A Better Measure of Institutional Informed Trading

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Initial version: September 2008
This version: January 2014

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Abstract

Although many studies show that the presence of institutional investors facilitates the incorporation of accounting information into financial markets, the evidence of informed trading by institutions is rather limited in the extant literature. We address these inconsistent findings by proposing PC_NII, percentage changes in the number of a stock's institutional investors, as a novel informed trading measure. PC_NII is better able to detect informed trading than are changes in institutional ownership (ΔIO)—the measure commonly used in previous studies—because (1) entries and exits are usually triggered by substantive private information and (2) only a small fraction of institutions have superior information. As conjectured, PC_NII subsumes the information content of ΔIO and other institutional trading and herding measures in the forecast of stock returns, and its strong predictive power for stock returns reflects mainly its close correlation with future earnings surprises. We also show that PC_NII helps address empirical issues that require a reliable measure of institutional informed trading.

Keywords: PC_NII, Informed Trading, Earnings Surprises, and Stock Returns

JEL: M40, M41, G14, G18

1. Introduction

Conventional wisdom suggests that *some* institutional investors possess superior information about publicly traded companies. Consistent with this view, extant studies, e.g., Walther (1997), El-Gazzar (1998), Bartov, Radhakrishnan, and Krinsky (2000), Jiambalvo, Rajgopal, and Venkatachalam (2002), Collins, Gong, and Hribar (2003), Piotroski and Roulstone (2004), Ke and Ramalingegowda (2005), and Lev and Nissim (2006), have found that the presence of institutional investors facilitates the incorporation of accounting information into financial markets. Because informed investors usually disseminate their private information through trading with uninformed investors, one would expect that trades of a stock by informed institutions should correlate closely with the stock's future performances. Many authors, e.g., Ali, Durtschi, Lev, and Trombley (2004), Ke and Petroni (2004), and Bushee and Goodman (2007), have intensively investigated this conjecture using changes in the fraction of shares owned by institutions (ΔIO) as a standard institutional informed trading measure. The evidence of informed trading by institutions, however, is rather limited and sometimes difficult to interpret.[1] If the presence of institutions helps impound information into stock prices, why is there only limited evidence of institutional informed trading? In this paper, we show that the inconsistent findings reflect mainly the fact that ΔIO is an inferior measure of institutional informed trading. We propose a novel informed trading measure, the percentage change in the number of a stock's institutional investors (PC_NII), and find that institutional informed trading is far more widespread than that documented in previous studies.

Our empirical findings over the 1982 to 2010 period lend strong support for the conjecture that PC_NII is a better proxy for institutional informed trading than is ΔIO. PC_NII correlates positively and significantly with stock returns in the following quarter. A hedge portfolio that is long in the top and short in the bottom PC_NII deciles garners an average quarterly return of 2.4%, with a *t*-statistic of 4.5. This result is robust to different weighting schemes, controlling for common risk factors, and/or using

[1] Ali et al. (2004; pp. 221) and Bushee and Goodman (2007; pp. 292) emphasize that informed trading by institutions is *not widespread*. Finance studies also routinely use ΔIO as an informed trading measure and document mixed empirical evidence. For example, its correlation with future stock returns is found to be positive in Nofsinger and Sias (1999), insignificant in Gompers and Metrick (2001), and negative in Cai and Zheng (2004).

characteristic-matched returns. PC_NII also has strong predictive power for earnings surprises. Interestingly, when we control for quarter *t+1* earnings surprises, the predictive power of quarter *t* PC_NII for quarter *t+1* stock returns becomes negligible, clearly indicating that PC_NII forecasts stock returns mainly because of its correlation with future earnings surprises. By contrast, ΔIO has negligible predictive power for stock returns in our sample; and controlling for ΔIO does not affect our main findings in any qualitative manner.[2]

Chen, Hong, and Stein (2002) show that ΔBREADTH—the change in the number of a stock's institutional investors (ΔNII) normalized by the number of *all* institutions in the market—correlates positively with future stock returns.[3] The extant literature interprets ΔBREADTH as a proxy either for changes in short-sale constraints (e.g., Chen, Hong, and Stein (2002)) or for changes in investor recognition (e.g., Lehavy and Sloan (2008)). In contrast, we find that, like PC_NII, ΔBREADTH is also a measure of informed trading because its predictive power for stock returns reflects mainly its information contents about future earnings surprises. Nevertheless, using a simple stylized model and via simulation, we illustrate that PC_NII is a better measure of informed trading than is ΔBREADTH because the former takes into account the fact that information contents of entries and exits vary across stocks with different numbers of institutional investors. PC_NII completely subsumes the return predictive power of ΔBREADTH in actual data as well.

We provide three examples to illustrate that PC_NII helps address empirical issues that require a reliable measure of institutional informed trading. First, the predictive power of PC_NII for stock returns—a direct measure of the economic value of informed institutions' private information—decreases monotonically with earnings quality, suggesting that improving earnings quality reduces information asymmetry. Second, the Regulation Fair Disclosure (FD) weakens but *does not* fully eliminate institutional informed trading. Last, informed institutions partially reverse or cash out their portfolio

[2] Previous studies, e.g., Ali et al. (2004), Ke and Petroni (2004), Bushee and Goodman (2007), and Yan and Zhang (2009), construct ΔIO using a subset of institutions that are deemed more likely to trade on private information. We find qualitatively similar results when controlling for these alternative ΔIO measures.

[3] Note that ΔBREADTH and ΔNII are perfectly correlated with each other in the cross-section. Sias, Starks, and Titman (2006) document a positive relationship between ΔNII and future stock returns.

positions after the public news releases.

In a concurrent paper, Reca, Sias, and Turtle (2011) investigate correlations of institutional investors' entry, exit, and position-adjustment trades with future stock returns. These authors show that entry and exit trades are mainly triggered by private information, while adjustments to existing positions reflect primarily the liquidity demand. The novel findings provide additional support for our argument that PC_NII is a superior institutional informed trading measure. Our paper, however, differs from Reca, Sias, and Turtle (2011) along two dimensions. First, we emphasize that entry/exit trades do not always reflect information because they can also be triggered by liquidity need, especially for big stocks. Second, while Reca, Sias, and Turtle (2011) focus mainly on the relation between disaggregated institutional demand and future stock returns, we emphasize that PC_NII is a superior institutional informed trading measure that has implications for many empirical issues.

The positive relation between PC_NII and future stock returns is potentially consistent with two alternative hypotheses. First, an increase or decrease in the number of institutional investors may be due to institutional herding because institutions tend to follow each other into or out of same stocks (e.g., Nofsinger and Sias (1999), Wermers (1999), and Sias (2004)). Second, Gompers and Metrick (2001) and others argue that an increase in institutional ownership causes persistent demand shocks in stocks preferred by institutions. These two explanations, however, cannot explain the following two findings of the paper: (1) PC_NII forecasts stock returns mainly because of its information contents about future earnings surprises, and (2) the predictive power of PC_NII becomes weaker after the introduction of Regulation FD. Moreover, we show that standard measures of herding or demand shocks do not subsume information contents of PC_NII for future stock returns; on the contrary, their information contents about future stock returns are completely subsumed by PC_NII.

The remainder of the paper is organized as follows. Section 2 discusses the information content of PC_NII and develops the main hypotheses that we test in the paper. Section 3 describes the data. Section 4 shows that PC_NII has strong predictive power for one-quarter-ahead stock returns. Section 5 examines whether the relation between PC_NII and future stock returns is driven mainly by informed institutions' superior information about future earnings surprises. Section 6 provides three examples to illustrate implications of PC_NII in empirical studies. Section 7 offers some concluding remarks.

2. Hypothesis Development

Informed investors' trading reveals their private information. This is the economic rationale for the relation between institutional trading measures (e.g., PC_NII, ΔNII, and ΔIO) and future performances. PC_NII and ΔNII, however, differ from ΔIO in several significant ways. First, institutions have heterogeneous skills and information sets, and only a small fraction of them have informational advantages. For example, many studies, e.g., Jensen (1968) and Carhart (1997), have shown that fund managers on average are unable to outperform the market. By construction, ΔIO captures only trades between institutions and individual investors and completely ignores the information content of trades of informed institutions with uninformed institutions. Its predictive power for stock returns thus hinges on the very restrictive assumption that institutions as a group are better informed than are individual investors. In contrast, for PC_NII and ΔNII, we need a weaker and more realistic assumption that a fraction of institutions has private information. That is, unlike ΔIO, PC_NII and ΔNII take into account the well-documented empirical facts that institutions are heterogeneous in their skills and information sets and that informed institutions trade frequently with uninformed institutions. When only a small fraction of institutions has superior information, their entries or exits will affect PC_NII and ΔNII but may have a negligible effect on ΔIO due to their trades with uninformed institutions. The resulting informational loss in ΔIO can be economically large because the vast majority of trades occur among institutions rather than between institutions and individual investors (e.g., Kaniel, Saar, and Titman (2008)).

Second, as Chen (2007) and others point out, ΔIO has substantial measurement errors because institutions often trade without information; and these measurement errors significantly attenuate the relation between ΔIO and future performances. As a result, ΔIO has low power to reject the null hypothesis of no informed trading. In contrast, entries and exits are usually triggered by substantive private information.[4] By focusing on stocks in extreme entry and exit quintiles or deciles, our setting, while less restrictive, is similar in spirit to that of Ke and Petroni (2004), who analyze stocks that have a break in a string of consecutive quarterly earnings increases.

Third, because market makers can at least partially observe trades by institutional investors, extreme changes in institutional ownership can have a substantial price impact and thus a weak correlation with future stock returns. In contrast, entry and exit decisions are private information at the time of trading, i.e., market makers are unable to distinguish between an entry/exit trade and a position-adjustment trade until institutions file 13f reports with the Securities and Exchange Commission (the SEC hereafter) weeks later. Therefore, entry and exit trades, which are more likely to be triggered by substantive private information than are position-adjustment trades, would have a smaller price impact per unit of information, especially when only a small fraction of institutions have superior information.[5] Because the majority of trades by institutions are position-adjustment trades (e.g., Reca, Sias, and Turtle (2011)), we expect that PC_NII should have a stronger correlation with future stock returns than should ΔIO. This difference is particularly important for the low-frequency (quarterly) f13 data, which are commonly used in empirical studies, including ours.

Last, as we discuss below and in an online Appendix, unlike ΔIO (and ΔNII), PC_NII takes into account the fact that institutions also trade for liquidity reasons.[6]

The following example illustrates that an informed entry or exit affects PC_NII or ΔNII but has a

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[4] Because investing in new stocks requires substantial information costs (e.g., Merton (1987)), an institution is more likely to enter into a stock when it has strong positive private information about the stock's fundamentals, *ceteris paribus*. On the other hand, the routine portfolio rebalance normally does not require liquidating a stock due to trading costs. In addition, an institution usually has multiple funds managed by different traders with different investment strategies; thus, a synchronized exit from a stock likely reflects significant negative private information.

[5] This point can be illustrated using the SEC allegation that the hedge fund SAC traded drug companies Elan and Wyeth's shares using insider information in 2008. Upon receiving private information of poor drug trial results, a SAC head trader liquidated the hedge fund's entire position in the two companies under the instruction to *do so in a way so as to not alert anyone else, inside or outside of the Hedge Fund*. When the negative news was released to the public after the SAC liquidation trade, Elan's and Wyeth's stocks fell by 42% and 12%, respectively. See http://online.wsj.com/article/SB10001424127887323713104578130930796204500.html for details.

[6] A potential disadvantage of PC_NII is that it ignores the information content of position-adjustment trades. However, the majority of position-adjustment trades are likely to be triggered by reasons other than information. For example, Reca, Sias, and Turtle (2011) document an inverse relationship between the number of institutional investors who increases or decreases their holdings and future stock returns.

negligible effect on ΔIO when the informed institution trades mainly with uninformed institutions. Suppose a public company has ten institutional investors and many individual investors. First consider the case of an informed entry. Because institutional investors' trading volume dominates overwhelmingly that of individual investors (e.g., Kaniel, Saar, and Titman (2008)), it is likely that the informed institution enters into the stock by purchasing most shares from the uninformed institutional investors. Moreover, without any substantive negative private information, the uninformed institutions are unlikely to liquidate their positions. Thus, an informed entry leads to a positive PC_NII of 10% and a positive ΔNII of 1 but has negligible effects on ΔIO. Next consider the case of an informed exit. For two reasons, the existing uninformed investors of the company (shareholders) are more likely to be the buyers than the other uninformed investors who currently have no stake in the company (non-shareholders). First, information costs prevent the current non-shareholders to initiate a position in the company's shares. Second, Miller (1977) and many others argue that, in the presence of divergence of opinions and short-sale constraints, the current shareholders are more optimistic about the prospect of the company than are the current non-shareholders. Thus, if the informed institution exits from the stock by selling most shares to other existing institutional investors of the company, the informed exit leads to a negative PC_NII of -10% and a negative ΔNII of -1 but again has negligible effects on ΔIO.[7]

H1: PC_NII correlates positively with future stock returns and this correlation is stronger than the correlation between ΔIO and future stock returns.

There is a caveat, however. Entries and exits can also be triggered by liquidity reasons: An institution may enter into a stock when it has extra funds and exit from a stock when it has liquidity need. Liquidity-based entries and exits make ΔNII (or ΔBREADTH, which correlates perfectly with ΔNII in the cross-section) a noisy measure of informed trading. To address this issue, we note that the frequency of information-based relative to that of liquidity-based entries or exits increases with trading costs and information costs because those costs deter liquidity-based entries and exits. That is, ΔNII is more

[7] These conjectures are consistent with Reca, Sias, and Turtle's (2011) finding that while institutional entry and exit trades reflect mainly private information, position-adjustment trades are motivated primarily by liquidity demand.

informative for stocks with higher trading costs and information costs. In particular, ΔNII is more informative for small stocks than for big stocks because the former have higher trading costs (e.g., Amihud and Mendelson (1986)) and information costs (e.g., Merton (1987)). Diamond and Verrecchia (1991) suggest that big stocks attract more institutional investors than do small stocks, and many empirical studies (e.g., Gompers and Metrick (2001) and Bennett, Sias, and Starks (2003)) document strong empirical support for this conjecture. Thus, if the information content of ΔNII for future stock performances decreases with the number of institutional investors, PC_NII, a normalization of the former by the latter, is a better measure of informed trading than is ΔNII.

In an online Appendix, we formally illustrate this point using a simple stylized model and via simulation. Our simulation results show that PC_NII is a better informed trading measure than is ΔNII (i.e., the information content of ΔNII or ΔBREADTH is subsumed by PC_NII) when the frequency of information-based trading relative to that of liquidity-based trading is higher for small stocks with few institutional investors than for big stocks with many institutional investors. Note that one may normalize ΔNII by other measures of trading costs and information costs, and results should be qualitatively similar because these measures correlate closely with each other. Specifically, in Section 4 (Table 3), we show that commonly used measures of trading costs and information costs provide little information beyond PC_NII in the forecast of stock returns.

H2: ΔNII or ΔBREADTH has a stronger correlation with future stock returns for stocks with high trading costs and information costs than for stocks with low trading costs and information costs. Such an asymmetric relation is weaker for PC_NII. PC_NII has better predictive power for stock returns than does ΔNII or ΔBREADTH.

The mandatory quarterly earnings announcement is arguably the most important channel through which public companies regularly disseminate cash flow information that has a direct and immediate impact on their stock prices. Consistent with this view, the extant literature suggests that firm-level stock price volatility reflects mainly news about corporate fundamentals (e.g., Vuolteenaho (2002)). If PC_NII is an institutional informed trading measure, it should convey institutions' substantive private information about a public company's future earnings. Moreover, because earnings are the main gauge of a public company's prospects, the predictive power of PC_NII for stock returns should reflect mainly its correlation with future earnings surprises. To the best of our knowledge, this latter conjecture, which provides a direct test for informed trading and helps differentiate it from alternative hypotheses, is novel.

H3: PC_NII correlates positively with future earnings surprises. The correlation between PC_NII and future stock returns reduces significantly after controlling for future earnings surprises.

3. Data

We obtained quarterly institutional ownership data from the Thomson Financial 13f database over the January 1982 to December 2010 period.[8] Data of stock returns, stock prices, outstanding shares, and trading volume are from the Center for Research on Security Prices (CRSP). We include only common stocks (CRSP codes 10 or 11) listed on NYSE, AMEX, or NASDAQ. To mitigate market microstructure-related issues, we follow Jegadeesh and Titman (2001) and many others by including only stocks with a price of no less than $5 at the end of the portfolio-formation period. Compustat provides earnings and other accounting data such as the book value of equity, and we obtain analyst earnings forecast data from I/B/E/S.

PC_NII is the percentage change in the number of a stock's institutional investors:

$$\text{PC\_NII}_{\text{i,t}} = \frac{\text{\# of inst. holding stock } i \text{ at time } t - \text{\# of inst. holding stock } i \text{ at time } t\text{-1}}{\text{\# of inst. holding stock } i \text{ at time } t\text{-1}} * 100\,.$$

When the denominator, a stock's number of institutional investors in quarter *t-1*, is small, PC_NII may have large values in magnitude. We alleviate the concern about potential outliers by winsorizing PC_NII at the 1 and 99 percentiles in each quarter. For firms that have no institutional investors in

[8] The Thomson financial 13f database maintained by Wharton Research Data Services (WRDS) underwent an important change in July 2008. For each MGRNO-RDATE (i.e., institution-report date) combinations, there may be multiple records (multiple FDATE or vintage dates). Before July 2008, WRDS filtered out the redundant records. After July 2008, WRDS provides all data as it is from Thomson without any screenings. In the first version of this paper, we used the filtered pre-July 2008 13f database. In this version, we used post-July 2008 13f database and filtered out redundant records ourselves. We find qualitatively similar results for the two datasets, and the pre-July 2008 results are available on request.

quarter *t-1* but have a positive number of institutional investors in quarter *t*, PC_NII is assigned as a missing observation for quarter *t*.[9] In each quarter, we calculate the number of institutional investors for each stock. Figure 1 shows a steady increase in its cross-sectional median (dashed line) across time from ten institutions in 1982 to one hundred and ten institutions in 2010. The pattern is qualitatively similar for the cross-sectional mean (solid line). The cross-sectional mean is substantially larger than the cross-sectional median, indicating that the number of institutional investors is positively skewed.

Figure 2 plots the cross-sectional twenty-five (solid line) and seventy-five (dashed line) percentiles of changes in the number of institutional investors across time. Because the median change in institutional investors is close to zero, the absolute value of the twenty-five percentile is a proxy for the median number of exits, while the seventy-five percentile is a proxy for the median number of entries. The twenty-five percentile varies across time with a tight range between 0 and -4, with the exception of -7 during the 2008 financial crisis. Similarly, the seventy-five percentile has a range between 2 and 8, with the exception of 9 during the 2009 rebound following the 2008 financial crisis. Moreover, Table 1 shows that a substantial fraction of stocks (an average of 14.7% over the 1982 to 2010 period) has zero change in the number of institutional investors. These results suggest that, every quarter, only a relatively small fraction of institutions exit from or enter into a stock possibly because an entry or exit is usually triggered by substantive private information. Table 1 also shows that the cross-sectional mean is always positive and the cross-sectional median is mostly positive for PC_NII across time because of the steady increase of institutional investors in our sample, as shown in Figure 1. Moreover, the mean is substantially greater than the median, indicating that PC_NII is positively skewed.

For comparison, we consider several commonly used measures of institutional trading. First is the change in institutional ownership—the most commonly used measure of institutional informed trading:

$$\Delta IO_{i,t} = \text{\% of stock } i \text{ held by inst. at time } t - \text{\% of stock } i \text{ held by inst. at time } t\text{-}1.$$

Following Ke and Petroni (2004) and Bushee and Goodman (2007), we also construct ΔIO for transient,

[9] Results are qualitatively similar or stronger if we exclude stocks with less than five institutional investors in quarter *t-1* (untabulated).

quasi-indexing, and dedicated institutions, as classified by Bushee (1998, 2001).[10] Similarly, Yan and Zhang (2009) use an investment horizon measure based on institutions' portfolio turnover, and find that short-term or high-turnover institutions' ΔIO has significant predictive power for earnings surprises and stock returns. For comparison, we follow Yan and Zhang's (2009) procedures and construct the short-term ΔIO. Second, we construct the change in the breadth of institutional ownership as follows:

$$\Delta\text{BREADTH}_{i,t} = \frac{\text{\# of inst. holding stock } i \text{ at time } t - \text{\# of inst. holding stock } i \text{ at time } t\text{-}1}{\text{Total \# of 13f filers in the market at time } t\text{-}1} * 100\,.$$

As in Chen, Hong, and Stein (2002) and Lehavy and Sloan (2008), when calculating ΔBREADTH, we include only 13f filers that are in the sample in both quarter *t* and quarter *t-1* for (1) the number of institutions that hold the stock and (2) the number of all institutions in the market.[11] Third, we follow Sias, Starks, and Titman (2006) and construct the change in the number of institutional investors:

$$\Delta\text{NII}_{i,t} = \text{\# of inst. holding stock } i \text{ at time } t - \text{\# of inst. holding stock } i \text{ at time } t\text{-}1\,.$$

Note that, in any quarter *t*, ΔNII is proportional to ΔBREADTH because the denominator for ΔBREADTH is identical for all stocks. For brevity, we report only the results based on ΔBREADTH because the results are virtually identical for ΔNII. Last, previous studies, e.g., Nofsinger and Sias (1999), Wermers (1999), and Sias (2004), find a positive relation between institutional herding and short-term future stock returns. For comparison, we construct standard institutional herding measures advocated by (1) Lakonishok, Shleifer, and Vishny (1992), LSV_HM, (2) Sias (2004), S_HM, and (3) Brown, Wei, and Wermers (2014), BWW_HM.

For robustness, we use two different measures of future earnings news or surprises. We define the one-quarter-ahead earnings surprise, Future E_SURPRISE, as the difference between actual quarterly earnings per share disclosed in quarter *t+1* and median analyst forecast at the beginning of quarter *t+1*,

[10] Transient institutions, which have a short-term focus, are investors with high turnover and high diversification. Quasi-indexing institutions are passive investors with low turnover and high diversification. Dedicated institutions follow a relationship approach to investing with low diversification and low turnover. We are grateful to Brian Bushee for making the institution classification data available to us through his personal research website: http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html.

[11] The restriction that institutions must be in the sample in both quarter *t* and quarter *t-1* does not affect our main findings in any qualitative manner. These results are omitted for brevity but are available on request.

scaled by the stock price at the end of quarter *t*. Both actual earnings per share and median analyst forecast are from I/B/E/S (adjusted) detail history file. We define the one-quarter-ahead seasonal earnings growth, Future E_CHANGE, as the change in quarterly earnings before extraordinary items (Compustat item: IBQ) from a year ago scaled by average total assets, disclosed in quarter *t+1*. In each quarter we winsorize both earnings news variables at the 1 and 99 percentiles.

PC_NII correlates closely with ΔBREADTH, with an average cross-sectional correlation coefficient of 45% in the sample. Nevertheless, the correlation is far from being perfect because of the substantial variation in the number of institutional investors across stocks. For example, over our full sample spanning the 1982 to 2010 period, its twenty-five and seventy-five percentiles are thirteen and one hundred and four institutions, respectively (untabulated). Thus, we may observe quite different values of PC_NII for stocks with the same value of ΔNII or ΔBREADTH. Because, as we show in Section 4, the number of institutional investors correlates negatively with the informativeness of entries and exits, its substantial cross-sectional variation highlights the importance of using PC_NII instead of ΔBREADTH as a measure of institutional informed trading. PC_NII correlates positively with ΔIO, with a correlation coefficient of 32%. The correlation is relatively weak partly because, as we mentioned in Section 2, institutional investors' trading volume dominates that of individual investors and informed institutions trade frequently with uninformed institutions. Moreover, entry and exit trades account for only a fraction of institutional investors' total trading activities. PC_NII also correlates positively with the short-term ΔIO and herding measures, but the correlations (around 20% to 30%) are not particularly strong. Lastly, we find a positive correlation (around 3% to 6%) of PC_NII with the most recently disclosed (i.e., disclosed in quarter *t*) E_CHANGE and E_SURPRISE. For brevity, we do not tabulate these results but they are available on request.

4. PC_NII and One-Quarter-ahead Stock Returns

In this section, we test H1 and H2 using both portfolio sorts and Fama and MacBeth (1973) cross-sectional regressions, and find qualitatively similar results for the two empirical specifications.

4.1 Single Sort on PC_NII

At the end of each quarter, we sort stocks equally into ten portfolios by PC_NII, and hold them over the next three months. Panel A of Table 2 reports selected characteristics for each decile. D1 (D10) is the decile of stocks with the lowest (highest) PC_NII. We observe substantial variation in PC_NII across the deciles: The time-series mean of average PC_NII ranges from -22% for D1 to 59% for D10.[12] Both ΔBREADTH and ΔIO increase monotonically from D1 to D10. We are more likely to observe extreme PC_NII for small stocks than for big stocks; this is because small stocks have substantially less institutional investors, the denominator in the calculation of PC_NII.[13] Because small stocks tend to have high idiosyncratic volatility and to be illiquid, PC_NII is likely to have extreme values for stocks with high idiosyncratic volatility (IV) and high Amihud's (2002) illiquidity measure (AMIHUD). PC_NII has an inverse relationship with the book-to-market equity ratio (BM) and a positive relationship with the stock return in the past 6 months (MOM). Similarly, PC_NII increases monotonically with contemporaneous, i.e., the most recently disclosed, seasonal earnings growth (E_CHANGE) and earnings surprises (E_SURPRISE).[14] These results, which suggest that institutions prefer growth stocks and tend to be momentum traders, are consistent with those reported in earlier studies (e.g., Wermers (1999, 2000), Cai and Zheng (2004), Sias (2004, 2007), and Ke and Ramalingegowda (2005)).

In Panel B of Table 2, we investigate the relation between PC_NII and future portfolio returns. Consistent with H1, we document a strong positive correlation of PC_NII with one-quarter-ahead equal-weighted portfolio returns. Among the ten portfolios, the bottom (top) PC_NII decile has the

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[12] As we show in Table 1, PC_NII equals zero for a substantial fraction of stocks. To sort stocks evenly into deciles, we add a small uniform-distributed random variable (i.e., 10^{-9}*Uniform) to PC_NII as a tie breaker. Because PC_NII has a large cross-sectional variation, such a small perturbation has no effect on the rankings of the top and bottom deciles, which are the main concern of our empirical investigation. As a robustness check, we also use the raw data for PC_NII in Fama and MacBeth cross-sectional regressions and find qualitatively similar results. We use the tie breaker for ΔBREADTH as well.

[13] Recall that we filtered out stocks with a price less than $5 and that our main results are qualitatively similar or stronger when we remove stocks that have less than five institutional investors. Moreover, we form portfolios first on market capitalization and then on PC_NII, and find that the information content of PC_NII for future stock returns does not concentrate in only small stocks (untabulated).

[14] When we require analyst forecast data, our dataset reduces from 373,498 observations to only 175,653 observations (a 53% reduction). To address this issue, we calculate the decile portfolio median E_SURPRISE using the subsample with valid earnings surprise observations.

lowest (highest) raw return. The hedge portfolio of longing the top and shorting the bottom PC_NII deciles has an average raw return of 2.4% per quarter, with a *t*-statistic of 4.5. To ensure that our results do not simply reflect the fact that many institutions adopt certain investment styles, we follow Daniel, Grinblatt, Titman, and Wermers (DGTW hereafter; 1997) and use their characteristics-adjusted returns, and find qualitatively similar results (2.4% per quarter with a *t*-statistic of 5.3).[15] Similarly, the return difference cannot be explained by standard risk factor models either. Its loadings on excess market returns and the size premium are statistically insignificant at the 5% level (untabulated). Because the top PC_NII decile has a lower book-to-market equity ratio than does the bottom PC_NII decile, the hedge portfolio has a negative loading on the value premium. As a result, the Fama and French (1996) three-factor alpha of the hedge portfolio is 2.9%, which is actually larger than the raw return. On the other hand, because institutions tend to buy past winners and sell past losers, the loading on the momentum factor is positive. Nevertheless, when we include the control for the momentum factor, the Carhart (1997) four-factor alpha is 1.8% with a *t*-statistic of 4.8. Moreover, further controlling for the loading on the illiquidity risk factor proposed by Pastor and Stambaugh (2003) in a five-factor model does not affect our results in any qualitative manner. The five-factor alpha is 1.8% per quarter with a *t*-statistic of 5.3. As robustness checks, we find that results are qualitatively similar when using (1) DGTW characteristics-adjusted portfolio returns to calculate hedge portfolio alphas, (2) delisting returns advocated by Beaver, McNichols, and Price (2007), and (3) value-weighted portfolio returns (untabulated). For example, the value-weighted hedge portfolio formed on PC_NII generates a Carhart (1997) four-factor alpha of 2.7% with a *t*-statistic of 3.8. By contrast, ΔIO has negligible predictive power for stock returns. For example, the Carhart (1997) four-factor alpha of the hedge portfolio of longing the top and shorting the bottom equal-weighted ΔIO deciles is 0.42% with a *t*-statistic of 1.2 (untabulated).

PC_NII forecasts stock returns partly because of its information contents about future earnings

[15] The DGTW characteristics-adjusted return of a stock is the difference between the stock's raw return and the return of the stock's benchmark portfolio matched by size, book-to-market, and momentum. DGTW benchmarks are available from http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm. We thank Russ Wermers for making the data available to us through his website.

surprises. To investigate this conjecture, we follow Ali et al. (2004) and construct the raw return and the DGTW characteristics-adjusted return over a three-day event window around the earnings announcement date. Panel B of Table 2 shows that, as hypothesized, the difference between the top and bottom deciles is significantly positive at the 1% level for both the raw return and the DGTW characteristics-adjusted return. The magnitude, however, is somewhat small. For example, the raw return difference is 0.3% over the three-day window around the earnings announcement date, compared with 2.4% for the whole quarter. This pattern is consistent with the finding by Ball and Shivakumar (2008) that returns around earnings announcements account for a relatively small fraction of variation in quarterly stock returns.[16] We will elaborate on the relation between PC_NII and future earnings surprises in the next section.

Ke and Petroni (2004) find that ΔIO of transient institutions correlates positively with future stock returns but the predictive power is negligible for quasi-indexing and dedicated institutions. In Panel B of Table 2, we revisit the issue by forming decile portfolios on PC_NII constructed for each institution group. For example, PC_NII of transient institutions is the change in a stock's number of transient institutional investors in portfolio formation quarter *t* scaled by the stock's number of all institutional investors at the beginning of the quarter. Interestingly, we find that PC_NII of all three institution groups has significant predictive power for stock returns; nevertheless, transient institutions appear to have the best market timing ability. Results are qualitatively similar when we use (1) common risk factors to adjust for systematic risk and (2) value-weighted portfolio returns (untabulated). The novel evidence of informed trading by quasi-indexing and dedicated institutions helps address the puzzle stressed by Ke and Petroni (2004, pp.925) why these institutions do not execute profitable trades although they could have information similar to that of transient institutions. Our results suggest that the puzzle reflects the fact that, as we propose in H1, ΔIO is a poor institutional informed trading measure.

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[16] Extant studies (e.g., Ali et al. (2004) and Yan and Zhang (2009)) use either equal-weighted or median returns around earnings announcement dates. Interestingly, untabulated results show that the relationship between PC_NII and future returns around earnings announcement dates is positive albeit statistically insignificant when we use value-weighted portfolio returns. This result possibly reflects the fact that big stocks disseminate information faster than do small stocks (Diamond and Verrecchia (1991)). For example, Ball and Shivakumar (2008) show that, for those relatively large stocks that have analyst following, substantial amount of information is incorporated in analyst forecast revisions prior to earnings announcements.

In Figure 3, we plot the annual hedge portfolio returns across time, which we construct by compounding quarterly returns on the hedge portfolio that is long in the top PC_NII decile and short in the bottom PC_NII decile. Over the sample period of almost three decades, the equal-weighted return (solid line) is always positive or close to zero (and it exceeds 10% for 15 out of the 29 years) except for the years 2001 (the tech bubble burst) and 2009 (the aftermath of the subprime mortgage crisis), during which the hedge portfolio has a sizable negative return of -19% and -9%, respectively. The dashed line in Figure 3 shows that results are qualitatively similar for the value-weighted hedge portfolio return. It is tempting to interpret these results as evidence that the hedge portfolio's poor performance in the years 2001 and 2009 reflects mainly systematic risk; therefore, the superior performance of the hedge portfolio formed on PC_NII is the compensation for the disastrous risk that cripples the financial market. This conjecture is not supported by the data, however. Specifically, the poor performance in 2001 is primarily due to the substantial negative hedge portfolio return in the 4th quarter, while the excess market return is 12% for that quarter. Similarly, the poor performance in 2009 is mainly due to the substantial negative hedge portfolio return in the 2nd quarter, during which the excess market return is 18%.

There are two alternative explanations. First, institutions' trading is significantly affected by liquidity demand of their clients during financial market meltdowns. Therefore, during market meltdowns, changes in the number of institutional investors of a stock are more likely to reflect the increased liquidity demand from the clients of institutions than to reflect the private information about the stock's fundamentals. Consistent with this explanation, Figure 2 documents an unusually high level in magnitude for the twenty-five percentile of changes in the number of institutional investors in 2008, indicating that institutions rushed for exits during the financial crisis. Similarly, Figure A1 in the online Appendix shows that the increase in exits is especially pronounced for liquid stocks, i.e., stocks with a large number of institutional investors. Therefore, PC_NII is a less reliable measure of private information during these two episodes than during normal market conditions. Second, the noticeable poor performance of the trading strategy based on PC_NII in 2001 and 2009 also reflects the fact that many institutions are momentum traders. The momentum portfolio of buying past winners and selling past losers has substantial negative returns of -16% and -40% for the 4th quarter of 2001 and the 2nd quarter of 2009, respectively, during which the hedge portfolio formed on PC_NII performs poorly. That is, when PC_NII is a poor proxy of institutions' private information during market turmoil, the performance of the hedge portfolio formed on PC_NII is primarily influenced by the performance of the momentum portfolio. Nevertheless, PC_NII does reveal private information about future stock returns during normal market conditions. Recall that in Table 2 the hedge portfolio has a significant DGTW characteristics-adjusted return and a significant alpha after we control for the momentum factor.[17]

4.2 PC_NII versus ΔBREADTH

To test H2, we measure a stock's trading costs and/or information costs using seven proxies—market capitalization, the number of institutional investors, Amihud's (2002) illiquidity measure, analyst earnings forecast dispersion, the number of analysts following the stock, turnover, and the probability of informed trading (PIN) advocated by Easley, Hvidkjaer, and O'Hara (2002). For each of these measures, we sort stocks equally into two portfolios each quarter and construct a dummy variable that equals one for the stocks with *low* trading and/or information costs and equals zero otherwise. For example, "Large Size" equals one if a stock's market capitalization is larger than the cross-sectional median and equals zero otherwise. In Fama and MacBeth (1973) cross-sectional regressions, we use (1) the measure of institutional trading, i.e., ΔBREADTH or PC_NII, (2) the dummy variable for trading costs and/or information costs, and (3) their interaction term to forecast one-quarter-ahead stock returns. In H2, we conjecture that ΔBREADTH is more likely to reflect liquidity-based trading than information-based trading for stocks with *lower* trading costs and/or information costs. Thus, we anticipate that the interaction term is significantly negative for ΔBREADTH. By contrast, because the asymmetric effect is taken into account for PC_NII, we expect that its interaction term is statistically indifferent from zero.

Panel A of Table 3 reports the Fama and MacBeth (1973) cross-sectional regression results for

[17] To explicitly control for the fact that institutions tend to be momentum traders, in each quarter we also regress PC_NII on returns over the past 6 months and find the orthogonalized PC_NII (i.e., orthogonalized by momentum) correlates positively and significantly with future stock returns (untabulated).

ΔBREADTH. The first column lists the variables that we use to construct the dummy variable for trading costs and/or information costs. Each row in Panel A represents a regression model using ΔBREADTH, the dummy variable, and the interaction term between ΔBREADTH and the dummy variable as the independent variables.[18] Consistent with the finding by Chen, Hong, and Stein (2002) and Sias, Starks, and Titman (2006), we find a significantly positive correlation of ΔBREADTH with future stock returns. Moreover, as conjectured, the interaction term of ΔBREADTH with the dummy variable is always significantly negative at least at the 10% level across all the seven proxies for trading costs and/or information costs. In contrast, Panel B shows that the interaction term of PC_NII with the dummy variable is always statistically insignificant at the 10% level, while PC_NII is always significantly positive at the 1% level, in all regression models. These novel findings, which are consistent with H2, suggest that liquidity-based trades have a significant effect on informed trading measures.

In Table 4, we test the implication that PC_NII is a better measure of informed trading than is ΔBREADTH by forming portfolios using these two measures. In Panel A, we investigate whether PC_NII forecasts stock returns when we control for ΔBREADTH. In each quarter we first sort stocks equally into five portfolios by ΔBREADTH; and then within each ΔBREADTH quintile we sort stocks equally into five portfolios by PC_NII. The Carhart (1997) four-factor alpha of the equal-weighted return difference between the top and bottom PC_NII quintiles is always positive for all ΔBREADTH quintiles; and it is statistically significant at least at the 5% level for three out of five ΔBREADTH quintiles. In the last row of Panel A, we aggregate each PC_NII quintile returns across five ΔBREADTH quintiles using the equal weight, and find that the return difference between the top and bottom aggregate PC_NII quintiles is about 1% per quarter, with a *t*-statistic of 5.5. In contrast, in Panel B, we show that ΔBREADTH has negligible predictive power for stock returns when we control for PC_NII. For example, when we aggregate across PC_NII quintiles, the difference between the top and

[18] In the regression, we also control for standard cross-sectional stock return predictors, including market beta, market capitalization, the book-to-market equity ratio, the return in the previous six months, Amihud's (2002) illiquidity measure, and past seasonal earnings growth. For brevity, we omit the regression results for these control variables but they are available on request.

bottom ΔBREADTH quintiles is economically negligible (0.03%) and statistically insignificant. In subsection 4.3, we find qualitatively similar results using Fama and MacBeth (1973) cross-sectional regressions with control for a variety of stock return predictors. To summarize, we document strong empirical support for the conjecture that PC_NII is a better informed trading measure than ΔBREADTH.

4.3 Fama and MacBeth Regressions

In this subsection, we investigate the predictive power of PC_NII for stock returns using Fama and Macbeth (1973) cross-sectional regressions, in which we control for (1) commonly used stock return predictors and (2) standard institutional trading and herding measures. To alleviate the concern for outliers, we follow Bernard and Thomas (1990) and use the decile ranks instead of the raw observations for all explanatory variables.[19]

Table 5 shows that PC_NII has strong predictive power for stock returns in Fama and MacBeth (1973) regressions. First, PC_NII has a strong positive correlation with one-quarter-ahead stock returns in the univariate regression (Model 1). Second, the predictive power of PC_NII is not subsumed by commonly used stock return predictors. Model 2 shows that the predictive power of PC_NII remains statistically significant at the 1% level when we control for market beta, size, book-to-market equity ratio, momentum, illiquidity, and idiosyncratic volatility. The results are qualitatively similar when we also include the most recently disclosed seasonal earnings growth (Model 3) or earnings surprises (Model 4) in the forecast regression to control for the post-earnings announcement drift, as documented by Bernard and Thomas (1989) and many subsequent studies. Third, the predictive power of PC_NII does not simply reflect its correlations with commonly used institutional trading and herding measures. In Model 5, we include PC_NII along with ΔBREADTH, ΔIO, Yan and Zhang's (2009) short-term ΔIO, IO, and Brown, Wei, and Wermers' (2014) signed herding measure, BWW_HM, as independent variables, and find that

[19] In an earlier version of the paper, we use raw observations of all explanatory variables in Fama and MacBeth (1973) cross-sectional regressions and find qualitatively similar results.

PC_NII is statistically significant at the 1% level.[20] In contrast, the other institutional trading and herding measures are either statistically insignificant at the 10% level or have wrong signs. Fourth, PC_NII remains a significant predictor when we include both cross-sectional stock return predictors and other institutional trading and herding measures as explanatory variables (Models 6, 8, and 9). Last, because analysts play a crucial role in incorporating accounting information into financial markets, the information content of PC_NII may reflect its correlation with analyst coverage. To address this issue, in Model 7, we control for both the number of analysts following the stock, ANAL, and the percentage change in the number of analysts, PC_ANAL, and find that the correlation of PC_NII with future stock returns remains statistically significant at the 1% level.

PC_NII drives out the other institutional trading and herding measures when we include only one of these measures at a time along with PC_NII in cross-sectional regressions. As a robustness check, by forming portfolios using sequential double sorts, we show that the predictive power of PC_NII for stock returns is not a manifestation of well-known asset pricing anomalies. Similarly, in sequential portfolio double sorts, PC_NII remains a significant predictor of stock returns when we control for commonly used institutional trading or herding measures; by contrast, these institutional trading or herding measures have negligible predictive power for stock returns when we control for PC_NII. For brevity, these results are not reported here but are available on request.

To summarize, the Fama and MacBeth (1973) regression results suggest that the predictive power of PC_NII for stock returns is not a manifestation of commonly used return predictors, and PC_NII drives out commonly used institutional trading and herding measures in cross-sectional forecast regressions.

5. PC_NII and One-Quarter-ahead Earnings Surprises

In this section, we test H3 that PC_NII forecasts earnings news and PC_NII forecasts stock returns because of its information contents about future earnings news.

[20] The results are qualitatively similar when we control for the herding measure by Lakonishok, Shleifer, and Vishny (1992), LSV_HM, or by Sias (2004), S_HM (untabulated).

In Panel A of Table 6, we investigate whether PC_NII forecasts one-quarter-ahead seasonal earnings growth, Future E_CHANGE, using Fama and MacBeth (1973) cross-sectional regressions. Again, we follow Bernard and Thomas (1990) and use the decile ranks for all explanatory variables; and results are qualitatively similar for raw observations (untabulated). Model 1 shows that PC_NII correlates positively and significantly with Future E_CHANGE (which is disclosed in the quarter following the PC_NII measurement quarter and winsorized at the 1 and 99 percentiles each quarter) at the 1% level in the univariate regression. The top PC_NII decile outperforms the bottom decile by 0.9 percentage points (i.e., 9*0.1=0.9) in Future E_CHANGE, with a *t*-statistic exceeding 23. To control for autocorrelation in E_CHANGE, in Model 2, we include the most recently disclosed E_CHANGE as an additional independent variable in the cross-sectional regression and find qualitatively similar results. Ou and Penman (1989), Lev and Thiagarajan (1993), Abarbanell and Bushee (1997, 1998), and others, find that many accounting-based fundamental signals forecast earnings. As a robustness check, we add these fundamental signals to the cross-sectional regressions in Models 3 and 4. We follow Abarbanell and Bushee (1998) to construct fundamental signals, including INV (inventory), AR (accounts receivable), CAPX (capital expenditures), GM (gross margin), S&A (selling and administrative expenses), AQ (audit qualification), LF (labor force), ETR (effective tax rate), and EQ (earnings quality).[21] ETR and EQ have many missing observations; for robustness, we exclude them from the regression in Model 3 but include them in Model 4. Again, we find a significantly positive correlation of PC_NII with one-quarter-ahead E_CHANGE after controlling for the fundamental signals, with *t*-statistics exceeding 12. Consistent with the extant studies, we find that seven out of the nine fundamental signals have significant forecasting power for E_CHANGE. Panel B of Table 6 shows that results are qualitatively similar for forecasting the one-quarter-ahead earnings surprises, Future E_SURPRISE.

Bernard and Thomas (1989) and many subsequent studies document a strong positive relationship

[21] To utilize the most recently disclosed accounting information, we obtain the data used to calculate INV, AR, GM, S&A, and LF from Compustat quarterly file up to the fiscal quarter ending in the quarter before the PC_NII measurement quarter. To avoid look-ahead bias, we obtain the data used to calculate CAPX, AQ, ETR, and EQ from Compustat annual file up to the fiscal year before the fiscal year of the fiscal quarter ending in the quarter before the PC_NII measurement quarter.

between stock returns and contemporaneous earnings news. In Table 7, we confirm this stylized fact using either seasonal earnings growth (Model 1) or earnings surprises (Model 5). Because as an institutional informed trading measure PC_NII has a strong correlation with one-quarter-ahead earnings news (Table 6), its predictive power for one-quarter-ahead stock returns may reflect mainly its information contents about the one-quarter-ahead earnings news, as we conjecture in H3. To investigate formally this conjecture, in each quarter we first perform a regression of PC_NII on the one-quarter-ahead seasonal earnings growth and then use the regression residual or orthogonalized PC_NII to forecast stock returns.[22] Model 2 shows that, when we control for its correlation with future seasonal earnings growth, the predictive power of PC_NII for stock returns becomes statistically insignificant at the 10% level in the univariate regression. The predictive power becomes even weaker when we control for commonly used stock return predictors (Models 3 and 4). Similarly, when we use PC_NII orthogonalized by future earnings surprises, its effects on future stock returns are significant at only the 5% level (Model 6). The significance reflects the fact that institutions tend to be momentum traders. When we control for momentum and past seasonal earnings changes or past earnings surprises, the orthogonalized PC_NII has negligible predictive power for stock returns (Models 7 and 8). Results are again similar when we use raw observations instead of decile ranks for all explanatory variables in Table 7 (untabulated). Thus, consistent with H3, we find that PC_NII forecasts stock returns mainly because of its information contents about future earnings surprises.

As a robustness check, we further investigate H3 by performing portfolio double sorts first by future seasonal earnings growth and then by PC_NII. Specifically, at the end of each quarter, we first sort stocks equally into five portfolios by one-quarter-ahead seasonal earnings growth; within each seasonal earnings growth quintile, we then sort stocks equally into five portfolios by PC_NII. Consistent with the Fama-MacBeth regression results reported in Table 7, when we control for future seasonal earnings growth, the positive relationship between PC_NII and future stock returns disappears completely. In

[22] In the first regression, we use raw observations of PC_NII and the one-quarter-ahead seasonal earnings growth (both winsorized at the 1 and 99 percentiles). In the second regression, we use the decile ranks of the residual obtained from the first regression as an explanatory variable.

particular, the Carhart (1997) four-factor alpha of the return difference between the top and bottom aggregate PC_NII quintiles is 0.04%, with a *t*-statistic of 0.2. The results are qualitatively similar when we use future earnings surprises as a control variable: The Carhart four-factor alpha is -0.32%, with a *t*-statistic of -0.9. For brevity, we do not tabulate these results.

Similarly, as conjectured, we find that the predictive power of ΔBREADTH for stock returns reflects mainly its correlation with future earnings news as well. ΔBREADTH has significant predictive power for earnings; and interestingly, its predictive power is stronger for stocks with higher trading costs and/or information costs. More importantly, when we control for ΔBREADTH's correlation with future seasonal earnings growth or future earnings surprises, its correlation with one-quarter-ahead stock returns becomes statistically insignificant or even negative. These results, which we omit for brevity but are available on request, strongly suggest that ΔBREADTH predicts stock returns because it is a measure of informed trading, albeit a much noisier one compared with PC_NII. The results pose a challenge to both the short-sale constraint hypothesis and the investor recognition hypothesis.

To summarize, consistent with the conjecture that PC_NII is an institutional informed trading measure, PC_NII strongly predicts one-quarter-ahead earnings news and its return predictive power reflects mainly its information contents about future earnings news. Our results cast serious doubts on the alternative explanations that PC_NII forecasts stock returns because of its correlations with momentum, post-earnings announcement drift, herding, or demand shocks.

6. Implications of PC_NII as a Superior Institutional Informed Trading Measure

We have shown that PC_NII is a superior institutional informed trading measure. In this section, we illustrate through three applications that PC_NII can help future researchers address empirical issues that require a reliable measure of institutional informed trading.

6.1 Earnings Quality and Information Asymmetry

The conjecture that improving earnings quality reduces information asymmetry (e.g., Diamond and

Verrecchia (1991)) is a crucial building block of the disclosure literature and has important regulatory implications. For example, it is a key assumption of the popular albeit contentious view that high quality accounting standards (e.g., good earnings quality) improve liquidity and lower the cost of capital.[23] Extant empirical studies have investigated intensively whether earnings quality affects the cost of capital. There are, however, few studies on the relation between earnings quality and information asymmetry, as noted by Beyer, Cohen, Lys, and Walther (2010; pp. 308): *their results are difficult to interpret because … Francis et al. (2004, 2005a, 2005b) document a link between earnings quality and cost of capital without establishing a link between earnings quality and information asymmetry*.

Ecker, Francis, Kim, Olsson, and Schipper (2006) and Bhattacharya, Desai, and Venkataraman (2013) are two noticeable exceptions. Both studies document statistically significant correlations of earnings quality with standard information asymmetry proxies, e.g., bid-ask spreads, price impact of trade, and Easley, Hvidkjaer, and O'Hara's (2002) probability of informed trading (PIN). However, *these correlations…are relatively weak in economic terms* (Ecker, Francis, Kim, Olsson, and Schipper (2006; pp. 752)). One possible reason for the weak empirical evidence is that these standard information asymmetry proxies have substantial measurement errors (e.g., Lee, Mucklow, and Ready (1994), Heflin, Shaw, Wild (2005), Mohanram and Rajgopal (2009)), the attenuation effect of which may bias the correlation estimate toward zero. In this subsection, we address the issue by proposing an information asymmetry measure based on our earlier finding that PC_NII is a superior institutional informed trading measure.

The predictive power of PC_NII for a stock's returns provides a better measure of that stock's information asymmetry than standard information asymmetry measures. This is because the return predictive power of PC_NII *directly* reflects the economic value of informed institutional investors'

[23] Another key assumption is a positive effect of information asymmetry on the cost of capital. In addition to this indirect effect, Lambert, Leuz, and Verrecchia (2012) and others note that earnings quality can affect costs of capital directly through its influence on information precision. Bhattacharya, Ecker, Olsson, and Schipper (2012) find that while both effects are statistically significant, the indirect effect appears to be much less important economically due to a weak correlation of earnings quality with information asymmetry. However, we need to interpret their findings with caution because, as we show below, the weak correlation likely reflects the fact that their information asymmetry proxies have substantial measurement errors.

private information—a major source of information asymmetry in financial markets. Our information asymmetry measure is hence less prone to measurement errors and easier to interpret than are those measures used in previous studies, and allows us to address more precisely empirical issues related to information asymmetry. Specifically, we can test the conjecture that improving earnings quality alleviates information asymmetry by examining whether the predictive power of PC_NII for stock returns is stronger for low earnings quality stocks than for high earnings quality stocks. The intuition is as follows. Informed institutions are able to execute profitable trades likely because they have better skills in processing publicly available earnings information than do other investors, and such skills are especially useful when earnings quality is poor. *Ceteris paribus*, these sophisticated institutions possess more informational advantages, and hence there is more information asymmetry, for poor earnings quality stocks than for good earnings quality stocks.

Following recent earnings quality studies (e.g., Francis, LaFond, Olsson, and Schipper (2005), Rajgopal and Venkatachalam (2011), Chaney, Faccio, and Parsley (2011), and Bhattacharya, Desai, and Venkatachalam (2013)), we use two discretionary accruals-based earnings quality measures. DA_Quality is the standard deviation of discretionary accruals in the past five fiscal years and Abs_DA is the median absolute value of discretionary accruals in the past five fiscal years.[24] A high value of DA_Quality or Abs_DA implies low earnings quality. In Table 8, we test the implication that improving earnings quality reduces the predictive power of PC_NII for stock returns using Fama-MacBeth cross-sectional regressions of forecasting one-quarter-ahead stock returns. Specifically, we expect a positive coefficient on the interaction term of PC_NII with DA_Quality or Abs_DA. In Model 1, we use PC_NII and DA_Quality to predict one-quarter-ahead stock returns. PC_NII has strong predictive power for the cross-section of stock returns, while the coefficient on DA_Quality is statistically insignificant. We then include their interaction term, PC_NII*DA_Quality, as an additional explanatory variable in models 2 and 3. As conjectured, the coefficient on the interaction term is significantly positive at the 1% level. Moreover, the interaction term drives out PC_NII in the Fama-MacBeth regression, suggesting that

[24] Results are qualitatively similar for the augmented Dechow and Dichev (2002) earnings quality measure.

informed institutions have informational advantages mainly for low earnings quality stocks. Models 4 to 6 show that results are qualitatively similar for Abs_DA.

To illustrate the economic significance of the effect of earnings quality on information asymmetry, we first sort stocks equally into five portfolios by earnings quality; and then within each earnings quality quintile we sort stocks equally into five portfolios by PC_NII. The results are reported in Table 9. As conjectured, when using DA_Quality (Abs_DA) as the earnings quality measure, the difference in Carhart (1997) four-factor alphas between the highest and lowest PC_NII quintiles increases monotonically from -0.05% (0.47%) per quarter for the highest earnings quality quintile to 2.43% (2.80%) per quarter for the lowest earnings quality quintile. These results clearly indicate that, in contrast with previous findings, the effect of earnings quality on information asymmetry is economically very large. The difference likely reflects the fact that information asymmetry proxies used in previous studies have substantial measurement errors.

We also use our information asymmetry measure to address Rajgopal and Venkatachalam's (2011; pp. 3) conjecture that *improving disclosures and quality of financial reporting mitigate information asymmetries about a firm's performance and reduce the volatility of stock prices*. In model 7 of Table 8, we find that the interaction term of PC_NII with idiosyncratic volatility correlates positively and significantly with future stock returns. This result indicates a close relation between idiosyncratic volatility and information asymmetry. In models 8 and 9, we show that idiosyncratic volatility affects the predictive power of PC_NII for stock returns mainly because of its correlation with earnings quality proxied by DA_Quality and Abs_DA, respectively. This result suggests that the effect of idiosyncratic volatility on information asymmetry reflects its close correlation with earnings quality. Overall, our empirical findings are consistent with Rajgopal and Venkatachalam's (2011) conjecture that earnings quality, rather than idiosyncratic volatility, directly affects information asymmetry.

6.2 Regulation FD

Regulation FD requires companies to make significant information public simultaneously to all investors. Because its main objective is to reduce the informational advantage of institutional investors relative to individual investors and level the playing field among market participants, if Regulation FD is effective, its enactment should significantly attenuate the predictive power of PC_NII for stock returns. Note that, as we document in the previous subsection, institutions' informational advantages may come from their better skills in analyzing public information. In addition, some institutions may receive tips from corporate insiders or from third parties that have private information of a firm.[25] Thus, Regulation FD may not fully eliminate institutional informed trading.

Figure 3 shows that the equal-weighted return on the hedge portfolio of longing the top and shorting the bottom PC_NII deciles appears to have attenuated substantially since the enactment of Regulation FD in October 2000, while there is a much smaller difference for the value-weighted return. Indeed, untabulated results show that the change in the hedge portfolio performance post the Regulation FD is statistically significant for the former but not for the latter. Because the value-weighted portfolio return gives more weight to big stocks than does the equal-weighted portfolio return, our results suggest that Regulation FD is more successful in reducing information asymmetry for small stocks than for big stocks.

Our finding that Regulation FD weakens but does not eliminate informed trading is in contrast with that by Ke, Petroni, and Yu (2008), who show that the predictive power of transient institutions' ΔIO for stock returns has disappeared in the post Regulation FD period. Our finding corroborates recent studies by Markov, Muslu, and Subasi (2011), Bushee, Jung, and Miller (2013), and Solomon and Soltes (2013), who find that in the post Regulation FD period, managers communicate their private information in a delicate manner to selected institutions through various channels, e.g., invitation-only conferences and one-on-one meetings. Because the new communication channels are more common practices for big companies than for small companies, these recent studies also offer an interesting explanation for our

[25] In an earlier draft, we find that PC_NII forecasts corporate events of firms becoming takeover targets, although the predictive power attenuates substantially in the post Regulation FD sample. Because these events cause large price movements around their announcements and are essentially unpredictable by publicly available information, our results suggest that some institutions have superior information acquisition.

empirical finding that Regulation FD appears to be more effective for small stocks than for big stocks.[26]

6.3 Cashing Out after Intensive Entry and Exit Trades

In this subsection, using PC_NII as a superior informed trading measure, we test an important implication of informed trading theories (e.g., Kim and Verrecchia (1997) and Brunnermeier (2005)) that informed investors will reverse or cash out their portfolio positions after the public news announcement. (For brevity, we do not tabulate the empirical results but they are available on request.) This test, as Bushee and Goodman (2007) emphasize, helps differentiate alternative explanations for a positive relation between institutional trading and future stock returns, e.g., institutional informed trading versus institutional momentum trading or herding. Specifically, because entries and exits are usually triggered by substantive private information, stocks in the two extreme PC_NII quintiles have significant news to be released publicly in the holding period. If an informed institution trades on private information, it will buy high PC_NII stocks and sell low PC_NII stocks in the portfolio formation quarter and will reverse their portfolio positions in the quarters following the public news releases. Consistent with the finding by Bushee and Goodman (2007) that institutional investors as a group are unable to profit from private information, we do not observe significant cashing out for *all* institutions. In contrast, we find that institutions that execute entry or exit trades do significantly albeit partially reverse their portfolio positions after the portfolio formation quarter. This result is consistent with the conjecture that entry/exit trades are usually triggered by private information.

Bushee and Noe (2000) suggest that dedicated institutions have better access to private information than do transient and quasi-indexing institutions due to their close relationship with managers of the firms

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[26] Ahmed and Schneible (2007), Eleswarapu, Thompson, and Venkataraman (2004), Gomes, Gordon, and Madureira (2007), and others also find that Regulation FD is more effective for small stocks than for big stocks. These authors suggest that big companies have more leeway for selective disclosures than do small companies. For example, Regulation FD has a number of exclusions, including the disclosure of nonpublic information to credit rating agencies. Jorion, Liu, and Shi (2005) examine the effect of credit rating changes on stock prices and find that the informational effect of downgrades and upgrades is much greater in the post Regulation FD period. To the extent that companies with access to the bond market tend to have large market capitalization, the selective disclosure of non-public information to credit rating agencies might help explain the limited success of Regulation FD on big stocks.

in which they have large stakes. Consistent with this view, we find that dedicated institutions as a group have significant market timing skills. They buy high PC_NII stocks and sell low PC_NII stocks in the portfolio formation quarter (Q0) and partially reverse their portfolio positions in the following quarter (Q1). Similarly, consistent with Ke and Petroni's (2004) argument that transient institutions are more likely to trade on their private information, we also find that transient institutions as a group buy high PC_NII stocks and sell low PC_NII stocks in the portfolio formation quarter and partially reverse their portfolio positions a few quarters after the portfolio formation. In contrast, we do not observe cashing out for quasi-indexing institutions. Therefore, our evidence suggests that, although quasi-indexing institutions are heterogeneous in their skills and information sets, they are on average less likely to be informed investors than are transient and dedicated institutions.

7. Conclusion

This paper contributes to the extant literature of informed trading by institutional investors along several dimensions. First, we show that ΔIO is an inferior measure of institutional informed trading, and propose PC_NII as a better alternative measure. As conjectured, PC_NII subsumes the information content of ΔIO and other commonly used institutional trading and herding measures in the forecast of stock returns, and its predictive power for stock returns reflects mainly its information contents about future earnings surprises. Second, using PC_NII as a novel institutional informed trading measure, we help reconcile the inconsistent findings in the literature by documenting strong evidence of informed trading across different types of institutions. Our results suggest that institutional informed trading is far more widespread than that documented in the extant literature and thus confirm the important role of institutions in disseminating accounting information. Last, we find that ΔBREADTH is also a measure of informed trading, albeit a much noisier one compared with PC_NII.

We use three application examples of PC_NII to illustrate that it can help address empirical issues that require a reliable measure of institutional informed trading. First, we document a strong inverse relation between earnings quality and information asymmetry. Second, Regulation FD weakens but does not fully eliminate institutional informed trading. Last, informed institutions partially reverse or cash out their portfolio positions in the quarters following the public news releases. These results suggest that, as a superior institutional informed trading measure, PC_NII can be used by empirical researchers to address many other accounting and finance issues.

REFERENCES

Abarbanell, J., and B. Bushee, 1997, Fundamental analysis, future earnings, and stock prices, Journal of Accounting Research, 35, 1-24.

Abarbanell, J., and B. Bushee, 1998, Abnormal stock returns to a fundamental analysis strategy, The Accounting Review, 73, 19-45.

Ahmed, A., and R. Schneible, 2007, The impact of regulation fair disclosure on investors' prior information quality: Evidence from an analysis of changes in trading volume and stock price reactions to earnings announcements, Journal of Corporate Finance, 13, 282-299.

Ali, A., C. Durtschi, B. Lev, and M. Trombley, 2004, Changes in institutional ownership and subsequent earnings announcement abnormal returns, Journal of Accounting, Auditing, and Finance, 3, 221-248.

Amihud, Y., 2002, Illiquidity and stock returns, Journal of Financial Markets, 5, 31-56.

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, Journal of Financial Economics, 17, 223-249.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns, Journal of Finance, 51, 259-299.

Ball, R., and L. Shivakumar, 2008, How much new information is there in earnings? Journal of Accounting Research, 46, 975-1016.

Bartov, E., S. Radhakrishnan, and I. Krinsky, 2000, Investor sophistication and patterns in stock returns after earnings announcements, The Accounting Review, 75, 43-63.

Beaver, W., M. McNichols, and R. Price, 2007, Delisting returns and their effect on accounting-based market anomalies, Journal of Accounting and Economics, 43, 341-368.

Bennett, J., L. Starks, and R. Sias, 2003, Greener pastures and the impact of dynamic institutional preferences, Review of Financial Studies, 16, 1203-1239.

Bernard, V., and J. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research, 27, 1-36.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, Journal of Accounting and Economics, 13, 305-340.

Beyer, A., D. Cohen, T. Lys, and B. Walther, 2010, The financial reporting environment: Review of the recent literature, Journal of Accounting and Economics, 50, 296-343.

Bhattacharya, N., H. Desai, and K. Venkataraman, 2013, Does earnings quality affect information asymmetry? Evidence from Trading Costs, Contemporary Accounting Research, 30, 482-516.

Bhattacharya, N., F. Ecker, P. Olsson, and K. Schipper, 2012, Direct and mediated associations among earnings quality, information asymmetry and the cost of equity, The Accounting Review, 87, 449-482.

Brown, N., K. Wei, and R. Wermers, 2014, Analyst recommendations, mutual fund herding, and overreaction in stock prices, Management Science, 60, 1-20.

Brunnermeier, M., 2005, Information leakage and market efficiency, Review of Financial Studies, 18, 417-457.

Bushee, B., 1998, The influence of institutional investors on myopic R&D investment behavior, The Accounting Review, 73, 305-33.

Bushee, B., 2001, Do institutional investors prefer near-term earnings over long-run value? Contemporary Accounting Research, 18, 207-46.

Bushee, B., and T. Goodman, 2007, Which institutional investors trade on private information about earnings and returns? Journal of Accounting Research, 45, 289-321.

Bushee, B., M. Jung, and G. Miller, 2013, Do investors benefit from selective access to management? Unpublished Working Paper, University of Pennsylvania.

Bushee, B., and C. Noe, 2000, Corporate disclosure practices, institutional investors, and stock return volatility, Journal of Accounting Research, 38, 171-202.

Cai, F., and L. Zheng, 2004, Institutional trading and stock returns, Finance Research Letters, 1, 178-189.

Carhart, M., 1997, On persistence in mutual fund performance, Journal of Finance, 52, 57–82.

Chaney, P., M. Faccio, and D. Parsley, 2011, The quality of accounting information in politically connected firms, Journal of Accounting and Economics, 51, 58-76.

Chen, Q., 2007, Discussion of which institutional investors trade based on private information about earnings and returns? Journal of Accounting Research, 45, 323-332.

Chen, J., H. Hong, and J. Stein, 2002, Breadth of ownership and stock returns, Journal of Financial Economics, 66, 171-205.

Collins, D., G. Gong, and P. Hribar, 2003, Investor sophistication and the mispricing of accruals, Review of Accounting Studies, 8, 251-76.

Daniel, K., M. Grinblatt, S., Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, Journal of Finance, 52, 1035-1058.

Dechow, P., and I. Dichev, 2002, The quality of accruals and earnings: The role of accrual estimation errors, The Accounting Review, 77, 35-59.

Dechow, P., R. Sloan, and A. Sweeney, 1995, Detecting earnings management. The Accounting Review, 70, 193-225.

Diamond, D., and R. Verrecchia, 1991, Disclosure, liquidity, and the cost of capital, Journal of Finance, 46, 1325-1359.

Easley, D., S. Hvidkjaer, and M. O'Hara, 2002, Is information risk a determinant of asset returns? Journal of Finance, 57, 2185-2221.

Ecker, F., J. Francis, I. Kim, P. Olsson and K. Schipper, 2006, A returns-based representation of earnings quality, The Accounting Review, 81, 749-780.

Eleswarapu, V., R. Thompson, and K. Venkataraman, 2004, The impact of regulation fair disclosure, Journal of Financial and Quantitative Analysis, 39, 209-225.

El-Gazzar, S., 1998, Predisclosure information and institutional ownership: A cross-sectional examination of market revaluations during earnings announcement periods, The Accounting Review, 73, 119-129.

Fama, E., and K. French, 1996, Multifactor explanations of asset pricing anomalies, Journal of Finance, 51, 55-84.

Fama, E., and J. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, Journal of Political Economy, 81, 607-636.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2005, The market pricing of accruals quality, Journal of

Accounting and Economics, 39, 295-327.

Gomes, A., G. Gorton, and L. Madureira, 2007, SEC regulation fair disclosure, information, and the cost of capital, Journal of Corporate Finance, 13, 300-334.

Gompers, P., and A. Metrick, 2001, Institutional investors and equity prices, Quarterly Journal of Economics, 116, 229-259.

Heflin, F., K. Shaw, and J. Wild, 2005, Disclosure quality and market liquidity: Impact of depth quotes and order sizes, Contemporary Accounting Research, 22, 829-866.

Jegadeesh, N., and S. Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, Journal of Finance, 56, 699-720.

Jensen, M., 1968, The performance of mutual funds in the period 1945-1964, Journal of Finance, 23, 389-416.

Jiambalvo, J., S. Rajgopal, and M. Venkatachalam, 2002, Institutional ownership and the extent to which stock prices reflect future earnings, Contemporary Accounting Research, 19, 117-45.

Jones, J., 1991, Earnings management during import relief investigations, Journal of Accounting Research, 29, 193-228.

Jorion, P., Liu, Z., and Shi, C., 2005, Informational effects of Regulation FD: Evidence from rating agencies, Journal of Financial Economics, 76, 309-330.

Ke, B., and K. Petroni, 2004, How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases, Journal of Accounting Research, 42, 895-927.

Ke, B., K. Petroni, and Y. Yu, 2008, The effect of Regulation FD on transient institutional investors' trading behavior, Journal of Accounting Research, 46, 853-883.

Ke, B., and S. Ramalingegowda, 2005, Do institutional investors exploit the post-earnings announcement drift? Journal of Accounting and Economics, 39, 25-53.

Kim, O., and R. Verrecchia, 1997, Pre-announcement and event-period private information, Journal of Accounting and Economics, 24, 395-419.

Kothari, S., A. Leone, and C. Wasley, 2005, Performance matched discretionary accrual measures, Journal of Accounting and Economics, 39, 163-197.

Lakonishok, J., A. Shleifer, and R. Vishny, 1992, The impact of institutional trading on stock prices, Journal of Financial Economics, 32, 23-43.

Lambert, R., C. Leuz, and R. Verrecchia, 2012, Information precision, information asymmetry, and the cost of capital, Review of Finance, 16, 1-29.

Lee, C., B. Mucklow, and M. Ready, 1994, Spreads, depths, and the impact of earnings information: An intraday analysis, Review of Financial Studies, 6, 345-374.

Lehavy, R., and R. Sloan, 2008, Investor recognition and stock returns. Review of Accounting Studies, 13, 327-361.

Lev, B., and D. Nissim, 2006, The persistence of the accruals anomaly, Contemporary Accounting Research, 23, 193-226.

Lev, B., and S. Thiagarajan, 1993, Fundamental information analysis, Journal of Accounting Research, 31, 190-215.

Markov, S., V. Muslu, and M. Subasi, 2011, Analyst tipping: Additional evidence, Unpublished Working Paper, University of Texas at Dallas.

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information. Journal of Finance, 42, 483-510.

Miller, E., 1977, Risk, uncertainty, and divergence of opinion, the Journal of Finance, 32, 1151-1168.

Mohanram, P., and S. Rajgopal, 2009, Is PIN priced risk? Journal of Accounting and Economics, 47, 226-243.

Newey, W., and K. West, 1987, A simple, positive, semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica, 55, 703-708.

Nofsinger, J., and R. Sias, 1999, Herding and feedback trading by institutional and individual investors, Journal of Finance, 54, 2263-2295.

Ou, J., and S. Penman, 1989, Financial statement analysis and the prediction of stock returns, Journal of

Accounting and Economics, 11, 295-330.

Piotroski, J., and D. Roulstone, 2004, The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices, The Accounting Review, 79, 1119-51.

Rajgopal, S., and M. Venkatachalam, 2011, Financial reporting quality and idiosyncratic return volatility, Journal of Accounting and Economics, 51, 1-20.

Reca, B., R. Sias, and H. Turtle, 2011, Anatomy of Institutional Positions, Unpublished Working Paper, University of Arizona.

Sias, R., 2004, Institutional herding, Review of Financial Studies, 17, 165-206.

Sias, R., 2007, Reconcilable differences: Momentum trading by institutions, Financial Review, 42, 1-22.

Sias, R., L. Starks, and S. Titman, 2006, Changes in institutional ownership and stock returns: Assessment and methodology, Journal of Business, 79, 2869-2910.

Sloan, R., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review, 71, 289-315.

Solomon, D., and E. Soltes, 2013, What are we meeting for? The consequences of private meetings with investors, Unpublished Working Paper, University of Southern California.

Vuolteenaho, T., 2002, What drives firm-level stock returns? Journal of Finance, 57, 233-264.

Walther, B, 1997, Investor sophistication and market earnings expectations, Journal of Accounting Research, 35, 157-179.

Wermers, R., 1999, Mutual fund herding and the impact on stock prices, Journal of Finance, 54, 581-622.

Wermers, R., 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses, Journal of Finance, 55, 581-622.

Yan, X., and Z. Zhang, 2009, Institutional investors and equity returns: Are short-term institutions better informed? Review of Financial Studies, 22, 893-924.

Figure 1
Mean (Solid Line) and Median (Dashed Line) Number of Institutional Investors

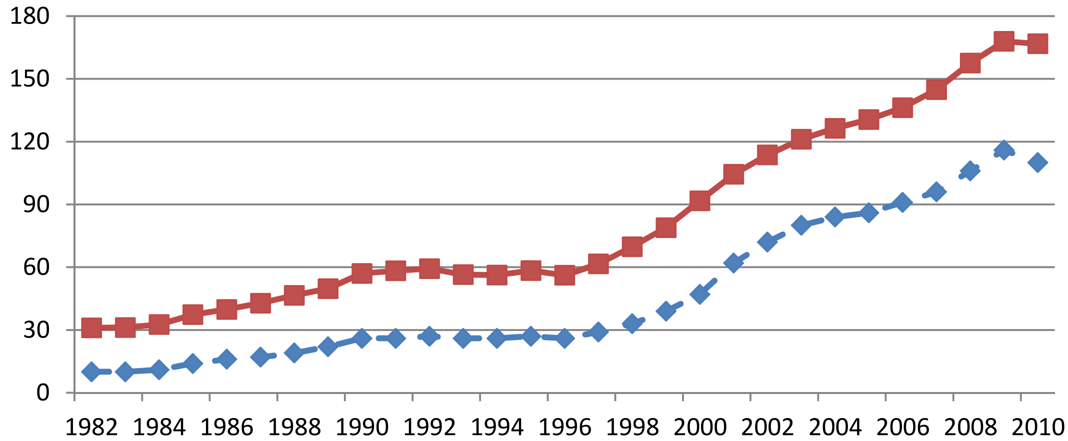

Figure 2
25 (Solid Line) and 75 (Dashed Line) Percentiles of Changes in Institutional Investors

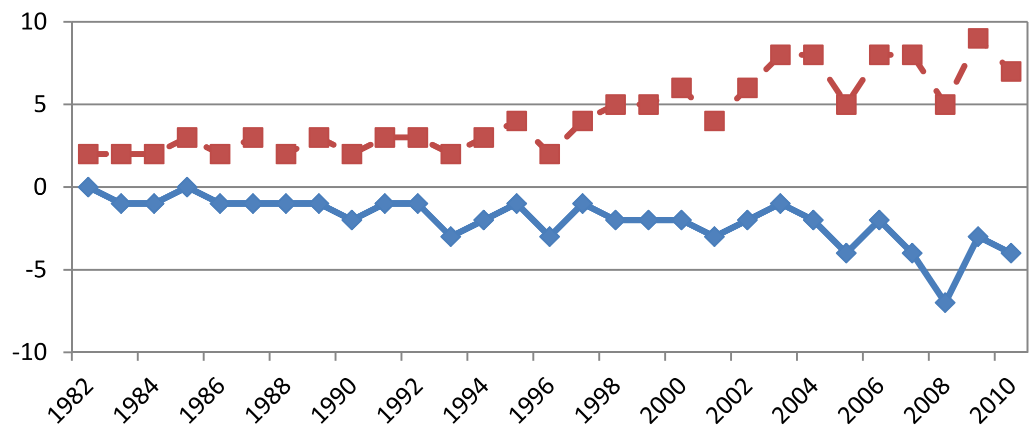

Figure 3
Annual Equal-Weighted (Solid Line) and Value-Weighted (Dashed Line) Returns on the Long-Short Portfolio Formed on PC_NII

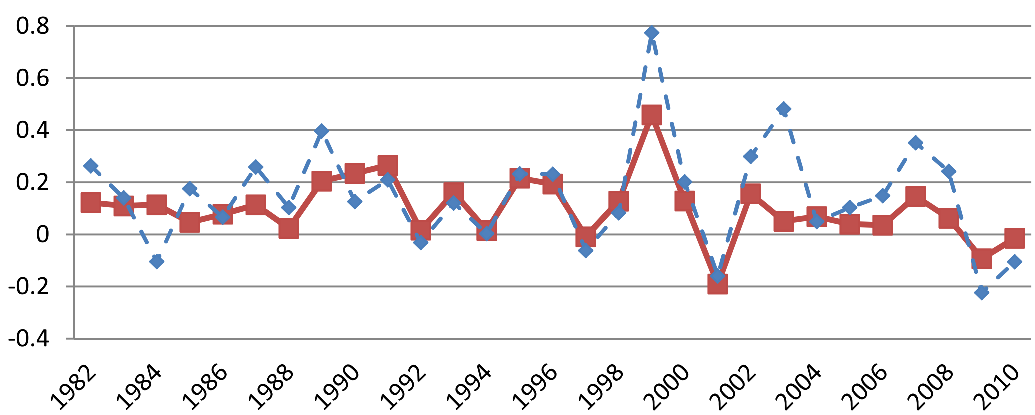

Table 1 Summary Statistics of PC_NII

	PC_NII					
Year	NOB	Mean	Median	Zero	25 Percentile	75 Percentile
1982	6698	13.94	0	26.19	0	20.00
1983	10391	16.36	0	24.54	-2.49	20.00
1984	11001	22.03	0	27.48	-5.00	11.11
1985	10948	21.95	3.63	22.79	0	20.00
1986	11427	14.88	0	20.57	-6.29	14.29
1987	11874	8.60	0	20.83	-4.76	14.29
1988	11313	11.46	0	20.03	-3.85	12.50
1989	11084	7.15	0	19.21	-6.25	13.04
1990	9879	4.43	0	21.29	-5.88	7.14
1991	10304	6.32	0	19.83	-4.13	9.80
1992	11633	11.45	1.25	16.99	-3.88	11.11
1993	13255	6.78	0	15.61	-8.33	9.43
1994	14663	15.16	0	16.72	-5.45	12.50
1995	15566	10.01	2.41	18.18	-2.22	12.12
1996	16948	12.06	0	15.34	-9.47	9.09
1997	17634	24.01	3.24	14.12	-3.13	14.29
1998	17158	28.73	1.97	11.08	-6.67	14.46
1999	16084	27.12	0.86	12.81	-6.25	12.50
2000	15301	17.94	1.06	12.37	-5.86	11.46
2001	13455	27.45	0	12.09	-4.59	10.00
2002	12555	18.72	1.19	9.90	-4.55	10.00
2003	12987	14.35	3.24	10.42	-1.33	11.43
2004	14073	18.83	3.33	8.48	-2.41	11.67
2005	14080	17.03	0	9.01	-5.71	6.33
2006	14435	23.36	2.78	8.70	-2.17	10.75
2007	14252	20.97	1.28	7.86	-4.76	9.09
2008	12165	8.46	-0.45	7.06	-6.90	6.12
2009	10757	15.74	1.22	6.85	-3.70	7.37
2010	11578	12.37	0.66	7.29	-4.14	6.55
1982-2010	373498	16.37	0.32	14.71	-4.76	11.11

Notes: The table reports the summary statistics of PC_NII, which is the percentage change in a stock's number of institutional investors. For each stock-quarter observation included in our sample, we require (1) common stocks (CRSP codes 10 and 11), (2) traded on NYSE, AMEX or NASDAQ, (3) with end-of-quarter close price no less than $5 per share, and (4) non-missing PC_NII value. Our data spans the 1982Q2 to 2010Q4 period. NOB is the number of observation. Mean is the cross-sectional mean. Median is the cross-sectional median. Zero is the percentage of stocks that have no change in the number of institutional investors. 25 Percentile is the cross-sectional 25 percentile. 75 percentile is the cross-sectional 75 percentile. Except for NOB, all variables are reported in percentage points.

Table 2 Decile Portfolios Sorted on PC_NII

Panel A: Stock Characteristics

Deciles	PC_NII	ΔBREADTH	ΔIO	SIZE	BM	MOM	IV	AMIHUD	E_CHANGE	E_SURPRISE
D1	-22.15	-0.52	-2.72	362.66	0.76	-1.98	3.12	2.12	-0.01	-0.27
D2	-9.25	-0.38	-0.94	978.58	0.72	-1.25	2.59	0.86	0.01	-0.18
D3	-4.35	-0.25	-0.28	2078.55	0.68	1.51	2.33	0.87	0.06	-0.16
D4	-1.52	-0.10	0.02	3103.15	0.67	5.47	2.31	1.35	0.07	-0.08
D5	0.54	0.03	0.28	3464.72	0.66	7.78	2.27	1.47	0.10	-0.06
D6	3.06	0.19	0.67	3926.02	0.61	9.65	2.19	1.02	0.13	-0.04
D7	6.39	0.34	0.96	2890.56	0.59	12.96	2.26	0.77	0.16	-0.01
D8	11.28	0.44	1.44	1788.34	0.59	17.69	2.38	0.58	0.21	-0.01
D9	20.06	0.50	2.31	876.33	0.57	24.94	2.66	1.00	0.27	0.01
D10	58.88	0.71	5.33	414.07	0.50	43.75	3.20	1.61	0.42	0.05
D10-D1	81.03	1.23	8.05	51.41	-0.26	45.72	0.08	-0.51	0.43	0.33
t-Statistic	(25.90)	(54.15)	(33.20)	(1.41)	(-14.12)	(12.84)	(1.43)	(-2.13)	(15.94)	(17.46)

Panel B: One-Quarter-ahead Stock Returns

Deciles	Raw Return	DGTW Return	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha	Raw EAR(-1,1)	DGTW EAR(-1,1)	DGTW Transient	DGTW Quasi-Indexing	DGTW Dedicated
D1	2.25	-1.25	-1.50 (-3.81)	-1.21 (-3.60)	-1.20 (-3.40)	0.20	0.01	-1.07	-0.73	-0.37
D2	2.91	-0.79	-0.89 (-3.01)	-0.41 (-2.01)	-0.38 (-1.89)	0.32	0.13	-0.52	-0.35	0.02
D3	3.39	-0.22	-0.28 (-0.98)	-0.02 (-0.09)	-0.02 (-0.07)	0.42	0.23	-0.29	-0.09	-0.19
D4	3.81	-0.02	0.07 (0.25)	0.25 (1.18)	0.32 (1.43)	0.50	0.26	0.01	-0.10	-0.24
D5	3.64	-0.26	-0.02 (-0.06)	0.03 (0.16)	0.06 (0.31)	0.38	0.21	-0.21	-0.29	-0.12
D6	3.22	-0.19	-0.28 (-0.98)	-0.27 (-1.01)	-0.22 (-0.83)	0.40	0.23	-0.54	-0.06	-0.22
D7	3.52	-0.00	-0.03 (-0.13)	-0.10 (-0.47)	-0.04 (-0.20)	0.30	0.14	-0.16	-0.01	-0.34
D8	4.15	0.31	0.67 (3.42)	0.42 (2.34)	0.45 (2.51)	0.38	0.20	0.10	0.08	0.09
D9	4.37	0.62	0.85 (3.78)	0.37 (1.89)	0.38 (1.99)	0.46	0.29	0.75	0.46	0.04
D10	4.67	1.12	1.39 (3.66)	0.57 (1.97)	0.65 (2.06)	0.51	0.33	1.21	0.40	0.72
D10-D1	2.42	2.37	2.89	1.78	1.84	0.31	0.32	2.28	1.13	1.09
t-Statistic	(4.47)	(5.27)	(5.39)	(4.83)	(5.28)	(3.64)	(3.96)	(4.95)	(2.99)	(3.98)

Notes: The table reports the averages of selected characteristics (Panel A) and equal-weighted stock returns (Panel B) of portfolios formed on PC_NII across the 1982 to 2010 period. PC_NII is the percentage change in a stock's number of institutional investors in portfolio formation quarter *t*, which is winsorized at 1% and 99% each quarter. SIZE is market capitalization in million dollars at the end of quarter *t*. BM is the book-to-market equity ratio, for which the book value of equity is from the most recently reported fiscal quarter with a four-month reporting lag and the market value of equity is the market capitalization at the end of quarter *t*. MOM is the stock return in the previous 6 months up to the end of quarter *t*. IV is the idiosyncratic volatility of quarter *t* constructed as in Ang, Hodrick, Xing, and Zhang (2006) with at least 44 daily return observations. AMIHUD is the Amihud (2002) illiquidity measure constructed using the daily return data of quarter *t*. E_CHANGE is the seasonal change in earnings before extraordinary items from the one-year-ago quarterly value scaled by average total assets for the fiscal quarter ended in quarter *t-1*, the quarter before the portfolio formation quarter. E_SURPRISE is the most recently disclosed earnings surprise up to the end of quarter *t*, which is the difference between actual earnings per share and earliest median analyst forecast (both obtained from I/B/E/S adjusted summary history file) scaled by the stock price at the end of quarter *t-1*. We use the portfolio median for E_CHANGE and E_SURPRISE and the portfolio mean for the other variables. Raw Return and DGTW Return are, respectively, the raw return and the Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) characteristic-adjusted return in the quarter following the portfolio formation quarter. RAW EAR(-1,1) and DGTW EAR(-1,1) are, respectively, the raw return and DGTW-adjusted return in the (-1,1) earnings announcement window in the quarter following the portfolio formation quarter. We calculate the three-factor alpha using the Fama and French (1996) three-factor model, the 4-factor alpha using the Carhart (1997) four-factor model, and the five-factor alpha using the Pastor and Stambaugh (2003) five-factor model. The last three columns of Panel B report the DGTW-adjusted returns of portfolios formed on transient, quasi-indexing or dedicated PC_NII, which is the change in a stock's number of transient, quasi-indexing or dedicated institutional investors in quarter *t* scaled by the stock's number of all institutional investors at the beginning of quarter *t*. The classification of institutions follows Bushee (1998, 2001). Returns and alphas are in percentage points. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 3 Forecasting One-Quarter-ahead Returns Using Interaction Terms

	Panel A: ΔBREADTH				Panel B: PC_NII			
	ΔBREADTH	Dummy	ΔBREADTH* Dummy	Adj. R^2	PC_NII	Dummy	PC_NII* Dummy	Adj. R^2
Large Size	1.43	-0.02	-1.29	6.39%	1.97	-0.09	-0.40	6.36%
	(3.48)	(-0.10)	(-3.05)		(3.96)	(-0.42)	(-0.46)	
Large N_INST	1.26	0.43	-1.19	6.41%	2.00	0.35	-0.10	6.40%
	(3.32)	(1.78)	(-3.13)		(4.15)	(1.48)	(-0.14)	
Low Amihud	2.15	-0.05	-2.02	6.44%	2.12	-0.16	-1.20	6.44%
	(4.62)	(-0.18)	(-4.27)		(4.11)	(-0.60)	(-1.29)	
Low Dispersion	0.39	0.36	-0.28	7.48%	3.86	0.40	-1.70	7.57%
	(2.53)	(1.61)	(-1.82)		(4.31)	(1.74)	(-1.48)	
High Following	0.90	0.44	-0.75	6.97%	2.77	0.31	-0.20	7.04%
	(3.72)	(2.09)	(-3.06)		(4.50)	(1.44)	(-0.20)	
High Turnover	0.72	0.15	-0.56	6.47%	1.97	0.13	-0.60	6.49%
	(3.72)	(0.62)	(-2.44)		(4.35)	(0.56)	(-0.74)	
Low PIN	0.68	0.08	-0.53	6.02%	2.47	0.05	0.05	6.09%
	(3.07)	(0.32)	(-2.62)		(3.02)	(0.22)	(0.03)	

Note: The table reports the results of Fama-MacBeth regressions of forecasting one-quarter-ahead stock returns. The dependent variable is one-quarter-ahead stock return. Each row in Panel A represents a Fama-MacBeth regression model using ΔBREADTH, a dummy variable, and the interaction term between ΔBREADTH and the dummy variable as the independent variables. Similarly, each row in Panel B represents a Fama-MacBeth regression model using PC_NII, a control variable, and the interaction term between PC_NII and the control variable. PC_NII is the percentage change in a stock's number of institutional investors, which is winsorized at 1% and 99% each quarter. ΔBREADTH is the change in the number institutional investors normalized by the total number of institutions in the market, as adopted in Chen, Hong and Stein (2002) and Lehavy and Sloan (2008). All of the control variables are dummy variables and their constructions are straightforwardly shown by their names. For example, Large Size equals 1 if the market capitalization of the stock is larger than the sample median in a quarter and equals 0 otherwise; Large N_INST equals 1 if the number of institutional shareholders of the stock at the beginning of a quarter is larger than the sample median in that quarter and equal to 0 otherwise; etc. Beta, Size, BM, Mom, Amihud, IV and E_CHANGE are added as control variables in each regression model of the table, but their coefficients are omitted from the table for brevity. Intercept is also included in each regression model but is omitted from the table for brevity. The coefficients of PC_NII and its interaction terms with control variables are multiplied by 100 for the ease of presentation. The adjusted R^2 is the time-series mean of adjusted R-squares obtained from cross-sectional regressions. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 4 Double Sort by ΔBREADTH and PC_NII

Panel A: First by ΔBREADTH then By PC_NII								
Control Variable		PC_NII						
		1(L)	2	3	4	5(H)	5-1	*t*-Statistic
	1(L)	-1.74	-0.91	-0.12	-0.12	0.24	1.98	3.73
	2	-0.50	-0.08	0.29	0.33	0.42	0.92	2.00
ΔBREADTH	3	-0.40	0.02	-0.60	-0.16	0.17	0.57	1.39
	4	-0.16	-0.24	0.15	0.06	0.20	0.36	0.77
	5(H)	0.05	0.17	0.58	0.53	1.00	0.95	2.31
	Avg.	-0.55	-0.21	0.06	0.13	0.41	0.96	(5.52)

Panel B: First by PC_NII then by ΔBREADTH								
		ΔBREADTH						
		1(L)	2	3	4	5(H)	5-1	*t*-Statistic
	1(L)	-1.19	-0.83	-0.86	-0.42	-0.81	0.38	0.63
	2	-0.11	-0.05	0.26	0.34	0.09	0.20	0.50
PC_NII	3	0.32	0.19	-0.27	-0.34	-0.31	-0.63	-1.90
	4	0.39	0.02	-0.01	0.44	0.04	-0.35	-0.87
	5(H)	0.41	0.02	0.41	0.47	0.98	0.57	0.81
	Avg.	-0.04	-0.13	-0.09	0.10	-0.00	0.03	(0.15)

Notes: The table reports the results of double sort by ΔBREADTH and PC_NII. In Panel A, we sort stocks each quarter equally into five portfolios by ΔBREADTH and then, within each ΔBREADTH quintile, we sort stocks equally into five portfolios by PC_NII. We calculate the equal-weighted return over the next three months for each of the twenty-five portfolios. The portfolios are rebalanced every quarter. We report the Carhart (1997) four-factor alphas for the twenty-five portfolios. For each PC_NII quintile, we also average returns across the ΔBREADTH quintiles and report the Carhart alphas for each aggregate PC_NII quintile. The analysis in Panel B is similar to that in Panel A except that we sort stocks each quarter first by PC_NII then by ΔBREADTH into twenty-five portfolios. PC_NII is the percentage change in a stock's number of institutional investors, which is winsorized at 1% and 99% each quarter. ΔBREADTH is the change in the number institutional investors normalized by the total number of institutions in the market, as adopted in Chen, Hong and Stein (2002) and Lehavy and Sloan (2008). Alphas are in percentage points. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 5 Fama and MacBeth Regressions of Forecasting One-Quarter-ahead Stock Returns

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	2.44	2.48	1.17	1.66	1.98	3.48	4.02	2.65	2.55
	(2.46)	(1.71)	(0.79)	(0.90)	(2.16)	(2.31)	(2.36)	(1.75)	(1.34)
PC_NII	0.21	0.14	0.13	0.11	0.33	0.24	0.25	0.23	0.19
	(3.81)	(5.29)	(4.62)	(3.34)	(6.67)	(5.77)	(4.99)	(5.49)	(2.12)
ΔBREADTH					-0.04	-0.06	-0.05	-0.07	-0.08
					(-0.63)	(-1.54)	(-1.20)	(-1.84)	(-1.23)
ΔIO					-0.07	-0.12	-0.16	-0.11	-0.08
					(-2.47)	(-5.38)	(-5.14)	(-4.91)	(-2.31)
Short-Term ΔIO					0.03	0.01	0.05	0.01	0.03
					(1.15)	(0.66)	(1.87)	(0.51)	(1.21)
IO					0.07	0.02	-0.05	0.01	-0.09
					(1.35)	(0.43)	(-0.92)	(0.12)	(-1.52)
BWW_HM					-0.05	0.05	0.08	0.04	0.04
					(-0.65)	(1.74)	(2.55)	(1.30)	(1.01)
Beta		0.08	0.08	0.05		0.08	0.10	0.08	0.06
		(1.22)	(1.19)	(0.76)		(1.27)	(1.40)	(1.28)	(0.90)
Size		-0.09	-0.08	-0.08		-0.17	-0.18	-0.16	-0.08
		(-0.83)	(-0.74)	(-0.62)		(-1.51)	(-1.37)	(-1.47)	(-0.54)
BM		0.12	0.17	0.11		0.12	0.06	0.16	0.12
		(1.60)	(2.26)	(1.22)		(1.55)	(0.66)	(2.14)	(1.39)
MOM		0.17	0.13	0.03		0.15	0.10	0.12	0.05
		(2.70)	(2.05)	(0.43)		(2.34)	(1.39)	(1.90)	(0.66)
Amihud		-0.01	-0.00	-0.03		-0.07	-0.11	-0.07	-0.09
		(-0.10)	(-0.02)	(-0.19)		(-0.58)	(-0.76)	(-0.60)	(-0.61)
IV		-0.18	-0.19	-0.22		-0.19	-0.20	-0.19	-0.24
		(-2.13)	(-2.16)	(-2.22)		(-2.05)	(-1.92)	(-2.09)	(-2.25)
ANAL							0.07		
							(1.34)		
PC_ANAL							-0.04		
							(-1.78)		
E_CHANGE			0.23					0.18	
			(6.24)					(4.73)	
E_SURPRISE				0.27					0.26
				(5.27)					(4.99)
Adjusted R^2	0.34%	6.13%	6.42%	7.27%	1.71%	6.86%	7.11%	7.11%	8.03%

Notes: The table reports the results of Fama-MacBeth regressions of forecasting one-quarter-ahead future stock returns. The dependent variable, one-quarter-ahead stock return, is in percentage. PC_NII is the percentage change in a stock's number of institutional investors. SIZE is the log market capitalization. BM is the log book-to-market equity ratio. BETA is market beta. MOM is the stock return in the previous 6 month. E_CHANGE is the seasonal earnings growth. E_SURPRISE is the earnings surprise. AMIHUD is the illiquidity measure. IV is the idiosyncratic volatility. ΔBREADTH is the change in the number institutional investors normalized by the total number of institutions in the market. IO is the fraction of shares owned by institutions. ΔIO is the change in IO. Short-term ΔIO is the change in short-term institutions' IO. BWW_HM is Brown, Wei, and Wermers' (2014) signed herding measure. ANAL is the number of analysts following the stock at the end of current quarter *t*. PC_ANAL is the percentage change in the number of analysts following the stock during current quarter *t*. All independent variables are ranked and the respective decile ranks (from 1 to 10) of these independent variables, not the raw variables themselves, are used in the regressions. The adjusted R^2 is the time-series mean of cross-sectional regression adjusted R^2. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 6 PC_NII and Future Earnings Surprises

	Panel A: Forecast Future E_CHANGE				Panel B: Forecast Future E_SURPRISE			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-0.42	-1.74	-2.45	-2.63	-0.46	-0.89	-0.97	-0.97
	(-7.02)	(-23.82)	(-22.18)	(-18.51)	(-9.63)	(-10.71)	(-10.38)	(-6.99)
PC_NII	0.10	0.05	0.07	0.07	0.05	0.02	0.03	0.04
	(23.25)	(15.85)	(14.20)	(12.56)	(11.01)	(3.61)	(6.78)	(4.17)
E_CHANGE		0.29	0.19	0.18				
		(39.02)	(30.33)	(31.18)				
E_SURPRISE						0.10	0.07	0.08
						(10.96)	(13.28)	(10.16)
INV			0.05	0.06			0.01	0.01
			(12.03)	(7.21)			(4.08)	(0.98)
AR			0.02	0.01			0.01	0.00
			(4.43)	(2.96)			(2.71)	(0.78)
CAPX			-0.02	-0.01			0.00	0.00
			(-4.68)	(-2.29)			(1.25)	(1.01)
GM			0.06	0.07			0.02	0.02
			(13.02)	(11.97)			(4.48)	(3.87)
S&A			0.07	0.07			0.00	0.00
			(13.21)	(11.73)			(1.14)	(0.46)
AQ			-0.01	-0.01			-0.01	-0.00
			(-1.18)	(-0.50)			(-0.77)	(-0.35)
LF			0.05	0.05			0.01	0.00
			(12.04)	(9.93)			(1.54)	(0.01)
ETR				0.01				-0.01
				(4.32)				(-1.24)
EQ				0.00				0.01
				(0.20)				(0.83)
Adjusted R^2	1.32%	12.19%	15.21%	15.87%	1.02%	5.66%	6.90%	7.77%

Notes: The table reports the results of Fama-MacBeth regressions of forecasting future E_CHANGE (Panel A) and future E_SURPRISE (Panel B). The dependent variable of Panel A, Future E_CHANGE, is the seasonal earnings growth (i.e., seasonal change in earnings before extraordinary items from the one-year-ago quarterly value, scaled by its average total assets) disclosed in quarter $t+1$, the quarter following the PC_NII measurement quarter. The dependent variable of Panel B, Future E_SURPRISE, is the earnings surprise (i.e., the difference between actual earnings per share and beginning-of-the-quarter median analyst forecast, scaled by the stock price at the end of quarter t) disclosed in quarter $t+1$, the quarter following the PC_NII measurement quarter. Both variables are in percentage points. PC_NII is the percentage change in a stock's number of institutional investors. E_CHANGE is the most recently disclosed seasonal earnings growth. E_SURPRISE is the most recently disclosed earnings surprise. INV (inventory), AR (accounts receivable), CAPX (capital expenditures), GM (gross margin), S&A (selling and administrative expenses), AQ (audit qualification), LF (labor force), ETR (effective tax rate) and EQ (earnings quality) are the fundamental signals identified in Lev and Thiagarajan (1993) and used by Abarbanell and Bushee (1997, 1998) to forecast future earnings changes. We follow Abarbanell and Bushee (1998) when constructing these variables. The dependent variables, Future E_CHANGE and Future E_SURPRISE, are winsorized at 1% and 99% each quarter. All independent variables are ranked and the respective decile ranks (from 1 to 10) of these independent variables, not the raw variables themselves, are used in the regressions. The adjusted R^2 is the time-series average of cross-sectional regression adjusted R^2. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 7 Fama and MacBeth Regressions with Control for Future Earnings Surprises

	Panel A: Controlling for Future E_CHANGE				Panel B: Controlling for Future E_SURPRISE			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-2.33	3.32	2.27	1.61	-5.78	2.51	2.64	3.12
	(-2.48)	(3.37)	(1.23)	(1.09)	(-5.82)	(2.45)	(1.40)	(1.89)
Future E_CHANGE	1.10							
	(19.37)							
Future E_SURPRISE					1.64			
					(28.96)			
ORTHO PC_NII		0.07	0.01	0.00		0.13	-0.02	-0.01
		(1.38)	(0.39)	(0.03)		(2.00)	(-0.52)	(-0.41)
Beta			0.06	0.08			0.05	0.05
			(0.83)	(1.17)			(0.70)	(0.70)
Size			-0.11	-0.08			-0.14	-0.13
			(-0.82)	(-0.72)			(-1.05)	(-1.07)
B/M			0.10	0.17			0.12	0.11
			(1.10)	(2.16)			(1.28)	(1.19)
Mom			0.07	0.16			0.09	0.14
			(0.96)	(2.66)			(1.03)	(2.04)
Amihud			-0.05	0.00			-0.05	-0.08
			(-0.35)	(0.02)			(-0.31)	(-0.58)
IV			-0.21	-0.18			-0.23	-0.19
			(-2.17)	(-2.15)			(-2.12)	(-1.90)
E_SURPRISE			0.28				0.29	
			(5.29)				(5.15)	
E_CHANGE				0.24				0.15
				(6.43)				(3.21)
Adjusted R^2	2.82%	0.25%	7.19%	6.42%	5.93%	0.42%	6.47%	7.50%

Notes: The table reports the results of Fama-MacBeth regressions of forecasting one-quarter-ahead future stock returns. In each quarter, we orthogonalize PC_NII on Future E_CHANGE or Future E_SURPRISE to obtain the residuals. In Panel A, ORTHO PC_NII is the orthogonalized PC_NII on Future E_CHANGE; In Panel B, it is the orthogonalized PC_NII on Future E_SURPRISE. Future E_CHANGE, Future E_SURPRISE, and PC_NII are all winsorized at the 1 and 99 percentiles each quarter before the orthogonalization. We then use the decile ranks (from 1 to 10) of ORTHO PC_NII in the regressions. All the other independent variables (which are described in the previous tables) are also ranked and the respective decile ranks (from 1 to 10) of these independent variables, not the raw variables themselves, are used in the regressions. The adjusted R^2 is the time-series average of cross-sectional regression adjusted R^2. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 8: Earnings Quality, Idiosyncratic Volatility, and Institutional Informed Trading

	DA_Quality as Earnings Quality Measure			Abs_DA as Earnings Quality Measure			Idiosyncratic Volatility		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 4	Model 5	Model 6
Intercept	2.76	3.89	2.33	3.13	4.27	2.68	2.03	2.62	2.97
	(3.10)	(4.59)	(1.67)	(3.36)	(4.65)	(1.93)	(1.36)	(1.88)	(2.13)
PC_NII	0.22	0.01	-0.03	0.23	0.02	-0.08	-0.03	-0.10	-0.13
	(3.33)	(0.17)	(-0.61)	(3.58)	(0.40)	(-1.73)	(-0.78)	(-1.72)	(-2.17)
DA_Quality	-0.08	-0.28	-0.21					-0.19	
	(-1.14)	(-3.73)	(-4.01)					(-3.82)	
PC_NII*DA_Quality		0.04	0.03					0.02	
		(4.38)	(3.75)					(3.23)	
Abs_DA				-0.13	-0.33	-0.26			-0.25
				(-1.72)	(-4.13)	(-4.58)			(-4.59)
PC_NII*Abs_DA					0.04	0.04			0.03
					(4.39)	(4.40)			(4.22)
IV							-0.33	-0.22	-0.21
							(-3.93)	(-2.35)	(-2.35)
PC_NII*IV							0.03	0.01	0.01
							(2.72)	(1.16)	(1.07)
Control Variables			Yes			Yes	Yes	Yes	Yes
Adjusted R^2	1.14%	1.18%	6.12%	1.25%	1.30%	6.03%	6.45%	6.16%	6.06%

Notes: The table reports estimation results of Fama-MacBeth regressions that investigate the effect of earnings quality and idiosyncratic volatility on the predictive power of PC_NII for the cross-section of stock returns. The dependent variable is one-quarter-ahead, i.e., quarter *t+1*, stock returns in percentage. We use two discretionary accruals-based earnings quality measures: DA_Quality is the standard deviation of discretionary accruals in the past five fiscal years and Abs_DA is the median absolute value of discretionary accruals in the past five fiscal years. Total accruals are calculated following Sloan (1996) and the accruals-decomposition model we use is based on the modified Jones (1991) model suggested by Dechow, Sloan, and Sweeney (1995). Following Kothari, Leone and Wasley (2005), we also add return on assets (ROA) as a regressor to the discretionary accruals model. In each quarter *t*, we use the data from the most recent fiscal year when constructing the DA_Quality and Abs_DA variables; to ensure that there is no look-ahead bias in our predictive regressions for stock returns, we allow for a four-month reporting lag for both variables. PC_NII is percentage change in a stock's number of institutional investors. IV is the idiosyncratic volatility of a stock constructed as in Ang, Hodrick, Xing, and Zhang (2006) with at least 44 daily return observations in a quarter. The control variables include market beta, market capitalization, the book-to-market equity ratio, past returns, the Amihud illiquidity measure, and past earnings changes. We rank all independent variables into deciles each quarter and use their decile ranks (from 1 to 10) in the Fama and MacBeth cross-sectional regressions. PC_NII*DA_Quality, PC_NII*Abs_DA, and PC_NII*IV are the products of the decile rank of PC_NII with that of DA_Quality, Abs_DA, and IV, respectively. The adjusted R^2 is the time-series average of cross-sectional regression adjusted R^2. The Newey and West (1987) corrected *t*-statistics are reported in parentheses.

Table 9: Double-Sort Portfolios first by Earnings Quality and then by PC_NII

Panel A: First by DA_Quality then by PC_NII								
Control Variable		PC_NII						
		1(L)	2	3	4	5(H)	5-1	*t*-Statistic
DA_Quality	1(L)	0.17	0.74	0.48	-0.03	0.12	-0.05	-0.13
	2	-0.12	0.59	0.29	0.38	0.89	1.01	2.34
	3	-0.14	0.64	0.24	0.19	1.06	1.19	2.78
	4	0.06	0.51	-0.01	0.86	1.44	1.38	3.13
	5(H)	-1.66	-1.14	-0.98	0.30	0.77	2.43	3.67
	Avg.	-0.34	0.27	0.00	0.34	0.86	1.19	4.17

Panel B: First by Abs_DA then by PC_NII								
		PC_NII						
		1(L)	2	3	4	5(H)	5-1	*t*-Statistic
Abs_DA	1(L)	0.06	0.52	0.49	0.12	0.54	0.47	1.36
	2	0.12	0.78	0.06	0.29	0.65	0.53	1.44
	3	-0.04	0.56	0.10	0.73	0.68	0.72	1.92
	4	-0.50	0.26	0.22	0.41	1.02	1.52	3.47
	5(H)	-2.33	-0.80	-0.99	-0.04	0.46	2.80	3.93
	Avg.	-0.54	0.26	-0.03	0.30	0.67	1.21	4.35

Notes: The table reports the results of double-sort portfolios first by DA_Quality or Abs_DA and then by PC_NII. In Panel A, we sort stocks each quarter equally into five portfolios by DA_Quality and then, within each DA_Quality quintile, we sort stocks equally into five portfolios by PC_NII. We calculate the equal-weighted return over the next three months for each of the twenty-five portfolios. The portfolios are rebalanced every quarter. We report the Carhart (1997) four-factor alphas for the twenty-five portfolios. For each PC_NII quintile, we also average returns across the DA_Quality quintiles and report the Carhart alpha for each aggregate PC_NII quintile. The analysis in Panel B is similar to that in Panel A except that we use Abs_DA as proxy for information asymmetry. DA_Quality is the standard deviation of discretionary accruals in the past five fiscal years. Abs_DA is the median absolute value of discretionary accruals in the past five fiscal years. Total accruals are calculated following Sloan (1996) and the accruals-decomposition model we use is based on the modified Jones (1991) model suggested by Dechow, Sloan, and Sweeney (1995). Following Kothari, Leone and Wasley (2005), we also add return on assets (ROA) as a regressor to the discretionary accruals model. In each quarter *t*, we use the data from the most recent fiscal year when constructing the DA_Quality and Abs_DA variables; to ensure that there is no look-ahead bias in our predictive regressions for stock returns, we allow for a four-month reporting lag for both variables. PC_NII is percentage change in a stock's number of institutional investors. Alphas are in percentage points. The Newey and West (1987) corrected t-statistics are reported in parentheses.