On Institutional Trading and Behavioral Bias

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Abstract

Are institutional investors skilled at short-term trading or do they trade too much? Using historical cost method, two recent studies provide contradictory answers to this question. The first suggests that institutions are skilled and earn 26-34 basis points higher benchmark-adjusted returns for their buy trades than sell trades. The second argues that the institutional fund managers earn -57 to -225 basis points benchmark-adjusted return on their short-term trades and investors in these funds would have been better off had these managers traded less. When we use a marked-to-market based fair value method – instead of the historical cost method – for measuring fund manager skills, we find that institutional managers make economically insignificant -4 to +9 basis points net profit on their short-term portfolio of buy – sell transactions. The negative net marked-to-market profit comes exclusively from trades with 1-day holding period. We find no evidence of overconfidence, biased self-attribution, or disposition effect among institutional investors. Pension fund managers outperform money managers. Institutions engage in short-term trades despite earning net zero return for liquidity, tax-minimization, risk-management, and window-dressing reasons. Among these non-profit maximizing rational motives for trading, liquidity trading motive is the strongest.

Are institutional traders skilled or do they trade too much? Why do institutional investors trade equities and how much trading constitutes too much? We expect institutions to trade primarily in order to maximize risk-adjusted net portfolio return and when marginal benefit from trading exceeds the marginal cost, including the opportunity cost of not trading and passively holding a market or benchmark portfolio.[1] If portfolio managers are able to do that, we infer that the managers are skilled at trading. Indeed, Puckett and Yan (2011) find a large number of representative institutions – both money managers and pension fund managers – earned 26 to 34 basis points higher benchmark-adjusted return after transaction cost on their buy trades than on their sell trades within the quarter from 1999 to 2005. They take this as evidence of "interim" trading-skill for institutions. Chakrabarty, Moulton, and Trzcinka (2017), on the other hand, present starkly different results – raw (benchmark-adjusted) return of -82 to -337 (-57 to -225) basis points before transaction cost for trades with 1-day to 3-month holding period between 1999 and 2009. Both these studies use the "historical cost" based accounting method for measuring fund manager performance.

A vast accounting and finance literature exist on the superior reliability and value-relevance of the marked-to-market based "fair-value" accounting method over the "historical cost" method for valuation of available for sell financial securities. Proponents of fair value method argue that gains and losses in fair value securities are value relevant; that the fair value estimates are less biased and more informative than the historical cost based estimates; and that fair value estimates of securities held by banks provide significant explanatory power over security values estimated based on historical cost but the reverse is not true (Barth (1994), Dietrich et. al. (2001), Hirst et al. (2004), Bleck and Liu (2007), Muller et al. (2015)). The opponents argue that marked-to-market based accounting method transmits mixed signals about value in certain cases, especially when hedging with derivatives (Gigler et al. (2007), Makar et al. (2013)), causes pro-cyclical leverage and/or lending resulting in further deterioration of market condition and financial instability in a low-liquidity environment (Allen and Carletti (2009)), exacerbates feedback-trading (Bhat et al. (2011)), and can introduce behavioral biases, e.g. sub-optimal hedging decision in an experimental set-up (Chen et al. (2013)). Both methods have a large number of defenders as well as critiques although the numbers tend to be highly skewed towards the desirability of the fair value method.[2]

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[1] Just as we expect elite alpine skiers to plan and ski in a tight line when the benefit of doing so, i.e. a faster time and a higher probability of securing a place on the podium, exceeds the cost, i.e. probability of not finishing or of an injury. How spectacular they appear to the audience on the slope and on TV are tertiary considerations.

[2] Among other proponents and/or defenders of fair value method against its critiques are, for e.g., Bernard et. al. (1995), Nelson (1996), Ahmed et al. (2006), Bleck and Liu (2007), Laux and Leuz (2010), Badertscher et al. (2012), Linsmeier (2013), Arora et. al. (2014), Choi et al. (2015), Ellul et al. (2015), Israeli (2015), Bratten et al. (2016), Demerjian et al. (2016), Laux (2016), Xie (2016), Amel-Zadeh et al. (2017), and Laux and Rauter (2017). Among the critiques of fair value method are, for e.g. Kirschenheiter (1997), Bhat et al. (2011), Datta and Zhang (2001), Plantin et al. (2008), Dong et al. (2014), and Chircop and Novotny-Farkas (2016).

One can argue that a fair-value method based performance evaluation of an institutional fund manager provides a more reliable measure of skill than the realized performance measure based on historical cost method. The accounting literature has established the superior reliability and value relevance of the fair value method over historical cost method and the minor concerns related to mixed signals and the sub-optimal outcome or potential behavioral bias related to hedging with derivatives are far less relevant for equity trades of the institutional fund managers.[3] Fair value method also allows us to measure a manager's performance at random hypothetical liquidation points. The advantage of such random hypothetical liquidation points is that these are less susceptible to manipulation by the fund managers. The second advantage is that at any specific realized liquidation point, the manager could have been subject to both liquidity demand from investors and specific market conditions – both in terms of direction and volatility – just as our alpine skiers might be subject to specific wind or visibility conditions that can change within a short period of time.

We use the full sample of the institutions between 1999 and 2012 and observe that institutions break-even in their mark-to-market adjusted portfolio holdings over short horizon (1-day to 4-week); transaction cost adjusted buy trades earn economically insignificant -4 to +9 basis points higher marked-to-market return than transaction cost adjusted sell trades. The negative net return is observed exclusively for those trades with a hypothetical holding period of 1-day. If the results we report are accurate, i.e. institutional investors break-even but do not make economically significant profits net of trading cost on their hypothetical short term trades, then the relevant question is, why do institutions execute short-term trades? Institutional investors may trade for liquidity reasons, to rebalance their portfolios, for risk-management purpose, for tax-minimization reasons, or for window dressing. Equity trading could also be part of a more complex strategy involving other assets. For instance, a long equity position could be part of a more complex transaction such as an arbitrage using futures and spot market or writing a covered call. Trading can also be used to signal the clients that the portfolio manager is devising an active strategy and executing these strategies rather than engaging in passive indexing. Trading may also occur to cultivate a beneficial relationship with the broker such that institutional investors with such relationship get preferential allocation of assets, e.g. undervalued shares from specific corporate events such as initial public offerings (e.g. Pollock, Porad, and Wade (2004), Reuter (2006), Nimalendran, Ritter, and Zhang (2007), Goldstein, Irvine, and Puckett (2011)). In presence of these complex multi-asset trades and a diverse set of

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[3] The evidence presented skews towards the advantage of fair-value method based on its superior reliability due to higher quality information content, value relevance, and lower bias. Most recent literature argues that concerns about procyclicality and overleveraging risk are overstated or studies raising these concerns suffer from methodological or inference problems. Some concerns about using fair value method for specific cases, e.g. for hedging application may hold but the outcome – either positive or negative – can depend on ex-post managerial behavior.

non-profit maximization motives, it is not enough to suggest that institutions trade too much because their equity trades fail to generate trading cost adjusted net profits. Hence, fund managers can find value in equity trading rather than passively holding a portfolio even when the trade return from the equity portfolio is close to zero or even slightly negative after adjusting for trading costs. Unfortunately, lack of appropriate data currently makes it difficult to test for many of these motives.

In addition to the rational reasons for trading, institutions might trade because of behavioral biases among which are overconfidence, biased self-attribution, and the disposition effect. Overconfident individuals have a greater subjective belief in their abilities and skills than supported by objective assessment of performance. Self-attribution bias occurs when someone attributes successful outcomes to her own skill but blames unsuccessful outcomes on bad luck. The disposition effect is the propensity displayed by investors to sell stocks that have gained in value too quickly and to hold on to stocks that have lost value for too long.[4] Our goal in this paper is not to provide a comprehensive set of tests to eliminate all possible alternative hypotheses for trading beyond profit maximizing. Rather, we have a more modest goal of testing the hypotheses that institutional investors trade due to systematic behavioral biases after controlling for as many of the alternative rational motivations for trading, including profit maximization, as possible.

Odean (1999) observes excessive trading among individuals with discount brokerage accounts and shows that these investors trade excessively because they are overconfident. A reasonable conclusion from his findings is that individual investors, in general, are overconfident traders. It is unclear, however, whether other investor groups, such as institutional investors, might also be overconfident.[5] Griffin and Tversky (1992) report that when predictability is low, as in the securities markets, the experts may be more prone to overconfidence than novices.[6] This would suggest that unlike the individual investors, institutions

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[4] While the first formal analysis of the disposition effect is attributed to Sheffrin and Statman (1985), the concept first appears in Schlarbaum, Lewellen, and Lease (1978), who use data from 2,500 individual brokerage house customers between 1964-1970 and find that the individual investors in their sample beat the market by 5 per cent per year and that about 60% of their trades result in a profit. Schlarbaum *et al.* raise the possibility that the investors' observed performance could be an outcome of a "disposition to sell the winners and hold on to the losers." However, they dismiss this possibility in favor of an explanation based on the stock picking skills of these investors. Empirical evidence on the disposition effect is provided by Lakonishok and Smidt (1986), Odean (1998), Heath, Huddart and Lang (1999), and Grinblatt and Keloharju (2001), among others.

[5] Odean (1999) suggests that excessive institutional trading might result from overconfidence (see, also, Ben-David and Doukas (2006) and Cremers and Pareek (2011)).

[6] Graham, Harvey, and Huang (2009) report a positive relation between competence and trading frequency where competence is a function of the investors' gender, education, income, and total investments. Using experimental evidence, Lichtenstein, Fischhoff, and Phillips (1982) show that the more difficult the task the greater the observed overconfidence while Weber and Camerer (1998)'s laboratory experiments yield opposite results. Participants are significantly more likely to realize gains relative to losses while buying and selling multiple risky stocks over multiple trading rounds. Bodnaruk and Simonov (2015) show that financial experts such as mutual fund managers do not exhibit lower behavioral biases in private portfolios decisions.

or the professional investors, who are considered to be the "experts", might fit the category of overconfident investors. On the other hand, there is a sizable body of the literature that conclude that institutions are, in fact, rational informed traders, i.e., not overconfident as an investor class (see, for example, Badrinath, Kale, and Noe (1995), Sias and Starks (1997), Chakravarty (2001), Sias, Starks, and Titman (2006), Parrino, Sias, and Starks (2003), among others). Hence, the evidence on whether institutional investors are overconfident, remains inconclusive.

We contribute to this strand of literature in two ways. First, we attempt to directly test for multiple biases that might cause excessive trading. Second, we use high frequency data that allows us to approximate the marked-to-market value of any hypothetical transaction over several different short horizons. Low frequency quarterly data used in analyzing trading behavior of, and behavioral biases among, U.S. institutions can lead to misleading conclusions. For e.g., changes in quarterly holdings data do not capture intra-quarter transactions where funds might purchase and sell or sell and repurchase the same stock within the same quarter. In addition, studies with quarterly holdings data typically assume that all trades occur at the end of the quarter but in reality they could occur at any time within the quarter. Thus, researchers employing such data are restricted in their ability to identify superior trading skills if trades are motivated by short term information and if such opportunities dissipate quickly. We use a large proprietary database of daily institutional trades in NYSE/AMEX stocks from ANcerno Ltd (formerly Abel Noser) over a period of 1999 through the first quarter of 2012 - over 31 million stock level institutional transactions spanning over 1,100 distinct institutions and involving over 3,300 distinct stocks - to test our behavioral bias hypotheses.

We find no evidence of trades driven by overconfidence in our institutional trading data; the stocks they buy perform significantly better than the stocks they sell.[7] The average difference between returns from a buy and a hypothetical sell transaction – used for the purpose of marking to market – ranges from 0.033% over a 1-day horizon, 0.072% over a 1-week horizon, and 0.092% over a 2-week horizon, and 0.087% over a 4-week horizon. This effect is stronger for smaller stocks where it is easier for institutional investors to earn trading profit based on their information. The effect is also stronger when we exclude trades motivated by liquidity, tax-minimization, window-dressing, or risk-management reasons. Hence, we conclude that institutional trades, although only break-even or have economically insignificant positive net

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[7] The theoretical models of investor overconfidence (see for example, Daniel, Hirschleifer and Subrahmanyan (DHS, 1998), Odean (1998), and Gervais and Odean (2001)) rely on two important assumptions grounded in psychology. The first is that the investors are prone to overestimating the precision of their private information. This would lead to an overconfident investor concluding she has private information when in fact she has none or that she has high precision information when in fact she has poor quality information. Such divergences between her beliefs and reality would imply that her buy trades would, in fact, underperform her sell trades.

return on a marked-to-market basis, do not reflect overconfidence. Among institutional investors, neither money managers nor pension fund managers suffer from overconfidence. Pension fund managers, however, outperform the money managers. Relative to the latter, they do better with their purchases than their sales especially for 1-day to 1-week horizon. Over a 1-week trading horizon the difference in marked-to-market return between their buys and sells is 0.105%.

If investors suffer from biased self-attribution then we would observe a positive correlation between lagged market returns and contemporaneous institutional buys. Using daily institutional level vector autoregressions and bootstrapping, to allow correlated trades across institutions, we find no significant correlation between our measures of (contemporaneous) daily institutional trading volume or turnover and lagged market returns that would suggest that institutions are unduly influenced by market movements, or overconfident because of self-attribution bias. Finally, we estimate a similar VAR model at the daily stock level, with bootstrapping, in order to examine if institutions display any disposition effects in their trading pattern. Specifically, if institutions suffered from the disposition effect we would expect a positive correlation between lagged stock returns and contemporaneous institutional sells. Here, too, we find no significant correlation between the two.

In sum, our results show that in our dataset and sample period, using a marked-to-market method based "fair-value" accounting, institutions expect to break-even on their short term trades. This implies that even if our sample institutions were forced to engage in short term trades for rational reasons such as need for liquidity, risk-management, tax-minimization, or window-dressing, they would break-even or earn economically insignificant positive or negative net return. They would neither make small positive net profit of 30 basis points after transaction cost nor would they incur huge losses to the tune of -57 to -225 basis points before transaction cost, as measured by the historical-cost based approach, and reported by Pucket and Yan (2011) and Chakrabarty, Moulton, and Trzcinka (2017), respectively. It is hard to explain why such large losses reported in the latter work exists in equilibrium. When we eliminate the trades most likely to be driven by liquidity motives, the expected short-term performance of the institutional fund managers improve significantly. We also conclude that institutional traders do not suffer from overconfidence, biased self-attribution, or disposition effect in their trading. Intuitively, we can explain the findings related to the lack of behavioral bias if we believe that experience, or the level of investor sophistication, attenuates any such biases associated with trading.[8]

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[8] Our research and findings also add to the body of literature on informed trading by institutions exemplified by Barclay and Warner (1993), Hasbrouck (1995), Keim and Madhavan (1995), Chakravarty (2001), Alexander and Peterson (2007), among others.

2. Data

We obtain high frequency institutional trading data from January 1999 to March 2012 from ANcerno Ltd. ANcerno is well known for providing consulting services to institutional investors through monitoring their equity trading costs. ANcerno collects data from their (institutional) customers and provides practitioners and academics detailed information on executed institutional trades such as client code, client manager code, ticker, cusip, side, execution price, closing price, date, volume, and commission fee. Several important recent studies have used this data set which perhaps attests to its growing importance in the research community.[9]

ANcerno data are ideally suited to answer our questions because it identifies the exact date and execution price of each institutional transaction and allows us to distinguish the trades of one institution from another, both in the cross section and over time, by using the unique institution identifier. The dataset also allows us to classify the traders by type of institutions such as mutual fund or pension fund, among others. Puckett and Yan (2011) and Franzoni and Plazzi (2013) estimate that ANcerno institutions account for 10% - a significant fraction - of all institutional trading volume. They argue that ANcerno's data have several appealing features for academic research. First, the characteristics of stocks held and traded by ANcerno's institutions are not significantly different from the characteristics of stocks held and traded by the average 13F institution. Second, given the data provider is focused on transaction cost analysis, and not on institutional performance, there should not be any misrepresentation bias from self-reporting. Third, the data are released in monthly batches and not updated after their release which makes them unlikely to suffer from survivorship bias. Finally, the dataset include trades that occurred only after the client became a client of ANcerno, which would make them free of any backfill bias.

Each observation within the dataset represents an execution of a specific order to buy or sell stock, by a given manager of an institution, in a given day. There could be several such executions by that institution in that same stock within that same day (representing both buy and sell orders) by the same, or different, account managers for that institution. We aggregate institutional data into daily stock level institutional transactions for all of our tests. *Ticker* and *cusip* are used to identify the stock traded. *Side* indicates a buy or a sell. For *price* and *volume*, ANcerno provides not only an execution price and its volume for a particular trade or transaction within a single observation level, but also a volume-weighted execution price and volume for the entire order. ANcerno also lists the commission fee for each execution. For our empirical analysis, we use all the information above, in order to calculate an average institutional round-

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[9] Among the studies that have used the ANcerno data to examine various questions related to institutional trading include Bethel, Hu, and Wang (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, Kandel, and Wiener (2009), Hu (2009), Goldstein, Irvine, and Puckett (2010), Puckett and Yan (2011), and Anand, Irvine, Puckett, and Venkataraman (2012), among others.

trip trading cost. We also obtain the daily returns on stocks that institutional investors buy or sell from CRSP.

We subject the data to a screening process in order to minimize potential errors in our analysis. Specifically, we delete transactions under 100 shares and $1.00 trading price following Keim and Madhavan (1997) and Hu (2009). Following Anand, Irvine, Puckett, and Venkataraman (2012), we eliminate stocks' tickets with volume greater than the stocks' CRSP volume on the same execution date. Furthermore, we focus attention only on common stocks in the ANcerno data set that are listed in the NYSE or AMEX and that are also included in the CRSP daily data base.[10] In case of multiple transactions by the same institution in the same stock on a given day, we simply aggregate such transactions separately on the buy and sell side and calculate the corresponding daily average volume weighted buy and sell prices. Thus, each institution in our data has only one daily buy and sell transaction record in a given stock from January 1999 to March 2012.

Our final sample (spanning January, 1999 – March, 2012) has 31,212,162 stock level institutional transactions spanning 1,137 distinct institutions involving 3,388 distinct stocks. Of these, 16,125,820 institutional transactions are for buys and 15,086,342 are for sells. Table 1 provides a year by year breakdown of our data in terms of the number of institutions, the average number of distinct stocks traded by an institution in a given year, and the average number of account managers per institution. We see that the average number of stocks traded tapers down from 1999 through 2002 before starting to pick back up again until about 2007 before going down significantly over the following years until 2011. The number of institutions captured in the data also shows a high in 1999 followed by an increase from 2000 through 2002, and a decline from 2006 through 2011. Overall, these trends are broadly consistent with the contemporaneous macroeconomic conditions prevailing in the economy.

3. Empirical Analysis

3.1. *Overconfidence - Average Institutional Returns following Purchases and Sales*

The primary goal in this section is to test whether institutional investors are overconfident traders. We do so by estimating the difference between the average marked-to-market return on stocks bought and the average returns to those stocks sold by institutional investors over trading horizons of (1) one day; (2) one week; (3) two weeks; (4) three weeks; and (5) one month.[11] Consistent with Odean (1999), we expect

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[10] See Statman, Thorley, and Vorkink (2006) for an explanation on restricting the focus only on the NYSE/AMEX listed common stocks.

[11] While Odean (1999) used longer return horizons (4 month, 1 year, and 2 years) because of the retail trades he examined, an earlier version of Chakrabarty, Moulton, and Trzcinka (2017) report that 96% of all institutions represented in the ANcerno database executed round trip trades within one month or less. Therefore, we restrict our attention to institutional trading horizons of one month or less.

that institutional investors that are not overconfident would earn a greater return on their purchases relative to their sales over the trading horizons that we consider. Stated differently, if institutions were overconfident as a trader group, their purchases would fare worse than their sales.

Following Odean (1999), we calculate the average returns to stocks bought (sold) by institutional investors over the different time horizons:

$$R_{P,T} = \frac{\sum_{i=1}^{N} \prod_{r=1}^{T}(1 + R_{ji,ti+r})}{N} - 1,$$

In addition, we calculate average abnormal returns to stocks bought (sold) by institutional investors over the various time horizons:

$$AR_{P,T} = \left(\frac{\sum_{i=1}^{N} \prod_{r=1}^{T}(1 + (R_{ji,ti+r} - MR_{i,ti+r}))}{N} \right) - 1$$

where N is number of buying (selling) transactions, T is institutional holding period (time horizons of trading days subsequent to buying (selling) transactions, and $R_{ji,ti+r}$ is CRSP daily return for stock j corresponding to institutional transaction i on day r after transaction day t, and $MR_{i,ti+r}$ is CRSP daily value weighted market return corresponding to institutional transaction i on day r after transaction day t. In order to calculate the return using ANcerno data, we initially construct the integrated daily stock level institutional data through the data integration process. This process allows our data to match with CRSP daily return for cumulative return($R_{ji,ti+r}$) and cumulative market return ($MR_{i,ti+r}$) computations. Using CRSP return, we calculate the cumulative returns and cumulative abnormal returns to stocks bought (sold) by institutional investors over various horizons of trading days ($\prod_{r=1}^{T}(1 + R_{ji,ti+r})$ and $\prod_{r=1}^{T}(1 + (R_{ji,ti+r} - MR_{i,ti+r})$). Then, we calculate the average returns and average abnormal marked-to-market returns corresponding to the stocks bought (sold).[12] The abnormal returns account for the possibility that some of the institutional gains associated with their purchases versus their sales might, in fact, be market gains unrelated to institutional strategy, consistent with the discussion in Bagehot (1971).

Panel A of Table 2 presents our findings related to the average raw marked-to-market returns associated with stocks that institutions bought and those that institutions sold over the various trading horizons between 1-day and 1-month. Under the assumption that different institutional trading strategies are independent of one another, the average difference marked-to-market returns between institutional buys and sells is 0.033% over a 1-day holding period; 0.072% over a 1-week holding period; 0.092% over a 2-week holding period; 0.076% over a 3-week holding period; and 0.087% over a 1-month holding period. Overall, institutional buy transactions perform better than the sells over these various trading horizons.

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[12] Odean (1999) proposes that one begin the return computation the day after a purchase or sale. Therefore, we select the second day after a purchase or sell as day one for our return calculations.

Therefore, institutions do not appear to be trading excessively based on our defined hurdle for overconfident investors. Our results are consistent with the experimental evidence provided by Budescu and Du (2007) that decision makers' probabilistic judgements about future stock prices at different confidence intervals are internally consistent and coherent, albeit slightly miscalibrated. Panel B of Table 2 reports the marked-to-market-adjusted abnormal returns for the buy and sell trades and the results are almost identical for transactions under 2-week horizon and stronger for longer horizon.

3.1.1. *Counterfactual Experiment – Are Institutional Investors Skilled?*

Next, we do a thought experiment. How would the institutions have fared had they picked random stocks of similar size and market-to-book ratio from the CRSP Universe? Specifically, for each stock purchased or sold by any institution, we randomly draw (with replacement) a replacement stock from the universe of CRSP stocks of the same size decile and same book-to-market quintile as the original stock. We then calculate the 1-day, 1-week, 2-week, 3-week, and 1-month returns subsequent to the date of purchase or sale. The ensuing average returns for these replacement stocks (assumed to be purchased or sold over the same dates as the stocks they replaced) are then computed. We repeat the process described above 1,000 times to generate 1,000 subsequent average returns for each institution over these various time horizons. Then we calculate the average of those average subsequent returns per institution.[13]

The results are provided in Table 3 and show that the size and market-to-book matched but randomly drawn bootstrapped sample results from the CRSP have worse buy – sell performance than the actual trades undertaken by the institutions in the ANcerno data. The bootstrapping results show that had institutional investors randomly drawn stocks matched to size and market-to-book ratio of the stocks they actually traded, they would have had poorer performance. This points to some trading skills among the average institutional traders in our sample.

3.1.2. *Institutional Transaction Cost including Price Impact*

A greater hurdle of institutional overconfidence (or lack thereof) or skill is one where the stocks that institutions buy outperform those they sell net of trading costs. There are several factors that make capturing institutional trading costs more challenging than those associated with retail investors examined by Odean (1999). Traditional measures like bid ask spreads are inappropriate as institutional trades are

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[13] The bootstrapping process is a computing intensive process involving 1,000 iterations. Each iteration involves a random selection of a replacement stock and a return calculation. There are total 31,212,162 observations (16,125,820 buys and 15,086,342 sells) corresponding to the daily institutional level trades, and we randomly draw a replacement stock for each observation from the universe of CRSP stocks of the same size decile and same book-to-market quintile as the original stock (a total 50 categories). The average number of stocks in each category is 117. Then we calculate the return on each replacement stock over the various time horizons. To repeat this process 1,000 times took over 2-weeks to complete in a powerful workstation with multiple processors. For robustness, we also ran a similar bootstrapping involving 5,000 iterations and did not observe material changes in our estimates relative to what we formally report.

large and take a while to fill. Moreover the true costs to an institutional trader might also include administrative costs of working an order as well as the opportunity costs of missed trades. Following previous works on institutional trading costs (see, for example, Keim and Madhavan (1997), Jones and Lipson (2001) and Chakravarty, Panchapagesan and Wood (2005)), we examine costs that can be explicitly measured, namely commissions and price impact.

Unlike commissions which are straightforward and reported in the data as a dollar value associated with a given institutional transaction, the price impact of a trade – the deviation of the transaction price from the unperturbed price that would prevail had the trade not occurred – is arguably difficult to measure.[14] At the very least, the measure should be such that it is least influenced by the trade itself. Keim and Madhavan (1997) discuss at length the importance of this issue. Following extant literature (see, for instance, Odean (1999) and Chakravarty, Panchapagesan and Wood (2005)), we characterize institutional trading costs as a sum of their commission costs (reported in the data) and the price impact of their trades. Consistent with Chakravarty et al. (2005), we use two of the most popular ways to define the unperturbed price: (1) the value weighted average trade price (VWAP) during the day associated with an order; and (2) the prevailing stock price at the time of the order placement.[15] Specifically, we measure the percentage deviation of the value weighted average execution price for each order from each of the three above benchmark prices. We multiply the deviation by -1 for sell orders to ensure that measures trading costs appropriately for buy and sell orders.

Table 4 presents our findings. We see that the price impact of institutional buys varies from 0.13% for the VWAP approach to 0.14% using the previous day's closing price. Similarly price impact for institutional sells range from -0.05% for the placement price approach to -0.11% for the VWAP approach. The commissions are 0.11% for buys and 0.12% for sells. Collectively, our estimate of the total round trip institutional trading costs range from 0.24% to 0.32% and are consistent with Puckett and Yan (2011) and prior literature.

For a 3-week hypothetical holding period, which gives us overall results most similar to the results reported in Puckett and Yan (2011), the buy minus sell portfolio breaks even (0 to 8 basis point profit) on a marked-to-market basis after transaction cost instead of making a 34 basis point profit in Puckett and Yan (2011). Yet these differences are much smaller and we can't draw a conclusion that the institutions lose money over short-term trade even before subtracting transaction cost as inferred in Chakrabarty, Moulton, and Trzcinka (2017). Table 5 presents the details of the marked-to-market buy and sell portfolio

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[14] In order to compute the commission component of round trip trading cost, we scale a dollar value of commissions paid by the total principal value of the institutional transaction from ANcerno data.
[15] We do not use the closing price of the stock from the day before the trade because that measure is more relevant for those who use low-frequency daily data.

performance net of transaction cost for all the different holding periods. Except for 1-day holding period where such trades are most likely to be driven by liquidity needs, the remaining net returns are marginally positive.

3.2   *Biased Self-attribution*

The second hypothesis about excessive trading due to behavioral reasons is that the investors suffer from biased self-attribution. Self-attribution bias occurs when someone attributes successful outcomes to her own skill but blames unsuccessful outcomes on bad luck. An implication of biased self-attribution is that the confidence of the investor should grow when the public information is in agreement with her information but should not decline proportionately when public information contradicts her private information. Put differently, biased self-attribution would cause the degree of overconfidence and the level of trading to vary with the realized market returns. So far, we have taken a micro approach to investigating for possible institutional overconfidence by comparing the marked-to-market returns associated with a given institution's stock buys and sells over various time horizons. In this section, we take our analysis a step further and explore whether self-attribution bias might potentially be displayed by institutional investors on a market wide, or macro, basis.

Our data allows us to directly investigate the (potential) connection between institutional buying turnover and lagged stock market returns and, thereby, to produce a precise test of whether, as a group, institutions might display a self-attribution bias. Our empirical framework is based on a time series model and built on the aggregated daily observations of all institutional trading within the ANcerno data. Specifically, we use vector autoregressions (VAR) and impulse response functions to test specific implications of how institutional trading activity might relate to lagged market returns. Our Vector Auto Regression (VAR) model is as follows:

$$Y_t = \alpha + \sum_{k=1}^{K} A_k\, Y_{t-k} \;+\; \sum_{l=0}^{L} B_l X_{t-l} \;+\; e_t$$

where Y_t is an n·1 vector of period t observations of endogenous variables such as institutional (buying and selling) turnover, and market return; X_t is a vector of period t observations of the exogenous variables such as market volatility and e_t is an n·1 residual vector. Operationally, our daily-level VAR model with the relevant variables looks as follows:

$$\begin{bmatrix} \text{ibturn}_t \\ \text{isturn}_t \\ \text{sret}_t \\ \text{mret}_t \end{bmatrix} = \begin{bmatrix} \alpha_{\text{ibturn}} \\ \alpha_{\text{isturn}} \\ \alpha_{\text{sret}} \\ \alpha_{\text{mret}} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} \text{ibturn}_{t-k} \\ \text{isturn}_{t-k} \\ \text{sret}_{t-k} \\ \text{mret}_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} \text{dis}_{t-l} \\ \text{vol}_{t-l} \end{bmatrix} + \begin{bmatrix} e_{\text{ibturn},t} \\ e_{\text{isturn},t} \\ e_{\text{sret},t} \\ e_{\text{mret},t} \end{bmatrix}$$

The endogenous variable, institutional buy turnover (*ibturn*) is calculated daily by the sum of the volume of all stocks bought by the ANcerno institutions normalized by each stock's outstanding share volume. Institutional sell turnover (*isturn*) is similarly calculated daily by dividing the ANcerno institutional selling volume in each stock in the data normalized by the stock's outstanding share volume. The third endogenous variable, taken from the CRSP daily files, is the daily value-weighted market return (*mret*). The daily stock return is specified by *sret*. The exogenous variable is given by: dispersion (*dis*), the daily average standard deviation of the stock returns and market volatility (*vol*). Based on the AIC and SIC criteria, we choose to estimate the VAR model with 10 daily lags for the endogenous variables and 2 daily lags for the exogenous variables. We also conduct a Phillips and Perron unit root test to check if the institutional turnover measures exhibit any non-stationarity over time. In almost all of the cases, the tests reject the null of non-stationarity at the 5% level or better. Therefore, we use the institutional turnover as is (without detrending) in our daily VAR estimations.[16]

Our goal is to estimate the VAR model specified above on an institution by institution basis. We have 851 separate estimations of the VAR model corresponding to the 851 distinct institutions over the period covered in our data. Recall that if institutions as a group suffer from biased self-attribution we would expect to see a high market return followed by a spike in institutional buy volume. In order words, we would expect a positive correlation between current institutional buy turnover and lagged market returns. If we do not see such activity, we should reject the null hypothesis of biased self-attribution by institutions. However, it is also likely that the daily institutional trading strategies are correlated with one another especially since they are (at least partially) trading in the same/similar stocks. In that case, estimating the VAR model on an institution by institution basis is likely to provide inflated standard errors which would adversely impact the power of our tests.

We therefore conduct a daily VAR-bootstrap estimation on the lines of Runkle (1987) and used subsequently by STV (2006). To do so, we first conduct 851 distinct VAR estimations for each institution. We then store the estimated coefficients and the fitted residuals. Since we have three endogenous variables, we create a T x 4 matrix of random variables corresponding to each institution where T is the number of trading days associated with each institution. Since we require each institution to have at least 50 days of transactions, the minimum value of T is 50. Furthermore, each institution has a different T x 4 matrix because each has a different number of trading days. Therefore, each column for the time vector T in the matrix has a different size. After creating this matrix, we randomly select only one fitted residual with

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[16] The average market return is 0.02%; the average daily individual stock level returns is -0.09%; the average market volatility is 2.67%; and the average stock dispersion is 2.46%.

replacement from each column of the T vector. We then consistently apply the randomly selected fitted residuals to all of the 851 institutions.[17] We repeat this process a total of 1,000 times.

Table 6 presents the results from the VAR estimations. For brevity, we simply present the coefficient estimates of interest: The lagged market returns corresponding to the endogenous variables, $ibturn_t$ and $isturn_t$.[18] There is no evidence of biased self-attribution by institutional investors. The lagged market returns in the $ibturn_t$ equation are statistically insignificant. In fact, the $isturn_t$ equation estimates show that there is evidence of short term institutional selling in underperforming markets. Taken together, we find no evidence of institutional biased self-attribution.

3.3.   *The Disposition Effect*

The return-volume causal link can also provide evidence on the third behavioral hypothesis about disposition effect, which captures the desire of investors to realize investment gains by selling stocks that have recently appreciated in value but to delay selling of stocks that have depreciated in value. The Disposition Effect, first defined by Sheffrin and Statman (1985), is the propensity displayed by investors to sell stocks that have gained in value too soon and to hold on to stocks that have lost value for too long. The observable (and, therefore, testable) part of the disposition effect relates to only one side of the trade: the sell side. This is different from investor overconfidence and biased self-attribution that we have examined before which relate to primarily the buy side of the market. Furthermore, while overconfidence and biased self-attribution can be thought of as pertaining to trading in general, the disposition effect describes investor attitudes toward specific stocks in their portfolios.[19] Past empirical evidence on the disposition effect is provided by Lakonishok and Smidt (1986), among others. They find seasonal variation in trading volume and past performance. Trading volume is abnormally high for past losers in December and past winners in January, thereby leading to the inference of tax-inefficient sell and disposition effect.

In this section, we formally test whether institutions display any significant disposition effect with regard to their trading in specific stocks. To do so, we use the same VAR model we employed in the previous section since biased self-attribution also explains an (institutional) investor's current trade based on past returns with one important caveat: that the disposition effect is stock specific. Therefore, we

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[17] For a numerical example to better understand what is going on, suppose there are only two institutions. Institution A has 50 days of daily trading while B has 100 days of daily trading. Therefore, we have two error terms over the first 50 columns (from column T_1 to column T_{50}) and one error term over the last 50 columns (from column T_{51} to column T_{100}). This is so because institution A has 50 estimated coefficients for each variable and 50 fitted residuals while institution B has 100 estimated coefficients for each variable and 100 fitted residuals. Then we randomly select one residual out of the two and apply this residual to both models for generating simulated values for institutional turnover, market return, and individual stock return to replace the original values. Next, we estimate the VAR with these simulated values which comprises a single iteration of the bootstrapping process.

[18] The full estimation details are available on request.

[19] The disposition effect can be interpreted as non-rational because an investor is giving up on the realization of tax benefits of realizing losses immediately and incurring the taxes associated with realizing gains too soon.

14

investigate the potential relationship between current institutional turnover in a given stock and the stock's past return. If institutions displayed a significant disposition effect, we would expect to see a high stock return followed by a spike in institutional sell volume in that stock. In other words, we would expect a positive correlation between current institutional sell turnovers and lagged stock returns. If we do not see such activity, we should reject the null hypothesis of the (presence of) institutional disposition effect.

Specifically, we perform the VAR estimations on a stock-by-stock basis and capturing trades by all institutions in our data in that stock on a given day. We also allow for the institutional trades to be correlated with each other which, in turn, imply that the daily stock returns might be correlated with each other. To ensure that this correlation does not adversely inflate the standard errors of the VAR coefficient estimates, we bootstrap the stock level estimations 1,000 times following the same procedure that described in the last section, with the institution level estimations.

Table 7 presents the results from the VAR estimations. Once again, we simply present the coefficient estimates of interest: The lagged market returns corresponding to the endogenous variables, $ibturn_t$ and $isturn_t$. Examining the $ibturn_t$ model, we see that the coefficients of the lagged stock returns are mostly negative and statistically significant implying that institutions buy underperforming stocks in the immediate aftermath. From the $isturn_t$ model, we see that the lagged stock level returns (up to 10 lags or 10 trading days) are mostly statistically insignificant. While the stock returns corresponding to lags 5 and 7 are statistically significant, these coefficients have a negative sign implying that institutions are selling underperforming stocks relatively quickly rather than holding on to them.

Collectively, we find that institutions actively rebalance their portfolios by both buying and selling underperforming stocks in the short term and that there is no evidence of an institutional disposition effect. These findings resonate with Scherbina and Jin (2010) who find that following changes in fund management, new mutual fund managers tend to sell off the loser stocks in the fund's portfolio. The tendency is even stronger after controlling for the trades of other mutual funds without manager changes that hold the same stocks. O'Connell and Teo (2009) also do not find evidence of the disposition effect among large institutions in the foreign exchange markets. Rather, these investors are more likely to sell a currency after experiencing losses.[20]

While we do not provide a direct test of prospect theory by Kahneman and Tversky (1979), Barberis and Xiong (2009) provide results that when measured over realized gain and loss from a transaction, predictions from prospect theory are similar to the disposition effect.[21] Shefrin and Statman (1985) and

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[20] Feng and Seasholes (2005) examine the disposition effect among Chinese investors and find that trading experience among investors attenuates the disposition effect.

[21] The testable predictions of prospect theory can be sensitive to model parameters. Liu, Tsai, Wang, and Zhu (2010) provide evidence that after prior wins (losses) traders take more (less) risk while Smith, Levere, and Kurtzman (2009) provide contradictory evidence that experienced poker players play less cautiously after a big loss even though both

Odean (1998) argue that the disposition effect could arise due to the prospect theory preference of certain investors given utility is concave over realized gains and convex over realized losses.[22] Based on survey data, Bodnaruk and Simonov (2016) show that mutual fund managers with higher aversion to losses also display a stronger disposition effect.

Hence, our test of disposition effect could also provide evidence on whether institutional investors suffer from behavioral bias originating in prospect theory and we find no such evidence.

3.4.   *Why then Do the Institutions Trade over Short Horizon?*

It is possible that a fraction of institutional trading activity may be driven by motives other than generating profits such as a pure liquidity trades or a desire to reduce portfolio risk exposure by moving to lower risk stocks. Accordingly, we attempt to eliminate such motives for trading and keep only those transactions that are most likely motivated by a pure desire to make profits by a given institution. Specifically, we eliminate: (1) stocks repurchased within three weeks of the sale of the same (so as to eliminate a potential liquidity related reason for trade);[23] (2) purchases where the size decile of the purchased stock is greater than the size decile of the sold stock (eliminating the potential of moving to a lower risk stock); (3) stocks sold in December and purchased by the same institution in January (thereby eliminating the potential tax-loss selling and window-dressing motivation).[24] The remaining observations are a good approximation of institutional trades that are purely profit motivated.

Table 8 provides the results. We see that the stocks institutional investors buy for the sole purpose of profit-maximization outperform the stocks they sell over a 1 day, 1-week, 2-week, 3-week, and 1-month intervals. The average difference between the marked-to-market return for institutional buys and sells for the purpose of profit maximization is 0.02% over a 1-day holding period; 0.11% over a 1-week holding period; 0.21% over a 2-week holding period; 0.19% over a 3-week holding period; and 0.19% over a 1-month holding period. Thus, the overall differences between the marked-to-market returns for institutional buys and sells for profit-maximization motive are much larger than those of the main results. Hence, a reasonable inference is that institutional investors often engage in trading despite earning close to zero statistically insignificant positive net return for rational reasons unrelated to profit maximization such as

studies claim that the findings are consistent with prospect theory. Using data from financial and real estate gains Massa and Simonov (2005) also find that prior gains (losses) increase (reduce) risk-taking. They reject the prospect theory hypothesis in favor of house-money effect or standard utility theory.

[22] Henderson (2012) provides a model to formally establish a link between prospect theory and the disposition effect and suggest that investors will sell at a loss when the asset has a sufficiently low Sharpe ratio.

[23] By imposing this condition, we also eliminate most if not all of the tax loss motivation for trading in the December/January period. Sialm and Starks (2012) shows that mutual funds with taxable investors consider tax-consequence of their investment decisions.

[24] For detailed discussions on tax-loss selling, January-effect, and window-dressing see Keim (1983), Roll (1983), De Bondt and Thaler (1985), and Lakonishok et. al. (1991). Odean (1999) follows a similar approach in his study of individual investors with retail brokerage accounts.

liquidity, risk-management, and tax-minimization and window-dressing.

When do we expect the need for liquidity the greatest? Undoubtedly, during the economic contractions there is a greater need for liquidity to finance consumption. If so, we expect to see an asymmetric results. During an economic contraction, this buy-sell difference would be predominantly driven by the sell transactions.

To further investigate this, we use the US Business Cycle Expansions and Contractions as defined by the National Bureau of Economic Research and available from the NBER website. Specifically, within the period covered by the ANcerno data, the NBER-defined contraction cycle lasts from: March 2001 to November 2001; and again from December 2007 to June 2009; while the expansion cycles are from January 1999 to March 2001; from November 2001 to December 2007; and again from June 2009 to March 2012. Table 9 presents our findings. Panel A (the expansion cycle) accounts for 82.2% of total transactions in our sample (25,671,170 transactions executed by 1,089 institutions) while Panel B (the contraction cycle) accounts for the remaining 17.8% (5,540,942 transactions executed by 642 institutions).

We find that the stocks that institutional investors buy outperform the stocks they sell both in the expansion and contraction cycles. The average difference in marked-to-market return between institutional buys and sells during the expansion (contraction) cycle is 0.033% (0.031%) over a 1-day holding period; 0.059% (0.127%) over a 1-week holding period; 0.066% (0.203%) over a 2-week holding period; 0.043% (0.210%) over a 3-week holding period; and 0.056% (0.210%) over a 1-month holding period. Marked-to-market institutional returns following both purchases and sales over the contraction cycles are mostly negative but institutional sales generate greater negative returns relative to the institutional buys for all of the horizons examined. Possible explanations points towards a liquidity-driven selling motive by the institutions. This is consistent with the findings by Sialm, Starks, and Zhang (2015) that during the contraction cycle many pension fund clients move out of equity to fixed income assets. Institutional sell may also be originate from asset liquidation by some clients to finance their consumption needs.

Large cap stocks display higher trading volume, lower volatility, and greater liquidity than small cap stocks. Is it possible that institutions might be differentially biased towards small cap stocks relative to larger stocks and that it might influence how they trade?[25] To investigate this, we divide the institutional transactions into three categories based on stock size (market cap) quintile. Specifically, for each year beginning with 1999, we calculate the market capitalization of each NYSE/Amex listed common stocks present in the CRSP universe based on its closing price on the last trading day of the previous year (for example, for 1999, we use the closing price of the stocks on December 31, 1998 if it was a trading day).

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[25] Blume and Keim (2012) document trends in the growth of institutional stock ownership using their 13F holdings and find that institutions have increased their holdings of smaller stocks and decreased their holdings of larger stocks from 1980 through 2010.

We then create size based quintiles for the CRSP stocks and merge the ANcerno and CRSP datasets for each year to obtain the quintile information for the stocks traded by the ANcerno institutions.

Table 10 presents our findings. Institutional buys outperform the sells on a marked-to-market basis over 1-day to 2-week horizon, especially for small stocks. In the relatively longer investment horizons of 3- and 4-weeks, however, the institutions perform better with large stocks. Given, information based trades are more likely to take place over shorter horizon, this is consistent with the intuition that institutions have better stock-picking or information based trading skills for small stocks than for larger stocks, especially in recent years. The superior institutional performance for the large cap stocks over horizons greater than 2-week points towards either sales of small stocks motivated by risk management reasons or lower liquidity for smaller stocks.[26]

Different type of institutions may have different liquidity or window-dressing needs. ANcerno provides two broad classifications of institutional investors in their data set: Money Managers and Pension Fund Managers. Lakonishok, Shleifer, Thaler, and Vishny (LSTV, 1991) investigate the investment strategies of pension fund managers and show that they tend to oversell stocks that have performed poorly in the recent past. LSTV conclude that pension fund managers appear to "window dress" their portfolios. Thus, it is possible that pension fund managers could be trading excessively relative to the money managers. On the other hand, using the same dataset as we do, Hu et. al. (2014) find no specific evidence of window dressing by institutions.

One challenge is performing this analysis, however, is that ANcerno provided this information on institutional type only over a limited period (from July, 2009, to September, 2011). Therefore, we can identify the type of institution unambiguously only for those institutions that transacted within this two year window. However, we also observe that each institution in the data appears to have a unique identification code which does not change over time. Therefore, we are able to extrapolate the information about institutional types over this shorter time period to trades made by the same institutions over earlier (and later) time periods. Table 11 presents the findings. We find that while both money managers and pension fund managers do better with their purchases than their sales over the various time intervals, pension fund managers outperform the money managers especially over 1-day to 1-week horizon where the difference in marked-to-market return between their buys and sells is 0.050% to 0.105%.[27] These findings are consistent with either greater short-term liquidity demand by money managers or more effective window

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[26] For a detailed discussion about potential causes of risk-shifting by mutual fund managers and the relation to manager skill, see for e.g., Brown, Harlow, and Starks (1996) and Huang, Sialm, and Zhang (2011), among others.

[27] In unreported tests, we also replicate Table 11 for only the two years where ANcerno explicitly identified the manager types. These are qualitatively similar to the results we report here.

dressing by pension fund managers.[28]

These results survive a battery of robustness checks. Some details are provided in the internet appendix.[29]

4. Conclusions

What the optimal level of trading should be and how much trading is too much has been the subject of much debate. A related question is whether traders possess specific skills and if not, what could be the reasons for "excessive trading". While the results for retail traders have been unambiguous, there is a lack of consensus among scholars regarding institutional traders on these two questions. In this paper, using a large, high frequency, transaction level, representative dataset, we attempt to answer some of these questions.

We find that the marked-to-market returns of the stocks that institutions buy are higher than such returns on the stocks that institutions sell. This effect is stronger for smaller stocks over shorter horizon where it is easier for institutional investors to earn trading profit based on their information. Yet, after transaction cost, intuitional investors on average earn economically insignificant positive marked-to-market return over a horizon of 1-day to 4-week. This raises the question why then do the institutional investors trade? We test several hypotheses and fail to find any evidence of behavioral biases, specifically overconfidence, biased-self-attribution, and disposition effect among institutional investors. The evidence is consistent with trading for liquidity reasons although some of the trades could also be motivated by risk-management and window-dressing or tax minimization reasons. Further analysis suggests that among these, liquidity demand could be responsible for much of the short-term trades, especially during the contraction cycle.

Our results should be interpreted with caution. If institutional investors over- or under- react to news – because of overconfidence or other behavioral biases – and such over- or under- reaction can be measured or corrected only over long horizon, our tests, which are based on a short-horizon of up to four weeks, will be unable to detect it.

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[28] An alternative explanation could be that that pension fund clients have longer investment horizon and lower short term liquidity needs. If some of the short term institutional trades are driven by liquidity reasons, then we expect pension fund managers to perform better than mutual funds for the short-term trades.

[29] Additional robustness results are available upon request.

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Table 1: Descriptive Statistics for ANcerno Institutional Trading Data

ANcerno collects information about institutional transactions in batches by its institutional clients. Although institution identification codes (clientcode) are unique both in cross-section and over time, institution manager codes (clientmgrcode) are not. However, within a batch, institution manager codes are unique. The minimum period of a batch is a month in the ANcerno data. Therefore, we calculate the number of institution managers during each month, and then divide the number of institution managers by the number of institutions over that month. Then we average this average on an annual basis. The study uses institutional transaction data from January/1999 to March/2012.

Year	Number of Stocks Traded by Institutions	Number of Institutions	Average Number of Account Managers per Institution
1999	2,071	379	9
2000	1,992	269	11
2001	1,802	299	18
2002	1,689	426	18
2003	1,745	400	23
2004	1,769	405	25
2005	1,782	376	23
2006	1,757	397	24
2007	1,734	373	33
2008	1,625	326	34
2009	1,505	315	30
2010	1,455	310	30
2011	1,450	264	44
2012	1,363	3	111

Table 2: Average Returns Following Purchases and Sales by ANcerno Institutions

Average returns to stocks bought (sold) by institutional investors over the various time horizons:

$$R_{P,T} = \frac{\sum_{i=1}^{N} \prod_{r=1}^{T}(1 + R_{ji,ti+r})}{N} - 1$$

Average abnormal returns to stocks bought (sold) by institutional investors over the various time horizons is:

$$AR_{P,T} = \left(\frac{\sum_{i=1}^{N} \prod_{r=1}^{T}(1 + (R_{ji,ti+r} - MR_{i,ti+r}))}{N} \right) - 1$$

where N is number of buying (selling) transactions, T is institutional holding period (time horizons of trading days subsequent to buying (selling) transactions, $R_{ji,ti+r}$ is CRSP daily return for stock j corresponding to institutional transaction i on day r after transaction day t, and $MR_{i,ti+r}$ is CRSP daily value weighted market return corresponding to institutional transaction *i* on day *r* after transaction day *t*. In order to calculate the return using ANcerno data, we initially construct the integrated daily stock level institutional data through the data integration process. This process allows our data to match with CRSP daily return for cumulative return($R_{ji,ti+r}$) and cumulative market return ($MR_{i,ti+r}$) computations. Using CRSP return, we calculate the cumulative returns and cumulative abnormal returns to stocks bought (sold) by institutional investors over various horizons of trading days ($\prod_{r=1}^{T}(1 + R_{ji,ti+r})$ and $\prod_{r=1}^{T}(1 + (R_{ji,ti+r} - MR_{i,ti+r})$). Then, we calculate the average returns and average abnormal returns corresponding to the stocks bought (sold). Statistical significance is indicated by [***] for 1% level, [**] for 5% level, and [*] for 10% level.

Panel A: Raw Return - All Transactions

	N	1 day	1 week	2 week	3 week	4 week
Purchases	16,125,820	0.069	0.243	0.438	0.625	0.836
Sales	15,086,342	0.036	0.171	0.346	0.549	0.749
Difference		0.033[***]	0.072[***]	0.092[***]	0.076[***]	0.087[***]

Panel B: Abnormal (Market-adjusted) Return - All Transactions

	N	1 day	1 week	2 week	3 week	4 week
Purchases	16,125,820	0.045	0.145	0.240	0.327	0.422
Sales	15,086,342	0.006	0.068	0.145	0.237	0.328
Difference		0.039[***]	0.077[***]	0.095[***]	0.090[***]	0.094[***]

Table 3: Average Returns Following Purchases and Sales (Bootstrapped Sample)

For each stock bought or sold by any of ANcerno institutions, we bootstrap or randomly draw (with replacement) a replacement stock from the universe of CRSP stocks of the same size decile and same book-to-market quintile as the original stock in our transaction data from ANcerno. The average returns for stocks bought (sold) by institutional investors over the various time horizons:

$$R_{P,T} = \frac{\sum_{i=1}^{N} \prod_{r=1}^{T} (1 + R_{ji,ti+r})}{N} - 1$$

where N is number of buying (selling) transactions, T is institutional holding period (time horizons of trading days subsequent to buying (selling) transactions, and $R_{ji,ti+r}$ is CRSP daily return for stock j corresponding to institutional transaction i on day r after transaction day t. In order to calculate the return using ANcerno data, we initially construct the integrated daily stock level institutional data through the data integration process. This process allows my data to match with CRSP daily return for cumulative return $(R_{ji,ti+r})$. Using CRSP return, we calculate the cumulative returns to stocks bought (sold) by institutional investors over various horizons of trading days $(\prod_{r=1}^{T} (1 + R_{ji,ti+r})$. Then, we calculate the average returns to the stocks bought (sold). The subsequent average returns for the replacement stocks (assumed to be purchased or sold over the same dates as the stocks they replaced) are then computed. We repeat the above process 1,000 times to generate 1,000 subsequent average returns for each institution over these various time horizons. Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

		Raw Return – Bootstrapped Sample from CRSP Universe				
	N	1 day	1 week	2 week	3 week	4 week
Purchases	16,125,820	0.047	0.209	0.422	0.636	0.872
Sales	15,086,342	0.055	0.215	0.410	0.632	0.851
Difference		0.008***	0.005***	0.013***	0.004***	0.021***

Table 4: Average Institutional Trading Cost for Buy and Sale Trades.

The average daily round-trip cost consists of a commission component and a price impact component. For the commission component of transaction costs, we calculate a dollar value of commissions paid scaled by the total principal value of the institutional transaction from ANcerno data. The price impact component of transaction costs is computed by the deviation of the value-weighted average trade price (the transaction price) from the unperturbed price as follows:

$$\text{Price Impact} = \text{Side} \cdot \frac{P_1 - P_0}{P_0}$$

where P_1 is each institution's value-weighted average daily trade price for each stock, P_0 is unperturbed price, and Side is a variable that equals 1 for a buying transaction and equals -1 for a selling transaction. We use two unperturbed prices:(1) the value-weighted average price across all trades over all days over which the decision was executed (VWAP); and (2) the price at placement time when the broker receives the ticket (Placement Price).

Unperturbed Price	Price Impact		Commission		Total Round-Trip Cost (%)
	Purchases	Sales	Purchases	Sales	
VWAP	0.1254	-0.1123	0.1079	0.1211	0.2421
Placement Price	0.1388	-0.0513	0.1079	0.1211	0.3165
Average	0.1321	-0.0818	0.1079	0.1211	0.2793

Table 5: Average Returns Following Purchases and Sales Net of Transaction Cost

Average returns to stocks bought (sold) by institutional investors over the various time horizons:

$$R_{P,T} = \frac{\sum_{i=1}^{N} \prod_{r=1}^{T}(1 + R_{ji,ti+r})}{N} - 1$$

where N is number of buying (selling) transactions, T is institutional holding period (time horizons of trading days subsequent to buying (selling) transactions, and $R_{ji,ti+r}$ is CRSP daily return for stock j corresponding to institutional transaction i on day r after transaction day t. In order to calculate the return using ANcerno data, we initially construct the integrated daily stock level institutional data through the data integration process. This process allows our data to match with CRSP daily return for cumulative return($R_{ji,ti+r}$) and cumulative market return ($MR_{i,ti+r}$) computations. Using CRSP return, we calculate the cumulative returns to stocks bought (sold) by institutional investors over various horizons of trading days ($\prod_{r=1}^{T}(1 + R_{ji,ti+r})$). Then, we calculate the average returns and average abnormal returns corresponding to the stocks bought (sold). Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

The average daily round-trip cost consists of a commission component and a price impact component. For the commission component of transaction costs, we calculate a dollar value of commissions paid scaled by the total principal value of the institutional transaction from ANcerno data. The price impact component of transaction costs is computed by the deviation of the value-weighted average trade price (the transaction price) from the unperturbed price as follows:

$$\text{Price Impact} = \text{Side} \cdot \frac{P_1 - P_0}{P_0}$$

where P_1 is each institution's value-weighted average daily trade price for each stock, P_0 is unperturbed price, and Side is a variable that equals 1 for a buying transaction and equals -1 for a selling transaction. We use two unperturbed prices:(1) the value-weighted average price across all trades over all days over which the decision was executed (VWAP); and (2) the price at placement time when the broker receives the ticket (Placement Price).

	N	1 day	1 week	2 week	3 week	4 week
Panel A: Return Net of Transaction Cost based on VWAP						
Purchases	16,125,820	-0.1643	0.0097	0.2047	0.3917	0.6027
Sales	15,086,342	-0.1974	-0.0624	0.1126	0.3156	0.5156
Difference		0.0331***	0.0721***	0.0921***	0.0761***	0.0871***

	N	1 day	1 week	2 week	3 week	4 week
Panel B: Return Net of Transaction Cost Based on Placement Price						
Purchases	16,125,820	-0.1777	-0.0037	0.1913	0.3783	0.5893
Sales	15,086,342	-0.1364	-0.0014	0.1736	0.3766	0.5766
Difference		-0.0413***	-0.0023***	0.0177***	0.0017***	0.0127***

Table 6: Vector Autoregression (VAR) Estimations for Overconfidence based on the Institutional Transaction Data Sorted at the Daily Institutional Level

The table reports results of the overconfidence tests based on the total 851 individual institution VAR on buy turnover (*ibturn*), sell turnover (*isturn*), institutional stock return(*ret*), and market return (*mret*) with 10 daily lags and two lags of the exogenous variables, volatility (*vol*) and dispersion (*disp*), mean coefficients and significance levels (p-value) are calculated. The p-values are calculated by bootstrapped standard errors from 1,000 iterations. The null hypothesis is the mean coefficient estimate across all institutions is zero.

		Lagged Market Return									
		$mret_{t-1}$	$mret_{t-2}$	$mret_{t-3}$	$mret_{t-4}$	$mret_{t-5}$	$mret_{t-6}$	$mret_{t-7}$	$mret_{t-8}$	$mret_{t-9}$	$mret_{t-10}$
$ibturn_t$	Mean Coeff	6.2E-5	-0.0006	0.0003	0.0002	0.0008	-0.0008	-8.5E-5	0.0002	-0.0009	-0.0001
	Mean SE	0.0004	0.0004	0.0005	0.0004	0.0003	0.0004	0.0004	0.0004	0.0003	0.0004
	p-value	0.8867	0.1096	0.6116	0.6282	0.0133	0.0272	0.8129	0.5998	0.0025	0.7321
$isturn_t$	Mean Coeff	-3.3E-5	0.0005	-0.0002	0.0008	-0.0007	-0.0017	-4.3E-5	0.0014	-0.0005	0.0001
	Mean SE	0.0004	0.0005	0.0003	0.0003	0.0003	0.0004	0.0004	0.0003	0.0004	0.0004
	p-value	0.9286	0.3018	0.5723	0.0188	0.0097	<.0001	0.9075	<.0001	0.1471	0.7334

Table 7: Vector Autoregression (VAR) Estimations for Disposition Effect based on the Institutional Transaction Data Sorted at the Daily Stock Level

The table reports results of the disposition effect test. Based on the total 2,272 individual security VAR on buy turnover (*ibturn*), sell turnover (*isturn*), stock return (*ret*), and market return (*mret*) with 10 daily lags and two lags of the exogenous variables, volatility (*vol*) and dispersion (*disp*), mean coefficients and significance levels (p-value) are calculated. For brevity, we just present here a part of the whole table involving only the buy/sell turnover and stock returns. The p-values are calculated by bootstrapped standard errors from 1,000 iterations. The null hypothesis is the mean coefficient estimate across all institutions is zero.

		Lagged Security Return									
		ret_{t-1}	ret_{t-2}	ret_{t-3}	ret_{t-4}	ret_{t-5}	ret_{t-6}	ret_{t-7}	ret_{t-8}	ret_{t-9}	ret_{t-10}
$ibturn_t$	Mean Coeff	-0.0002	-0.0002	7.0E-5	-7.4E-6	-0.0002	-9.5E-6	9.8E-5	-0.0001	7.6E-5	3.4E-5
	Mean SE	5.2E-5	3.4E-5	6.8E-5	4.8E-5	6.3E-5	4.1E-5	4.5E-5	5.7E-5	4.1E-5	6.9E-5
	p-value	<.0001	<.0001	0.3079	0.8785	0.0002	0.8189	0.0307	0.0641	0.0624	0.6287
$isturn_t$	Mean Coeff	-4.5E-5	0.0001	-0.0001	0.0002	-0.0002	7.7E-5	-0.0004	-4.7E-5	-9.1E-5	9.6E-5
	Mean SE	0.0002	0.0001	0.0001	0.0001	3.7E-5	6.9E-5	0.0001	4.2E-5	9.4E-5	8.4E-5
	p-value	0.7916	0.2685	0.2840	0.0839	<.0001	0.2682	0.0017	0.2551	0.3357	0.2510

Table 8: Average Returns Following Purchases and Sales – Transactions Exclusively for Profit Motive

We investigate the average returns associated with transactions for the purpose of making profitable trades. In this study, we eliminate the liquidity motivation (buybacks within three weeks of sales), moving to low risk stocks (size decile of purchase more than size decile of sale), and tax-loss selling motivation (sales on December and the same stock purchase by the same institution on January). Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

	Transactions Exclusively for the Purpose of Making Profits					
	N	1 day	1 week	2 week	3 week	4 week
Purchases	8,801,918	0.056	0.227	0.431	0.559	0.794
Sales	7,862,233	0.034	0.116	0.224	0.409	0.602
Difference		0.022***	0.111***	0.207***	0.190***	0.192***

Table 9: Average Returns Following Purchases and Sales - Business Cycle Effect

Panel A and B in Table 6 is partitioned based on market business cycles. According to the National Bureau of Economic Research, the contraction cycle is from March 2001 to November 2001 and from December 2007 to June 2009 while the expansion cycle is from January 1999 to March 2001, from November 2001 to December 2007, and June 2009 to March 2012 (we only consider available periods from ANcerno data). Panel A (extension cycle) accounts for 82.2% of total transactions in our sample (25,671,170 transactions out of 31,212,162 transactions) while Panel B (contraction cycle) accounts for 17.8% of total transactions in our sample (5,540,992 transactions out of 31,212,162 transactions). Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

	N	1 day	1 week	2 week	3 week	4 week
Panel A: Transactions of Institutional Investors - Expansion Cycle						
Purchases	13,279,200	0.083	0.337	0.620	0.896	1.20
Sales	12,391,970	0.049	0.278	0.555	0.854	1.15
Difference		0.033^{***}	0.059^{***}	0.066^{***}	0.043^{***}	0.056^{***}
Panel B: Transactions of Institutional Investors - Contraction Cycle						
	N	1 day	1 week	2 week	3 week	4 week
Purchases	2,846,620	0.006	-0.193	-0.411	-0.642	-0.87
Sales	2,694,372	-0.025	-0.320	-0.613	-0.852	-1.08
Difference		0.031^{***}	0.127^{***}	0.203^{***}	0.210^{***}	0.210^{***}

Table 10: Average Returns Following Purchases and Sales – Liquidity Demand

Institutional transactions are divided into three groups based on size (market cap) quintile. We calculate market capitalization of each stock in each year through exploiting CRSP data. Then, the market caps are partitioned into five categories based on the size of the market cap each year (size quintile). After that, the CRSP data with size quintile are merged with institutional transaction data (ANcerno data). Panel A examines transactions with large size quintile (quintile number 5). Panel B investigates transactions with medium size quintile (quintile number 4). Panel C examines transactions with small size quintile (quintile number 1, 2, and 3).Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

	N	1 day	1 week	2 week	3 week	4 week
Panel A: Transactions of Institutional Investors with Large Size						
Purchases	12,306,907	0.056	0.203	0.365	0.523	0.697
Sales	11,823,134	0.028	0.140	0.280	0.440	0.606
Difference		0.028***	0.063***	0.086***	0.083***	0.091***
Panel B: Transactions of Institutional Investors with Medium Size						
Purchases	2,910,506	0.097	0.331	0.607	0.876	1.20
Sales	2,486,431	0.060	0.257	0.536	0.869	1.17
Difference		0.037***	0.075***	0.071***	0.011	0.027**
Panel C: Transactions of Institutional Investors with Small Size						
Purchases	908,407	0.154	0.505	0.888	1.190	1.56
Sales	776,777	0.082	0.363	0.750	1.188	1.57
Difference		0.072***	0.142***	0.138***	-0.002	-0.01

Table 11: Performance of Mutual Funds vs Pension Funds

Panel A investigates transactions of money managers, and Panel B examines transactions of pension fund managers. ANcerno data provide a unique identification code for each institution both in cross-section and over time. However, ANcerno data provide an identification code for institution type (money manager and pension sponsor) in only limited period (from July/2009 to September/2011). Therefore, we can identify the institution type for only institutions which made transactions from July/2009 to September/2011. However, since each institution has a unique identification code over time, if the institutions with transactions from July/2009 to September/2011 made transaction in other period, we can identify the institution type for the institutions. Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

Panel A: Transactions of Money Managers						
	N	1 day	1 week	2 week	3 week	4 week
Purchases	7,328,337	0.051	0.210	0.418	0.625	0.855
Sales	7,119,728	0.043	0.168	0.341	0.567	0.778
Difference		0.008***	0.042***	0.077***	0.057***	0.077***
Panel B: Transactions of Pension Fund Managers						
	N	1 day	1 week	2 week	3 week	4 week
Purchases	3,373,137	0.077	0.240	0.413	0.587	0.785
Sales	3,120,262	0.026	0.135	0.328	0.512	0.703
Difference		0.050***	0.105***	0.085***	0.075***	0.082***

Internet Appendix

On Institutional Trading and Behavioral Bias

Internet Appendix A.1 – Additional Robustness

As a robustness check, we eliminate all transactions of the same stock on a given side (buy versus sell) within a 20-day period (1-calendar month) ensuring that there is only one institutional transaction in a given stock on a given side within this window. We do this to remove any instances overlapping returns of the same stock transacted by either different accounts within a given institutional account, or across distinct institutions. If there are multiple instances of institutions trading a given stock on a given side we only keep the earliest such occurrence. In so doing, we create a non-overlapping sample of stock returns associated with institutional trading on a given side and a given month in order to remove any potential correlation in stock returns across time and re-estimate the returns over the same time periods. Appendix Table A.1 reports the results and shows that institutional buys do even better than institutional sells over the different time horizons.

We also examine if our findings above might be driven by the relatively fewer larger and busier institutions. We focus our attention on the top 10% (as well as the bottom 90%) – based on trading frequency as well as trading volume – of the institutional investors. Appendix Table A.2 presents the results corresponding to the most active institutions in our data where activity is measured by trade frequency. For comparison, we also present our findings for the remaining 90% of our institutions. We find that neither the top 10% nor the remaining 90% of institutional investors trade excessively and are therefore not overconfident by our definition over a time horizon of 1-day, 1-week, 2-weeks, 3-weeks and 1- month. The average difference between institutional buys and sells for the top 10% of institutional investors who trade most is 0.016%, 0.047%, 0.073%, 0.056%, and 0.068%, over the trading horizons of 1-day, 1-week, 2-weeks, 3-weeks, and 1- month, respectively. For the remaining 90% of the institutions in our data, we see a similar positive difference between buys and sells over the same trading horizons.[30] Thus, not surprisingly, if we take out the top-decile of the institutions (with highest trading frequency) then the remaining institutions perform even better.

Different institutions may trade the same stock in overlapping time periods and stock returns are unlikely to be independent across time. Our bootstrapped results presented in Table 3 should alleviate this concern.[31]

Are institutions relatively overconfident traders over periods of economic expansion relative to periods of economic downturns? It might be reasonable to expect that when stocks are more likely to move

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[30] In unreported findings, we estimate similar numbers for institutions classified by trading volume in place of trading frequency.

[31] We bootstrap the empirical distribution of the differences in returns for stocks purchased and sold by different institutions in our dataset over the entire sample period. This empirical distribution is generated under the assumption that subsequent returns to stocks bought and sold by the various institutions are drawn from the same underlying distribution.

upwards than down, as would be the case during periods of economic expansion, that institutions might display a level of overconfidence which they would not at other times.[32] Our macroeconomic cycle results presents in Table 9 contradict this hypotheses. Institutional buys perform better than the sells during the contraction cycle and this is predominantly driven by the liquidity motivated sells during economic downturns.

For our transaction cost calculation, we also use the closing price of that stocks purchased or sold on the last trading day before the actual trade as the unperturbed price and our results are almost identical.

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[32] In an article in the Wall Street Journal in May, 2006, entitled "Behind Surging Stock Market: Old Fashioned Economic Boom," author E.S. Browning writes: "….*Instead, an economic rebound has sent corporate profits to an 11th consecutive quarter of double-digit gains, the longest streak since at least the 1950s. Surprisingly strong growth in the economy and corporate profits has shaken stocks out of their doldrums. The Dow Jones Industrial Average is now within sight of its record close. Unlike the great 1990s bull market, which was sustained by a wave of new technology, this one has the feel of an old-fashioned economic boom, the type investors saw in the 1950s and 1960s. What many thought would be a limited rebound created by Chinese industrial demand has turned into a long-running story as once-unloved sectors such as commodity producers and oil drillers continue to thrive. Helping fuel the U.S. stock surge are once-skeptical investors, who are now funneling money into the market in the hope of getting in on a lengthier boom."*

Internet Appendix A.2 - Supplementary Literature

While theoretical research by Kyle (1985), Glosten and Milgrom (1985), and Easley and O'Hara (1987) laid the foundation for the impact of trades by informed traders on market depth and the informativeness of prices, exactly who these informed traders might be has not been specified by this line of research. That void was filled by Sias and Starks (1997) and Chakravarty (2001), among others, who provide evidence to support the notion that institutions are smart/informed traders. Intuition suggests that institutions should not suffer from behavioral biases that have been attributed to individual investors. The former are expected to act rationally due to their education, training, and better tools at their disposal. Along those lines, Dhar and Zhu (2006) report that the propensity to sell winners, and the reluctance to sell losers, is significantly lower for individuals that are wealthier and work in professional occupations.

Daniel, Hirshleifer, and Subrahmanyam (1998) argue that overconfident investors overreact to private information and underreact to public information.[33] They show that such overconfidence driven trades will, on average, have lower profits because they are exposed to increased volatility as well as increased trading volume, which increases transaction cost. Gervais and Odean (2001) develop a multiperiod model of traders learning to become overconfident in the early stages of their career as they take too much credit for their successes and take appropriate credit for failures. With experience the overconfidence declines. They also show that overconfident traders trade aggressively, which increases the expected trading volume as well as volatility.[34, 35] Van den Steen (2011) provides a model in which Bayesian-rational agents overweight (underweight) information for which they overestimate (underestimate) the precision, resulting in an overestimation of the precision of the final estimate.

An important intuition from the theoretical literature is that investor overconfidence is developed over time through a confirmation process of signals. Specifically, in some explicit instances, investors' private information might be confirmed by how things subsequently emerge in the public domain. Therefore, if prior private information turns out to be true through revelation of such information in the

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[33] De Bondt and Thaler (1985) provide some of the earliest evidence of stock market overreaction to news based on behavioral or psychological bias of the market participants. Using monthly stock data from 1930 to 1975, they show that portfolios of past losers outperform the portfolios of past winners. This suggests an overreaction to news and subsequent adjustment.

[34] Kyle and Wang (1997) have argued that overconfident investors generate higher profits than their rational counterparts through more aggressive trading since overconfident investors have a relatively small window within which to obtain, interpret, and act on information signals. Similarly, Benos (1998) argues that overconfident investors could make higher profits than rational traders because they have a first mover advantage through aggressive trading.

[35] Odean (1998) develops a methodology to examine investor disposition effects based on gains and losses that are realized versus those on paper and then calculate two metrics on the proportion of gains and losses realized. He finds strong evidence of the disposition effect among retail brokerage clients.

public domain later, investor confidence is increased. This is another version of the biased self-attribution leading to overconfidence.

Odean (1999) empirically examines a proprietary sample of individual investor trades and finds that the profits from stock purchases do not exceed profits from sales even after ignoring trading costs. His findings support the notion that individual investors overestimate both the precision of information and their abilities to interpret the same information. In contrast, Statman, Thorley, and Vorkink (STV, 2006) approach the issue of investor confidence (and, in particular, about investors' biased self-attribution) from a macro standpoint by examining the proposition that when investors are overconfident about their valuation and trading skills we should see relatively high trading volumes. With biased self-attribution, trading volume should (positively) vary with past market returns. With market level monthly data from CRSP between 1962 and 2001, STV indeed show that share turnover is positively related to the lagged market returns for many months. They also show that this positive relationship holds for individual stock turnover as well which STV interpret as evidence of the disposition effect. Calvet, Campbell, and Sodini (2009) find strong evidence for disposition effect among Swedish households but less so for mutual funds. Using retail brokerage data from the US, Ivkovic and Weisbenner (2009) provide contradictory evidence that individual investors are reluctant to sell funds that have appreciated in value but willing to sell funds that have lost value. Kumar and Lim (2008) provide evidence that disposition effect is weak among individual investors when investment decisions are narrowly framed, as measured by clustered trade.

Although Odean (1999) and STV (2006) examine small investors with a retail brokerage account, researchers have also investigated the link between institutional trading and possible overconfidence but the results are inconclusive. Grinblatt and Keloharju (2001) find the presence of the disposition effect among all classes of investors, including individuals and institutions, in the Finnish market. They report that financial institutions appear to be more willing to liquidate larger losses. Locke and Mann (2005) find that professional futures traders at the CME hang on to losses significantly longer than gains, thus displaying disposition effect. Coval and Shumway (2005) provide similar evidence from the CBOT. Using data from a discount brokerage, Dhar and Zhu (2006) find that wealthier individuals, and those employed in professional occupations, and frequent traders are less susceptible to display the disposition effect. Using data from Korean stock index futures Choe and Eom (2009) find that institutions and foreign investors are less susceptible to disposition effect than individual investors and experienced and sophisticated traders are also associated with a smaller effect. Barber, Lee, Liu and Odean (2009) find support for the disposition effect among individuals, corporations, and dealers but not for mutual funds and foreign investors in the Taiwan Stock Exchange.

Ben-David and Doukas (2006) provide evidence that in presence of ambiguous information investors become overconfident and trade more frequently even while incurring losses from their trades.

Cremers and Pareek (2011) exploit the short stock holding duration as a proxy for overconfidence and consistent with the predictions of Daniel, Hirschleifer, and Subrahmanyam (1998), they find that the presence of short term institutional investors can help explain increases in idiosyncratic volatility because overconfident investors overreact to private information and underreact to public information.[36]

Using proprietary data from the United Kingdom and the US, Annaert, Heyman, Vanmaele, and Van Osselaer (2008) find that mutual fund managers are not overconfident, and are not associated with the disposition effect. Chuang and Susmel (2011) provide evidence that institutional investors are overconfident, but less so than individual investors because institutional investors are more informed. Yung, Sun, and Rahman (2012) find that private information is likely to be associated with high turnover in stocks with low institutional ownership, consistent with overconfident investor hypothesis. Using account level data on the TAIFEX from 2001-2006, Chou and Wang (2011) conclude that domestic institutions display an overconfidence bias but not a disposition bias and individual investors display both biases.

While these empirical works make important contributions to the literature on behavioral bias among investors, the evidence on the subject is mixed and many of them (especially those investigating institutional trading in the US markets) rely on quarterly holdings data. There are obvious problems of inferring institutional trades from their holdings data as has been effectively argued by Puckett and Yan (2011). Specifically they point to two important limitations. First, changes in quarterly holdings data do not capture intra-quarter transactions where funds might purchase and sell or sell and repurchase the same stock. Second, quarterly holdings do not identify the exact timing or the execution price of the trades. Specifically, studies with quarterly holdings data typically assume that all trades occur at the end of the quarter but in reality they could occur at any time within the quarter. Thus researchers employing such data are severely restricted in their ability to identify superior trading skills if trades are motivated by short term information and such opportunities dissipate quickly (see also Kothari and Warner (2001)) and likely to overestimate behavioral biased. By contrast, we use high frequency institutional transactional data that bypass the problems associated with quarterly data and are well suited to answer transactional level questions.

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[36] They make an additional assumption that institutional investors are more likely to be overconfident than the less experienced individual investors.

Internet Appendix A.3 - Difference between the current work and those of Puckett and Yan (2011) and Chakrabarty, Moulton, and Trzcinka (2017)

The works that most closely resemble ours are by Puckett and Yan (2011) and Chakrabarty, Moulton, and Trzcinka (2017), henceforth PY and CMT, respectively. In this section, we explain how our work, specifically, methodology and measurements, sample, results, and conclusions align with or differ from these two works.

As we have explained in the introduction, the most significant difference between our work and those of PY and CMT is the method for measuring an institutional manager's performance. We use fair value accounting method, which is more likely to track the net asset value (NAV) of a fund, and is more reliable and value-relevant for financial securities. PY and CMT use historical cost method of calculating security price change and fund manager performance. Historical cost method requires inventory matching based on certain assumptions that fair value accounting does not. This major difference in methodology can contribute to different outcome measurement and conclusions.

PY use buy minus sell performance after adjusting for Daniel, Grinblatt, Titman, and Wermers (1997), or DGTW adjusted return for the full sample of 3,816 funds from the ANcerno dataset for the sample period of 1999-2005. Given the difficulty of matching inventory of a specific stock in a portfolio to specific buy and sell transactions, these authors match sell transactions to the nearest preceding buy transactions (or last-in-first-out or LIFO method of inventory management) within the quarter, when such transactions occur, or assume a sell transaction at the end of the quarter. CMT use 1,186 funds present for at least five or more years in the ANcerno data universe of 4,053 funds for a sample period of 1999-2009 and present raw and DGTW-adjusted return using first-in-first-out or FIFO method. These authors define short-term trade as those transactions with a holding period of three months or less.

Our sample period is 1999-2011 and we use raw return from the sample (ANcerno transaction universe) as well as return from a size- and market-to-book ratio- matched bootstrapped sample (with replacement) from the CRSP universe. Instead of using either LIFO or FIFO method of inventory matching, we use the marked-to-marked based fair value method of available for sale financial asset valuation over a hypothetical holding horizon from 1-day to 4-week. We use this window based on our belief that information based and short term profit motivated transactions primarily occurs within a short horizon. Thus, our measure of return is based on a marked-to-market portfolio value used by the futures exchanges for the purpose of calculating margin balance in a trader's account. We acknowledge the possibility that the observed timing or price of the buy or sell transactions may not accurately reflect the time and price the fund manager intended for the transaction because of execution uncertainty with limit orders and price uncertainty with market orders.

PY find that institutional investors earn +67 (- 06) basis points DGTW adjusted equally-weighted return on buy (sell) transactions. Therefore, their equally weighted buy-sell portfolio earns economically and statistically significant profits after transaction cost. CMT find that institutions earn -0.82% to -3.37% raw return over a 1-day to 3-month holding period. Thus, these two works differ in their conclusions not only about the direction of short-term institutional trading performance (profit vs. loss) but also about the magnitude of the absolute performance.

Our results, obtained using fair value method, are consistent with the findings by CMT that institutions do not make an economically significant profit on their short term trade, as reported by PY. Our results, however, do not support the huge short-term underperformance of institutional traders measured by CMT. We conclude that institutions break-even on their short term trades; they neither make economically significant profit to infer that that they are skilled at short term trading, nor do they make huge amount of losses due to agency problem or behavioral bias. We find that institutions earn -16 to +60 basis points on their buy transactions and -20 to +52 basis points for the sell transactions after transaction cost over 1-day to 4-week holding period. Thus, institutions earn +3 to +9 basis points more on their short-term buy trades than their sell trades after transaction cost and these results are vastly different than the estimate of -1.0% to -5.2% average loss reported by CMT on the short-term trades of institutional investors. Our results for institutional short-term buy minus sell portfolio returns are in a range that could potentially justify such trades for a variety of reasons, including liquidity-driven trades. In contrast, it is hard to justify why in equilibrium the labor market for asset managers would tolerate such large losses as reported by CMT. This is especially true in light of the conclusion by CMT that the "excessive trading" is due to either the desire of fund managers to "look active," which is an agency problem based rational explanation, or "recency bias," which is a behavioral bias, of the managers. The first is a contracting problem and the last is a problem of lack of awareness and education and the effects of both can be attenuated. So why do these problems continue to exist, and more important, contribute to such large losses?

CMT acknowledge that in the full sample that PY and we use will contain more short-term trades. They also state that their results are qualitatively similar in the full ANcerno sample than those presented in their paper and the results are also qualitatively similar when they use holding period of 1-month or less to define short-term trade. Yet, we expect institutional performance to be worse if we include a higher proportion of short term trades and redefine short term trades from trades with holding horizon of less than 3-month to less than 1-month.[37]

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[37] They suggest that for most of their analysis their results are similar using either FIFO or LIFO method.

For buy trades, our average raw returns in the ANcerno sample and the bootstrapped returns from the CRSP universe are similar to those in magnitude for the DGTW-adjusted returns reported by PY for the holding period longer than 1-week but lower for a lower holding-period. The difference in our conclusion is primarily driven by the sell side of the analysis. In PY, the DGTW-adjusted raw return for the sell side is -03 to -06 basis points. We find that for a 3-week holding period, which gives us overall results most similar to the results reported in PY, the buy minus sell portfolio breaks even (0 to 8 basis point profit) rather than making a 34 basis point profit. Yet these differences are not as large as those between the results of PY and CMT. Unlike the latter, we can't draw a strong conclusion that the institutions lose money over short-term trade. Our results suggest significant heterogeneity in raw return for the buy and sell transactions depending on the different hypothetical holding period ranging from -16 to +60 basis points for buy transactions and -20 to +52 basis points for the sell transactions over 1-day to 4-week holding period.

A second major difference between PY and CMT is that pension funds perform better than money managers in the first work and the opposite is true for the latter work. This finding by CMT is surprising given pension fund managers have longer investment horizon and are subject to less pressure to engage in liquidity-driven trades due to lower liquidity demand from their clients over shorter horizon. These conclusions are also inconsistent with the literature that suggests that pension fund managers, and the clients of pension funds are more sophisticated and use superior performance metrics than mutual funds with retail and mixed clientele (Guercio and Tkac (2002)). Hence, pension fund managers are more likely to generate superior performance than mutual funds (Bauer, Cremers, and Frehen (2010)) and are more likely than the mutual funds to be penalized by clients for poor performance (Guercio and Tkac (2002)).[38] We find that pension funds perform better than money managers over shorter investment horizon and our results are consistent with PY.

To summarize, our results support neither the conclusions of PY that institutions are skilled at short-term trading and make a modest profit from these trades after transaction cost, nor those of CMT that short-term institutional trades are driven by agency problem or behavioral biased and these trades incur huge losses even before transaction costs. In general, despite methodological differences, our results are closer in magnitude to those reported by PY than the ones reported by CMT. We do not do any further tests of persistence of this non-performance "performance."

Instead, a logical follow-up, and the broader, question we then ask is why institutions trade in the short term. One of the most frequently used explanations is that the institutions suffer from behavioral biases. We provide a vector autoregression (VAR) and impulse response based method to directly test for three

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[38] Using bias-free data from US pension funds, Bauer, Cremers, and Frehen (2010) report that after expense and trading cost, the abnormal return earned by US pension funds are close to zero or slightly positive, a superior performance than has been reported for mutual funds.

specific behavioral biases: overconfidence, biased-self-attribution, and disposition effect. We find no evidence of any of these biases.

Once we have eliminated the common behavioral biases, as a next step, we separate out trades motivated by alternative rational reasons for trading beyond profit maximization and repeat our analysis. We conclude that institutions engage in short term trading activities despite earning close to zero net return after transaction cost for rational reasons such as liquidity, risk management, tax-minimization, or window dressing. There may be other rational reasons for undertaking these trades such as a desire to cultivate a stronger relationship with the brokerage houses in order to receive favorable allocation of undervalued assets such as IPO shares that we have not tested for. Due to data limitation we also cannot test whether these equity transactions are part of a broader trading strategy, e.g. arbitrage involving futures market or writing covered call.

CMT also provide robustness checks and/or discuss behavioral biases such as disposition effect or overconfidence. For overconfidence, they find that funds that have high DGTW-adjusted return in the base period do not engage in more short-term trades contemporaneously and in the next four semiannual periods and conclude that institutional investors do not display biased self-attribution driven overconfidence. They do not test for disposition effect directly but conclude that their results are not consistent with disposition effect either. CMT rule out these two behavioral biases. They provide evidence that the institutions would have performed better had they held on to their losses and hence these loss making sales were not to "cut further losses." [39] Using these eliminations, they conclude that the motivation for loss making trade could either be rational, i.e. to "look active," or behavioral and attributed to a "recency bias", where individuals overweight the most recent experiences while making decisions.

Literature suggests that pension fund clients seem not to flock to recent winners and hence pension fund managers are also less likely to display behavioral biases (Guercio and Tkac (2002)). If pension fund managers have lower propensity to suffer from behavioral biases, we expect them to perform better than mutual fund managers. This is what we find while CMT find the opposite. In addition, if institutions engage in loss making trades to look active, mutual funds are more likely to be under pressure to look active and perform worse than the pension funds. CMT find the opposite. Our results that pension funds perform better than mutual funds on short term trades are consistent with the "trading for liquidity" reasons hypothesis. This is because we expect mutual funds to have more frequent outflow unrelated to fund performance and due to liquidity (or risk-shifting) need of clients than pension funds and hence the mutual fund managers are more likely to engage in trades for liquidity reasons. We also observe that during economic contraction cycle, the underperformance of buy minus sell portfolio is driven almost exclusively

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[39] This does not rule out the alternative hypothesis that the capital that was freed up from the loss-making transactions might have performed better on a different (unobserved) investment choice relative to the "do nothing alternative."

by the sell transactions. As investors demand liquidity perhaps to finance consumption or for risk-shifting reasons during such periods, this is another evidence of liquidity-driven trade hypothesis.

In summary, although some of our basic results fall within the very wide spectrum of those contradictory results reported in PY and CMT, due to the difference in magnitude, our conclusions on short-term trading performance differ from both these works.   Although some of our conclusions on behavioral bias, or lack thereof, for institutional traders may be similar to those in CMT, we provide direct and more systematic tests for all the behavioral biases that we reject. We conclude that institutions engage in short term trading activities despite earning close to zero net return, after transaction cost, for rational reasons such as liquidity, risk management, tax-minimization, or window dressing. Although our results suggest that managers engaging in short-term trading are likely to earn zero net return or even lose a few basis points from these trades, for the vast majority of the cases – except for window dressing – those trades are in response to real constraints or frictions and welfare implications of these trades are minimal. Thus, our results and conclusions can survive the equilibrium argument.

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Internet Appendix Table A.1: Average Returns Following Purchases and Sales - after Removing Overlapping Returns

We create a subsample of institutional buys and sells such that there is only one (the earliest) instance of an institutional transaction of a given stock on a given side (buy or sell) in a 20 day period (1 calendar month). Average returns to stocks bought (sold) by institutional investors over the various time horizons is:

$$R_{P,T} = \frac{\sum_{i=1}^{N} \prod_{r=1}^{T} (1 + R_{ji,ti+r})}{N} - 1$$

where N is number of buying (selling) transactions, T is institutional holding period (time horizons of trading days subsequent to buying (selling) transactions, and $R_{ji,ti+r}$ is CRSP daily return for stock j corresponding to institutional transaction i on day r after transaction day t. In order to calculate the return using ANcerno data, we initially construct the integrated daily stock level institutional data through the data integration process. This process allows our data to match with CRSP daily return for cumulative return $(R_{ji,ti+r})$. Using CRSP return, we calculate the cumulative returns to stocks bought (sold) by institutional investors over various horizons of trading days $(\prod_{r=1}^{T} (1 + R_{ji,ti+r}))$. Then, we calculate the average returns to the stocks bought (sold). Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

	Transactions of Institutional Investors with One Month Interval					
	N	1 day	1 week	2 week	3 week	4 week
Purchases	2,804,835	0.062	0.147	0.301	0.489	0.758
Sales	2,908,818	0.005	0.058	0.183	0.367	0.598
Difference		0.057***	0.089***	0.117***	0.121***	0.160***

Internet Appendix Table A.2: Average Returns Following Purchases and Sales Based on Trade Frequency and Trading Volume

Panel A investigates the transactions made by the top 10% of the institutional investors in the sample who make the greatest number of trades. Panel B examines the transactions conducted by the remaining 90% of the institutional investors in the sample who trade least. Statistical significance is indicated by *** for 1% level, ** for 5% level, and * for 10% level.

	N	1 day	1 week	2 week	3 week	4 week
Panel A: The 10 Percent of Institutional Investors Who Trade Most Frequently						
Purchases	12,092,406	0.061	0.231	0.435	0.626	0.842
Sales	11,022,952	0.046	0.184	0.361	0.570	0.774
Difference		0.016***	0.047***	0.073***	0.056***	0.068***
Panel B: The 90 Percent of Institutional Investors Who Trade Least Frequently						
	N	1 day	1 week	2 week	3 week	4 week
Purchases	4,033,414	0.092	0.280	0.450	0.621	0.820
Sales	4,063,390	0.010	0.135	0.306	0.493	0.681
Difference		0.082***	0.145***	0.144***	0.128***	0.139***