2}$$

$$Iimbal_t = \alpha + \sum_{j=1}^{5} \beta_j R_{t-j} + \sum_{j=1}^{5} \gamma_j Iimbal_{t-j} + \varepsilon_{t,Iimbal} \tag{4.3}$$

where R_t is the adjusted stock return on day t and $Iimbal_t$ is the adjusted institutional trading imbalance on day t.

Cross-sectional average of the estimated loadings from equation (4.2) and (4.3), the percentage of securities with positive and negative estimates that are significant at conventional level, and the adjusted R-squares are reported in Table 4.4. Panel A of Table 4.4 reveals several interesting patterns. First, in equation (4.3) the cross-sectional average of estimated coefficients of the prior day's return is 0.04, suggesting that a one standard deviation increase in the day $t-1$ return leads to a 0.04 standard deviation increase in the net buying activity of institutions in day t. Moreover, 27 percent of the stocks have positive and significant coefficients at five percent level. However, the effect disappears with the 2−through 5−day lagged coefficients being either small or slightly negative. Griffin et al. (2003) use vector autoregression for 82 stocks that are member of Nasdaq 100 and find that a one standard deviation increase in the daily return leads to a 0.12 increase in the following day institutional net buying, and 34 percent of stocks have positive and significant coefficients. Second, abnormal institutional trading activity is highly autocorrelated with prior day institutional activity. The cross−sectional average coefficient on the previous day institutional buy−sell imbalance is 0.27 and more than 89 percent of the loadings are positive and statistically different from zero at five percent level. The lagged 2− through 5−day institutional buy−sell imbalance estimates are positive as well. These daily findings are in line with those found in Sias and Starks (1997) and Griffin et al. (2003) who find that there is strong persistence in the U.S. institutional investors trading activity. However, these results reveal a stronger persistence in institutional buy−sell imbalances compared to those documented in Griffin et al. (2003); probably due to that, our measure of institutional trading variable is a better proxy. Third, there is no evidence that institutional traders predict the next day returns. In the return equation of Panel, A in Table 4.4, the cross-sectional average coefficients for past institutional imbalances are close to zero, and approximately four percent of the stocks have positive coefficients that are statistically different from zero at five percent confidence level.

Table 4.4, Panel B, reports the results obtained from estimating a structural vector autoregression by including the contemporaneous returns in the institutional trading equation.[1] The results show a strong contemporaneous relationship between institutional buy-sell imbalances and returns; the cross-sectional average coefficients for the contemporaneous return is 0.12, indicating that a one standard deviation increase in day t return is associated with a 0.12 standard deviation increase in day t institutional net buying activity. More than 56 percent of stocks have significant positive coefficients at the five percent level and the average adjusted R^2 for the imbalance equation has increased from 0.13 to 0.16. It is interesting to note that the average coefficient on the past day return is unchanged and the percentage of positive significant coefficients increases from 27.18 percent to 28.84 percent.[2] The strong positive relation between daily institutional imbalances and daily returns is consistent with institutional investors ability to predict intradaily price movements, institutional investors follow intradaily prices, or institutional price pressure. To distinguish between these competing hypotheses,

[1] I add the contemporaneous return to measure the contemporaneous effect on institutional imbalances relative to the impact of prior day's return. I obtain similar strong relationship by including the contemporaneous institutional imbalances in the return equation.

[2] Griffin et al. (2003) document average coefficient for the contemporaneous return for 82 stock of Nasdaq 100 of 0.52 and all stocks have significant positive coefficients.

I examine the relation between institutional imbalances and returns at intradaily level in section 4.5.

Table 4.4: Daily VAR Estimates for Individual Stocks

This table reports the main results for the equations (3.2) and (3.3) in the main text. Both variables, returns and institutional imbalances, are adjusted by subtracting the equal-weighted average for the stocks comprising the Nasdaq-Amex-NYSE for the corresponding day. For each stock, the institutional buy-sell imbalance is the difference between the institutional buy and sell volumes for that day divided by the total number of outstanding shares. To facilitate interpretation, both variables are standardized prior to estimation of the VAR. The main results are reported in Panel A. Panel B reports results for a structural VAR with contemporaneous excess returns in the institutional imbalance equation. This table reports the cross-sectional averages of the coefficient estimates, the adjusted R^2s, the percentage of stocks with positive and negative coefficients that are significant at the 5% confidence level (% pos.sig. and % neg.sig.).

		Panel A						Panel B		
		Return			Iimbal			Iimbal		
		Coeff	% pos.sig.	% neg.sig.	Coeff	% pos.sig.	% neg.sig.	Coeff	% pos.sig.	% neg.sig.
	α	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Return	β_0							0.12	56.54	0.68
	β_1	−0.02	3.75	12.32	0.04	27.18	0.85	0.04	28.84	0.64
	β_2	−0.02	2.50	8.30	0.01	5.80	2.30	0.01	6.32	2.05
	β_3	−0.01	2.58	4.07	0.00	3.34	2.94	0.00	3.75	2.74
	β_4	−0.01	1.57	3.66	0.00	2.58	3.42	0.00	2.74	3.22
	β_5	−0.01	1.41	4.43	0.00	2.22	3.58	0.04	2.54	3.54
Iimbal	γ_1	0.00	3.71	3.46	0.27	89.65	0.00	0.27	89.93	0.00
	γ_2	0.00	3.50	3.02	0.07	38.66	0.56	0.07	39.23	0.52
	γ_3	0.00	3.26	3.66	0.05	24.45	0.44	0.05	24.73	0.56
	γ_4	0.00	3.58	4.03	0.03	14.78	0.77	0.03	14.78	0.85
	γ_5	0.00	3.75	3.34	0.04	18.45	0.48	0.04	19.13	0.40
	Adj.R^2	0.008			0.13			0.160		

4.3.7 Buying Winners or Selling Losers

Momentum trading strategy is based on buying past winners and selling past losers. In the context of this study, an equally important question is whether institutional investors' trading activity differs between loser and winner portfolios. To answer this question, I perform for each stock a piecewise linear regression with the median return as a knot, as follow:

$$Iimbal_t = \alpha + \sum_{j=0}^{5} \beta_j R_{L,t-j} + \sum_{j=0}^{5} \gamma_j R_{W,t-j} + \sum_{j=1}^{5} \lambda_j Iimbal_{t-j} + \varepsilon_{t,Iimbal} \tag{4.4}$$

where $R_{L,t} = min(R_t, \widetilde{R}_t)$ is the return on loser stocks on day t, $R_{W,t} = max(R_t - \widetilde{R}_t, 0)$ is the return on winner stocks, R_t is the daily stock return, $\widetilde{R}_t$ is the daily cross−sectional median returns, and $Iimbal_t$ is the adjusted institutional trading imbalance on day t. The piecewise linear regression that has been widely used in the flow−performance literature (Sirri and Tufano, 1998) allow us to compute two different regression loads for the return variable. One of the estimated coefficients refers to the slope of the segment above the cross−sectional median return (winner stocks), whereas the other estimated coefficient refers to the slope of the segment below the cross−sectional median (loser stocks). A positive relation between institutional imbalances and returns above (below) the median indicates that institutional investors tend to buy winners (sell losers) on average.

Results of equation (4.4) are presented in Table 4.5. Coefficients on the variable *Iimbal* are not reported for brevity. Panel A reports the results of full sample, whereas Panel B presents the sub−samples partitioned by time. The results of the full sample analysis reveal notable differences in the trading patterns of institutional investors between loser and winner stocks.

Table 4.5: Differences in Institutional Trading among Winners and Losers

This table reports the estimation results for equation (3.4) in the main text. All variables are adjusted by subtracting the equal-weighted average for the stocks comprising the Nasdaq-Amex-NYSE for the corresponding day. For each stock, the institutional buy-sell imbalance is the difference between the institutional buy and sell volumes for that day divided by the total number of outstanding shares. To facilitate interpretation, all variables are standardized. Panel A reports results for the full sample analysis. Panel B reports the results of sub-period samples. This table reports the cross-sectional averages of the coefficient estimates and adjusted R^2s, the percentage of stocks with positive and negative coefficients that are significant at the 5% confidence level (% pos.sig. and % neg.sig.).

	Losers							Winners						
Dep.Var	α	β_0	β_1	β_2	β_3	β_4	β_5	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	$Adj.R^2$
Panel A: Full Sample														
Iimbal	0.00	0.15	0.03	0.00	0.00	0.00	0.00	0.09	0.05	0.01	0.01	0.00	0.00	0.17
pos.sig.	7.3%	60.6%	22.1%	7.4%	6.4%	5.2%	4.5%	51.6%	28.4%	8.7%	5.0%	4.7%	4.3%	
neg.sig.	6.2%	5.3%	7.5%	8.7%	7.0%	6.2%	6.0%	6.6%	2.6%	4.0%	3.4%	4.1%	3.8%	
Panel B: Sub-sample														
1999-2000														
Iimbal	0.01	0.05	0.03	0.00	0.00	0.00	0.00	0.04	0.03	0.01	0.00	0.00	0.00	0.19
pos.sig.	4.8%	31.0%	16.0%	6.6%	5.4%	5.4%	3.4%	29.2%	19.4%	5.6%	2.6%	3.4%	2.2%	
neg.sig.	5.8%	8.2%	5.0%	4.6%	6.4%	3.2%	2.4%	5.2%	2.6%	2.8%	3.2%	3.0%	4.4%	
2001-2002														
Iimbal	-0.03	0.08	0.02	-0.01	-0.01	0.00	0.00	0.10	0.07	0.02	0.00	-0.01	-0.01	0.17
pos.sig.	3.7%	37.2%	10.8%	4.9%	4.4%	4.4%	3.2%	33.9%	22.3%	6.4%	2.7%	1.4%	2.2%	
neg.sig.	9.4%	7.2%	7.5%	7.6%	6.2%	3.7%	4.6%	3.7%	1.5%	2.3%	2.8%	3.7%	3.9%	
2003-2004														
Iimbal	0.02	0.19	0.06	0.01	0.01	0.00	-0.01	0.13	0.09	0.02	0.01	0.00	-0.01	0.19
pos.sig.	7.7%	43.2%	16.8%	5.7%	4.6%	3.9%	3.0%	33.8%	15.8%	4.6%	4.7%	3.6%	2.7%	
neg.sig.	4.0%	5.1%	6.4%	4.3%	4.1%	4.4%	3.9%	6.4%	1.9%	3.4%	2.9%	3.9%	3.2%	
2005-2006														
Iimbal	0.01	0.21	0.06	0.02	0.00	-0.01	0.00	0.12	0.08	0.02	0.01	0.01	0.00	0.22
pos.sig.	7.5%	50.3%	18.2%	7.0%	4.9%	3.9%	4.1%	39.1%	19.7%	6.4%	4.9%	4.4%	3.2%	
neg.sig.	4.1%	6.0%	5.2%	3.8%	5.0%	4.8%	4.3%	7.9%	2.6%	3.5%	2.3%	4.8%	4.3%	
2007-2009														
Iimbal	0.00	0.17	0.03	0.00	0.00	0.00	0.00	0.11	0.05	0.02	0.01	0.00	0.00	0.18
pos.sig.	6.8%	57.5%	15.9%	6.9%	5.8%	4.7%	3.8%	49.4%	21.3%	7.8%	3.9%	3.7%	3.5%	
neg.sig.	6.8%	4.0%	6.2%	6.7%	5.8%	5.4%	5.5%	6.0%	2.3%	4.2%	3.2%	3.5%	3.2%	
2010-2011														
Iimbal	-0.01	0.18	0.03	0.01	0.00	0.00	0.00	0.16	0.07	0.01	0.01	0.01	0.00	0.19
pos.sig.	4.9%	45.9%	13.5%	7.2%	5.1%	4.7%	3.5%	47.4%	16.7%	5.3%	4.0%	3.5%	3.7%	
neg.sig.	6.5%	5.0%	5.0%	4.8%	4.0%	3.8%	3.8%	5.8%	2.1%	3.3%	3.1%	3.0%	4.1%	

Contemporaneously, institutions tend to sell losers more often than buying winners. The cross-sectional average of the estimated coefficients on the loser portfolio is 0.15 and 60% of the securities have positive and significant coefficients at five percent level, whereas the cross−sectional average estimates on the winner portfolio is 0.09 and 51% of the stocks have positive and significant estimates at five percent level. On the other hand, institutions are momentum traders in both winner and loser stocks, however, they tend to buy prior day's winners more often than selling prior day's losers. The cross−sectional average coefficients on the winners is 0.05 and 28% of the stocks have positive and significant estimates at five percent level, whereas the cross−sectional coefficients on the losers is 0.03 and only 22% of the coefficients are positive and significant at five percent level.

The sub−period analysis shows similar trading patterns. Institutions tend to sell stocks experiencing poor performance (below the cross−sectional median) more often than buying stocks experiencing strong performance of the same day in all sub−periods except for the most recent one. Moreover, institutions tend to buy prior day's winners more often than selling prior day's losers in most of the sub−samples.

4.4 Robustness analysis

In this section, I investigate two potential explanations on what might be driving institutional trading activity in the same direction of previous day returns. One possible explanation is that institutional investors submit their orders based on the prior day price movements. Alternatively, it could be that institutional investors split the large orders and work them over several trading days. Institutions often break down the difficult orders to minimize the market impact costs of their trades. While it might not be possible to completely separate out these competing views, I follow Griffin et al. (2003) and test them in three different ways.

First, Griffin et al. (2003) argue that if institutional investors work orders over several days, then one would expect these trades to be the result of large block orders. Hence, they examine medium−size institutional trades to investigate whether institutional imbalances follow past returns. Using the same strategy, I investigate whether our results survive for medium−size institutional trades, that is, the analysis focuses on transactions where the number of shares is greater than or equal to 500 and less than 10,000 shares. Panel A of Table 4.6 shows that the medium-size institutional trades follow the prior day's return, although, not with the same magnitude as shown previously in Panel B of Table 4.4. A one standard deviation increase in the past day return leads to a 0.03 standard deviation increase in daily net buying activity of institutional investors. There are more than 19 percent of the firms with positive significant coefficients at the five percent level. Institutional imbalances are related to past imbalances with only weak evidence of predictability in daily returns. These findings are similar to those obtained by Griffin et al. (2003) who document that a one standard deviation increase in the prior day's returns leads to a 0.07 increase in medium−size daily institutional trades and 23.2% of the firms have positive and significant coefficients at the five percent level.

Second, since ANcerno data provide each transaction with the time stamp, I examine the relationship between afternoon institutional transaction and previous days' returns based on the argument provided by Griffin et al. (2003). According to these authors, institutional orders executed over several trading days may occur if institutions submit large orders near the closing hour, therefore, it is more likely that these orders will not be fully filled the same day but rather in the morning of the next day. More specifically, I use institutional transactions executed after 12:00 O'clock to examine this potential explanations. The results presented in Panel B of Table 4.6 suggest that our findings are not entirely driven by large institutional orders taking long time to be filled, but rather from institutional trades following past returns. A one standard deviation increase in the past day's return is associated with a 0.04 standard deviation increase in today's institutional net buying activity. The return in the day preceding institutional activity is an important factor in forecasting the afternoon's institutional imbalances in 27.88 percent of the firms at the 5 percent level. Results also show that the afternoon institutional imbalances are strongly related to the prior imbalances. Griffin et al. (2003) find that a one standard deviation increase in the prior day's returns leads to 0.12 standard deviation increase in the afternoon institutional imbalances and 31.7% of the stocks have positive and significant coefficients at five percent level.

Table 4.6: A Closer Examination of the Daily relation between Returns and Institutional Trading Activity

For each of the stocks in the sample the following daily structural vector autoregressions (VARs) with five lags are estimated:

$$R_t = \alpha + \sum_{j=1}^{5} \beta i R_{t-i} + \sum_{j=1}^{5} \gamma_i Iimbal_{t-i} + \varepsilon_{t,R}$$

$$Iimbal_t = \alpha + \sum_{j=0}^{5} \beta i R_{t-i} + \sum_{j=1}^{5} \gamma_i Iimbal_{t-i} + \varepsilon_{t,TI}$$

where R_t is the daily adjusted return and $Iimbal_t$ is the daily adjusted institutional buy-sell imbalance for a given stock. Both variables are adjusted by subtracting the equal-weighted average for the stocks comprising the Nasdaq-Amex-NYSE for the corresponding day. For each stock, the institutional buy-sell imbalance is the difference between the institutional buy and sell volumes for that day divided by the total number of outstanding shares, where the buy and sell volumes only include transactions that are greater than or equal to 500 and less than 10,000 shares. Applying these criteria the estimation results are base on 1466 stocks. Results for the VAR are reported in Panel A. Next, the following regression is estimated:

$$Iimbal_t^* = \alpha + \sum_{j=1}^{5} \beta i R_{t-i} + \sum_{j=1}^{5} \gamma_i Iimbal_{t-i} + \varepsilon_{t,TI}$$

where $Iimbal^*(Iimbal)$ is the daily adjusted institutional buy-sell imbalance from 12:00 p.m. to 4:00 p.m (for the whole day) for a given stock. For each stock, the institutional buy-sell imbalance is the difference between the institutional buy and sell volumes from 12:00 p.m. to 4:00 p.m (for the whole day) divided by the total number of outstanding shares. Applying these criteria the estimation results are based on 2378 stocks. Results for this regressions are reported in Panel B. Panel C reports results for the 576 most active stocks with average trading volume per year more or equal to 75 percentile across all stocks. To facilitate interpretation, both variables are standardized prior to estimation of the VAR. This table reports the cross-sectional averages of the coefficient estimates and adjusted R^2s, the percentage of stocks with positive and negative coefficients that are significantly different from 0 at the 5% confidence level (% pos.sig. and % neg.sig.) are shown.

	Panel A						Panel B			Panel C		
	Return			Iimbal			Iimbal			Iimbal		
	Coeff	%P.sig.	%N.sig.	Coeff	%P.sig.	%N.sig.	Coeff	%P.sig.	%N.sig.	Coeff	%P.sig.	%N.sig.
α	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89	−0.01	1.00	2.08
β_0				0.09	46.59	1.16						
β_1	−0.02	3.75	9.48	0.03	19.44	1.02	0.04	27.88	0.67	0.04	27.78	1.04
β_2	−0.02	2.39	8.53	0.00	4.02	3.14	0.01	6.85	2.23	0.00	3.82	3.99
β_3	−0.01	1.64	5.32	0.00	2.80	4.23	0.00	3.45	3.07	0.00	3.13	3.30
β_4	−0.01	1.64	4.64	0.00	3.21	4.37	0.00	3.07	2.94	0.00	2.26	5.38
β_5	−0.01	1.64	5.32	0.00	2.11	4.09	0.00	2.52	3.78	-0.01	2.08	5.73
γ_1	0.01	6.75	2.11	0.32	95.29	0.00	0.27	89.15	0.00	0.25	87.85	0.00
γ_2	0.00	2.80	3.62	0.08	37.79	0.14	0.07	37.97	0.42	0.06	37.50	0.52
γ_3	0.00	2.18	2.73	0.05	20.40	0.82	0.05	22.71	0.88	0.04	22.40	0.35
γ_4	0.00	2.46	2.80	0.03	13.85	0.75	0.03	13.41	0.84	0.03	15.97	0.69
γ_5	0.00	3.27	3.14	0.03	14.67	0.68	0.04	18.21	0.55	0.03	16.67	1.22
Adj.R^2	0.01			0.20			0.13			0.12		

Finally, I also examine whether our findings survive for a sub−sample of the most active stocks; I define active stocks as those that have an average trading volume per year higher than or equal to the 75 percentile of the average trading volume across all institutions. It is reasonable to think that institutional trend chasing may arise form the price impact of institutional trades. Therefore, if our findings are driven by institutional trades moving prices and taking long time to clear, then one should expect these patterns to be less severe in the most active stocks as they are extremely liquid stocks. Panel C reveals that a one standard deviation increase in previous day return leads to a 0.04 standard deviation increase in this afternoon's institutional imbalances and 27.78 percent of firms have positive significant coefficients at the five percent level. While it is not possible to rule out all potential explanations on what might be deriving institutional trades in the same direction of previous day's returns, our daily evidence indicates that these patterns are in large part the consequence of institutional orders being placed in the same direction of the price movements.

4.5 Intradaily Analysis

The strong daily contemporaneous relation between institutional imbalances and returns is consistent with institutional investors following intradaily prices, the institutional price pressure hypothesis, and institutional investors' ability to predict intradaily price movements. In this section, I conduct an intradaily analysis to examine the relation between returns and institutional imbalances to help distinguish between these competing explanations. More specifically, I investigate the relation between institutional trade imbalances and intradaily jumps in prices.

To capture both positive and negative jumps in the intradaily prices, I define two dummy variables. The dummy variable *pjump* (*njump*, capturing the positive (negative) jump, equals one if the change in the stock price is at least one standard deviations higher (lower) than the quarterly average change in stock price, and equals zero otherwise. I also examine the relation for larger jumps by considering a 1.5 and a 2 standard deviation jumps. To limit our sample and obtain the necessary data, I require at least five observations for each stock in each day. For the jump events, I require the time difference between the two consecutive price observations to be of maximum 60 minutes. I compute institutional buy-sell imbalances by considering two time intervals after a jump event, one-hour as well as two-hours interval after the jump occurs, with this framework, I estimate the following regression:

$$Imbal_{i,t} = \alpha + \beta_p Pjump_{i,t-1} + \beta_n Njump_{i,t-1} + \gamma Controls + \varepsilon_{i,t} \tag{4.5}$$

where $Pjump$ and $Njump$ are dummy variables capturing the positive and negative jumps, respectively, $Imbal$ measures the institutional imbalances. I also control for other stock characteristics such as prior-hour return, stock turnover, absolute return to proxy for stock volatility, firm size, bid-ask spread, and the previous day return.

A positive (negative) relationship between institutional imbalances and $Pjump$ ($Njump$) implies that institutional investors follow intradaily stock prices and this in turn may induce the positive contemporaneous relation between returns and institutional imbalances at daily level. Table 4.7 reports the regression results of equation (4.5) for each of the years in our sample; the regressions include firm fixed effects and monthly time dummies. In the left part of Table 4.7, institutional imbalances are computed within one-hour interval after the jump event, while in the right part, institutional trades are computed within two-hours interval. The empirical results reveal that there is a strong positive relation between institutional imbalances and positive jumps, in particular, for the most recent years, the relation holds for all jump sizes and for the different ways the institutional trades are computed (either one-hour or two-hours interval). For example, the coefficients on *pjump* are positive and significant at conventional levels for all sub−samples after 2002, suggesting that institutions increase their net buying activity after large increase in prices at intradaily level. However, the relation between institutional imbalances and negative jumps is insignificant except for some sub−samples of the very recent years. For example, for 1σ the coefficient on $njump$ is negative and significant at conventional levels only for the 2009 when computing institutional imbalances in one-hour interval and it is negative and significant at conventional levels from 2009 through 2011. For 1.5σ the coefficient on the negative jump is significant only in 2009 and 2010.

These findings provide some evidence in favor of institutional trend chasing at intradaily frequency. Institutions react faster and more often to positive jumps than to negative ones, and consequently they increase their stock holding after a positive jump and less often decrease their stock holding after the negative ones. These results are similar to those obtained by Griffin et al. (2003) who investigate the intradaily relationship between institutional imbalances and returns measured at 5−minutes intervals using vector autoregression analysis as well as by examining both institutional imbalances and returns around extreme institutional trading and return events. Their main findings suggest that institutional imbalances follow past prices at intradaily level and the institutional price impact is minimal.

Table 4.7: An Intradaily Analysis for Institutional Momentum Trading

This Table reports the regression results of the intradaily institutional imbalances against jumps in stock prices. Institutional imbalance is defined as the difference between the institutional buy and sell volumes for that day divided by the total number of outstanding shares, $Pjump$ ($Njump$) is a dummy variable capturing the intradaily positive (negative) jumps in prices. I consider three jump sizes, a 1σ, 1.5σ, and 2σ. Institutional imbalances are calculated considering two time intervals, a one-hour and two-hours after the jump event. The regressions include firm fixed effects and monthly time dummies. $t-$statistic in parenthesis.

	One Hour						Two Hours					
	$1\ \sigma$		$1.5\ \sigma$		$2\ \sigma$		$1\ \sigma$		$1.5\ \sigma$		$2\ \sigma$	
	$Pjump$	$Njump$	$Pjump$	$Njump$	$Pjump$	$Njump$	$Pjump$	$Njump$	$Pjump$	$Njump$	$Pjump$	$Njump$
99	0.00001	0.00002	0.00000	0.00001	-0.00013	-0.00001	0.00001	0.00000	-0.00008	-0.00007	-0.00013	-0.00001
	(0.34)	(0.44)	(-0.01)	(0.17)	(-1.75)	(-0.11)	(0.18)	(0.09)	(-1.24)	(-1.01)	(-1.75)	(-0.11)
00	0.00010	-0.00003	0.00020	-0.00005	0.00032	-0.00015	0.00011	-0.00008	0.00018	-0.00016	0.00032	-0.00015
	(1.68)	(-0.51)	(2.29)	(-0.61)	(2.56)	(-1.15)	(1.42)	(-1.05)	(1.65)	(-1.47)	(2.56)	(-1.15)
01	0.00006	0.00007	-0.00004	-0.00002	0.00000	-0.00003	0.00016	0.00029	-0.00005	0.00012	0.00000	-0.00003
	(0.33)	(0.39)	(-0.92)	(-0.46)	(0.01)	(-0.60)	(0.69)	(1.22)	(-0.6)	(1.4)	(0.01)	(-0.6)
02	0.00004	0.00002	0.00001	0.00005	0.00004	0.00005	0.00005	0.00002	0.00009	0.00006	0.00004	0.00005
	(1.89)	(1.31)	(0.39)	(1.86)	(1.29)	(1.48)	(2.13)	(0.65)	(2.38)	(1.59)	(1.29)	(1.48)
03	0.00003	0.00001	0.00004	0.00000	0.00004	0.00000	0.00003	0.00000	0.00005	-0.00001	0.00004	0.00000
	(3.38)	(1.31)	(2.80)	(-0.18)	(2.06)	(-0.2)	(2.58)	(0.02)	(3.43)	(-0.42)	(2.06)	(-0.2)
04	0.00004	0.00002	0.00005	0.00005	0.00005	0.00002	0.00007	0.00001	0.00006	0.00006	0.00005	0.00002
	(2.09)	(1.05)	(2.03)	(1.82)	(1.47)	(0.52)	(2.71)	(0.34)	(1.67)	(1.49)	(1.47)	(0.52)
05	0.00003	0.00001	0.00004	0.00001	0.00004	0.00000	0.00004	0.00002	0.00007	0.00003	0.00004	0.00000
	(3.41)	(1.28)	(3.65)	(1.44)	(3.09)	(-0.04)	(3.92)	(1.7)	(4.72)	(1.76)	(3.09)	(-0.04)
06	0.00003	0.00000	0.00004	0.00001	0.00004	0.00002	0.00003	0.00000	0.00005	0.00001	0.00004	0.00002
	(4.37)	(0.60)	(4.31)	(1.13)	(2.99)	(1.53)	(3.51)	(0.2)	(5.01)	(0.94)	(2.99)	(1.53)
07	0.00006	0.00000	0.00007	0.00000	0.00007	0.00000	0.00006	0.00001	0.00009	0.00002	0.00007	0.00000
	(5.29)	(0.00)	(4.90)	(-0.19)	(3.77)	(-0.03)	(4.6)	(0.47)	(5.97)	(1.07)	(3.77)	(-0.03)
08	0.00002	0.00000	0.00003	0.00001	0.00004	0.00001	0.00003	-0.00001	0.00005	0.00001	0.00004	0.00001
	(3.02)	(0.25)	(3.34)	(1.12)	(2.82)	(1.11)	(3.02)	(-0.52)	(3.95)	(0.6)	(2.82)	(1.11)
09	0.00003	-0.00001	0.00004	-0.00001	0.00005	-0.00002	0.00004	-0.00003	0.00006	-0.00003	0.00005	-0.00002
	(8.78)	(-3.66)	(8.90)	(-3.19)	(7.89)	(-2.64)	(7.17)	(-5.12)	(8.76)	(-4.43)	(7.89)	(-2.64)
10	0.00004	0.00000	0.00005	-0.00001	0.00006	0.00000	0.00005	-0.00002	0.00006	-0.00003	0.00006	0.00000
	(10.48)	(-0.66)	(10.39)	(-1.18)	(9.29)	(0.29)	(9.27)	(-3.4)	(9.08)	(-4.86)	(9.29)	(0.29)
11	0.00003	0.00000	0.00004	0.00000	0.00006	0.00000	0.00003	-0.00002	0.00005	-0.00001	0.00006	0.00000
	(8.53)	(-0.65)	(8.70)	(0.47)	(9.03)	(-0.44)	(7.02)	(-3.48)	(7.58)	(-1.45)	(9.03)	(-0.44)

Next, I examine the intradaily returns predictability of institutional imbalances. While the jump events are defined as previously, the institutional imbalances are computed in one hour and two hours interval before the jump takes place. A positive (negative) relation between lagged institutional imbalances and $pjump$ ($njump$) indicate to the ability of institutional investors to predict the intradaily price movements. To examine this hypothesis, I estimate the following two equations:

$$Pjump_{i,t} = \alpha + \beta_p Imbal_{i,t-1} + \gamma Controls + \varepsilon_{i,t} \tag{4.6}$$

$$Njump_{i,t} = \alpha + \beta_n Imbal_{i,t-1} + \gamma Controls + \varepsilon_{i,t} \tag{4.7}$$

The results of these two equations are presented in Table 4.8. The left part of Table 4.8 presents the results of yearly sub−samples for the negative jumps, whereas the right part presents the results for the positive jumps. These regressions include both firm fixed effects and monthly time dummies. The empirical results suggest that there is no evidence on the intradaily institutional returns predictability. The relationship between the lagged institutional imbalances and negative jumps is positive and significant at conventional levels in the most of the yearly sub−samples, whereas the relation between positive jumps and lagged institutional imbalances is mixed. These findings contrast those obtained in Griffin et al. (2003) who find an economically small but statistically significant intradaily return predictability for lagged institutional imbalances.

Table 4.8: An Intradaily Analysis for Institutional Return Predictability

This Table reports the intradaily regression results of positive (negative) jumps on institutional imbalances. Institutional imbalance is defined as the difference between the institutional buy and sell volumes for that day divided by the total number of outstanding shares, $Pjump$ ($Njump$) is a dummy variable capturing the intradaily positive (negative) jumps in prices. I consider three jump sizes, a 1σ, 1.5σ, and 2σ. Institutional imbalances are calculated considering two time intervals, one-hour and two-hours before the jump event. The regressions include firm fixed effects and monthly time dummies. $t-$statistic in parenthesis.

	One Hours			Two Hours			One Hours			Two Hours		
	$Njump$						$Pjump$					
	1 σ	1.5 σ	2 σ	1 σ	1.5 σ	2 σ	1 σ	1.5 σ	2 σ	1 σ	1.5 σ	2 σ
1999	-5.052	-0.470	-0.021	-0.153	0.084	0.326	-7.280	-3.668	-3.462	-0.301	-0.336	-0.275
	(-1.6)	(-0.28)	(-0.01)	(-0.18)	(0.12)	(0.53)	(-1.72)	(-1.74)	(-2.05)	(-0.37)	(-0.46)	(-0.45)
2000	0.501	1.630	0.955	1.094	0.580	0.301	-0.617	0.714	0.324	-0.220	0.022	0.014
	(0.43)	(2.33)	(1.64)	(2.67)	(1.36)	(0.83)	(-0.51)	(1.16)	(0.63)	(-0.65)	(0.07)	(0.05)
2001	0.025	0.036	0.028	0.043	0.047	0.032	0.203	0.039	0.031	0.083	0.059	0.040
	(0.31)	(0.63)	(0.61)	(0.62)	(0.78)	(0.65)	(0.43)	(0.68)	(0.69)	(1.16)	(0.98)	(0.81)
2002	0.635	0.661	0.730	0.885	0.982	0.994	0.594	0.544	0.670	0.639	0.570	0.637
	(1.09)	(2.25)	(2.97)	(2.63)	(3.34)	(3.93)	(1.14)	(1.8)	(2.65)	(1.92)	(1.93)	(2.48)
2003	0.760	0.635	0.774	0.744	0.681	0.836	0.279	0.484	0.608	0.227	0.468	0.698
	(1.51)	(2.18)	(3.21)	(2.1)	(2.1)	(3.03)	(0.56)	(1.63)	(2.54)	(0.64)	(1.44)	(2.53)
2004	-0.070	0.084	0.132	0.104	0.195	0.236	0.412	0.326	0.283	0.133	0.099	0.052
	(-0.43)	(0.83)	(1.61)	(0.86)	(1.81)	(2.61)	(2.71)	(3.27)	(3.49)	(1.12)	(0.94)	(0.58)
2005	0.774	0.571	0.644	0.298	0.202	0.601	1.019	0.420	0.454	0.504	0.386	0.338
	(1.65)	(2.26)	(3.14)	(1.99)	(1.53)	(2.97)	(2.41)	(1.7)	(2.03)	(1.78)	(1.53)	(1.49)
2006	0.572	0.682	0.770	0.451	0.751	0.824	0.108	0.261	0.248	0.037	0.136	0.242
	(1.83)	(3.49)	(4.86)	(2.03)	(3.36)	(4.3)	(0.34)	(1.31)	(1.54)	(0.16)	(0.66)	(1.38)
2007	0.768	0.563	0.459	0.687	0.687	0.602	-0.025	0.132	0.042	-0.056	0.099	0.063
	(3.3)	(3.59)	(3.62)	(3.99)	(4)	(4.08)	(-0.11)	(0.85)	(0.34)	(-0.32)	(0.6)	(0.44)
2008	1.665	1.170	0.909	1.461	1.469	1.212	-0.066	0.197	0.242	-0.148	0.238	0.444
	(7.33)	(7.95)	(7.59)	(7.79)	(8.66)	(8.29)	(-0.31)	(1.29)	(1.94)	(-0.88)	(1.43)	(3.05)
2009	3.908	2.245	1.761	2.460	2.088	1.614	-2.473	-1.092	-0.720	-2.148	-1.423	-0.934
	(7.2)	(7.19)	(6.99)	(7.5)	(7.02)	(6.35)	(-4.48)	(-3.54)	(-2.88)	(-6.79)	(-4.88)	(-3.7)
2010	3.881	2.773	2.409	3.419	3.016	2.807	-1.313	-0.213	-0.231	-2.290	-1.488	-1.133
	(6.86)	(7.54)	(8.07)	(7.81)	(7.59)	(8.14)	(-2.36)	(-0.58)	(-0.78)	(-5.25)	(-3.73)	(-3.32)
2011	4.452	4.127	3.204	4.799	5.185	4.233	-1.130	-0.301	-0.146	-1.627	-0.900	-0.159
	(5.47)	(8.07)	(7.7)	(7.45)	(8.95)	(8.49)	(-1.41)	(-0.59)	(-0.35)	(-2.61)	(-1.55)	(-0.32)

In sum, the intradaily analysis suggest that the daily contemporaneous relation between institutional imbalances and returns is mainly driven by institutions following intradaily prices. There are two possible explanation for these intradaily results. First, prices may move in the same direction of institutional trades either because institutions trade on common information or simply because institutions follow past prices. Alternatively, these findings are also consistent withe the price pressure hypothesis. For example, if institutions submit a buy order and then, in an attempt to accumulate the required number of shares, the market makers may bid up the prices before executing the trade. The overall results suggest that there is no evidence on institutional investors' ability to predict intraday returns.

4.6 Post Ranking Returns and Price Reversal

DeLong et al. (1990) note that trading activity by the feedback traders can push prices beyond fundamentals, thereby it may destabilize prices and threaten the efficiency of financial markets. However, although herding and feedback trading could drive prices away from fundamentals, it may also drive prices towards fundamentals if the information inferred from the trade of others is useful (Bikhchandani et al., 1992; Hong and Stein, 1999; Hirshleifer et al., 1994)

Examining the deviation of prices from the fundamental value is not an easy task. I follow Griffin et al. (2003) and test whether institutional trading have a destabilizing effect by investigating post−formation returns. It is possible, for instance, that institutional orders move prices away from fundamental values. If that is the case, return reversal will be observed as stock prices ultimately revert toward fundamental values. Alternatively, the absence of subsequent price reversals is consistent with the information hypothesis. However, return continuations in the days following the portfolio formation may reflect institutional investors continuing to move prices away from fundamental values. In either case, whether return reversals or continuations indicate destabilizing behavior depends on the time period considered Nofsinger and Sias (1999).

Table 4.9 reports the time−series average of the cross−sectional mean abnormal return for each decile created according to institutional imbalances in the ten days following the formation day. I find that in the two days following portfolio formation, the decile experiencing the largest institutional selling activity exhibits small negative and insignificant returns, while the decile experiencing the largest institutional buying activity exhibits small positive and insignificant returns. However, although the return reversal in the third day after portfolio formation has the correct sign, the return differential between high and low institutional buy−sell imbalance deciles is insignificant. Thus, these findings do not support the reversal hypothesis, one possible explanation is that, a longer time horizon is necessary to make a clear inference.

Table 4.9: Price Reversal and Post Ranking Returns

On each day the Nasdaq-Amex-NYSE stocks are ranked by their daily institutional buy-sell imbalances and assigned to one of 10 portfolios. For each stock, institutional buy-sell imbalance (expressed in percent) is the difference between the institutional buy and sell volumes for that day scaled by the total number of outstanding shares. This table reports the contemporaneous and post ranking returns. Returns are expressed in percent per day. The last row reports the mean difference between the high and low portfolios for each variable. The statistical significance reported in the last row is computed from a paired t-test estimated from the time series of the difference between the high and the low portfolios.

Rank	0	+1	+2	+3	+4	+5	+6	+7	+8	+9	+10
D1	−0.611	−0.005	−0.004	0.002	0.007	−0.010	−0.016	0.004	−0.001	−0.010	−0.009
D2	−0.373	−0.045	−0.016	−0.014	−0.023	−0.028	−0.012	−0.014	−0.015	−0.014	−0.007
D3	−0.240	−0.037	−0.025	−0.024	−0.021	−0.014	−0.018	−0.016	−0.015	−0.014	−0.016
D4	−0.135	−0.041	−0.026	−0.016	−0.016	−0.007	−0.011	−0.021	−0.001	−0.007	−0.020
D5	−0.052	−0.017	−0.023	−0.016	0.000	−0.004	0.000	−0.004	−0.010	−0.009	0.003
D6	0.012	−0.009	−0.005	−0.006	−0.008	0.003	−0.012	−0.008	−0.013	−0.004	−0.011
D7	0.088	−0.001	−0.014	−0.014	−0.015	−0.016	−0.011	−0.004	−0.009	−0.005	−0.016
D8	0.209	0.004	−0.003	−0.007	−0.005	−0.016	−0.012	−0.020	−0.018	−0.011	−0.005
D9	0.363	0.018	0.001	−0.013	−0.015	−0.006	−0.014	−0.016	−0.008	−0.013	−0.003
D10	0.626	0.020	0.002	−0.006	−0.016	−0.013	−0.010	−0.013	−0.021	−0.021	−0.028
H-L	1.237[a]	0.024	0.006	−0.008	−0.022	−0.003	0.006	−0.017	−0.020	−0.011	−0.020

a Significance at 1%.

b Significance at 5%.

4.7 Conclusions

I use proprietary institutional transaction data to examine the trading behavior for a sample of institutional investors from January 1999 through September 2011. The paper provides empirical evidence on (i) the cross-sectional relationship between institutional trading and contemporaneous and prior day's returns, and (ii) institutional investors' ability to predict returns. I find strong evidence that institutional trades follow past returns at daily level, the results being economically and statistically significant. On the day subsequent to extreme return performance, institutional investors are 13.6 percent more likely to be net buyers in stocks that are in the top decile of return performance than those in bottom decile. Moreover, there is a strong positive contemporaneous relationship between the trading activity of institutional investors and daily returns. The intradaily analysis suggest that the contemporaneous relation found at a daily horizon is primarily driven by institutions following the intradaily prices. In addition, I find no evidence that institutional imbalances predict price movements. There is considerable time variation in the institutional trading among loser and winner stocks. This result of daily institutional trades following past returns and the persistence of institutional trades is robust to different trade-size classifications and methodologies.

A possible explanation for these patterns is that institutions observe return movements or firm's related information and trade accordingly, or due to institutional price impact, institutions move prices in the direction of their trades. Similarly, I find that the afternoon institutional trades strongly follow past return movements at a daily level, even for most active stocks. This suggests that our findings are not specific to institutional order splitting. While there are likely several explanations for our results, it appears that institutions view recent positive return movements or the information related with them as a buying signal. Although the fact that institutional investors following past returns may have a destabilizing influence, I find no evidence that institutional activity leads to price reversals.

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