Are Accruals Profits Illusory to Informed Traders?*

Qiao Liu † Rong Qi ‡

First Draft: April 2005

Abstract

We find that accruals mispricing is more pronounced for stocks with higher level of probability of informed trading (PIN). We interpret it as the evidence of informed traders using their proprietary information on accruals quality to trade against average investors. The informed traders' arbitrage generates an annualized size and book-to-market adjusted abnormal return of 19.81% over the 1993-2002 period. Using three different methods to estimate the transaction costs and the impact of various market frictions on the accruals strategy, we find that informed traders make an abnormal return of 6.5%–17.53% after trading costs. Our findings are robust to testing methods, asset pricing models used, and various ways of controlling for trading costs. They suggest that the persistence of accruals anomaly might be driven by the non-diversifiable information risk rather than higher trading costs of extreme accruals stocks. We also design a strategy for uninformed traders to mimick informed traders' behavior, and find that it generates profits equivalent to those obtained by the informed traders.

JEL Classification: G1, M4
Keywords: accruals anomaly, information cost, trading cost, limited arbitrage, trading strategy

---

*This research was substantially supported by a grant from the University Grants Committee of the Hong Kong Special Administrative Region, China (Project No. AOE/H-05/99). The views expressed are those of the authors and do not reflect official positions of Hong Kong S.A.R. All errors remain our own responsibility.

†School of Economics and Finance, Faculty of Business and Economics, University of Hong Kong, Pokfulam, Hong Kong. Phone: (852)2859-1059. Fax: (852)2548-1152. E-mail: qliu@hku.hk.

‡Tobin College of Business, St. John's University, Jamaica, NY, 11439. E-mail:rchi_1999@yahoo.com.

Are Accruals Profits Illusory to Informed Traders?

Abstract

We find that accruals mispricing is more pronounced for stocks with higher level of probability of informed trading (PIN). We interpret it as the evidence of informed traders using their proprietary information on accruals quality to trade against average investors. The informed traders' arbitrage generates an annualized size and book-to-market adjusted abnormal return of 19.81% over the 1993-2002 period. Using three different methods to estimate the transaction costs and the impact of various market frictions on the accruals strategy, we find that informed traders make an abnormal return of 6.5%–17.53% after trading costs. Our findings are robust to testing methods, asset pricing models used, and various ways of controlling for trading costs. They suggest that the persistence of accruals anomaly might be driven by the non-diversifiable information risk rather than the higher trading costs of extreme accruals stocks. We also design a strategy for uninformed traders to mimick informed traders' behavior, and find that it generates profits equivalent to those obtained by the informed traders.

JEL Classification: G1, M4

Keywords: accruals anomaly, information cost, trading cost, limited arbitrage, trading strategy

1 Introduction

One of the most robust market anomalies in the recent asset pricing literature is that the stock prices fail to impound the implications of accruals for future earnings (Sloan, 1996). It is well documented that investors fail to fully understand the differential persistence of accruals and cash flows — they tend to overweight (underweight) accruals (cash flows) when forming future earnings expectations. As a result, high-accruals firms earn lower abnormal returns than low-accruals firms.[1] A longstanding puzzle in the accruals literature is: Given the economic magnitude (around 10% in most studies) and persistence of accruals mispricing, why is the accruals anomaly not arbitraged away? Put it another way, why would the more sophisticated investors not exploit this opportunity and quickly eliminate accruals mispricing?

A priori, there are at least two reasons to expect that informed traders would exploit the accruals mis-pricing. First, informed investors have incentives to detect the information in accruals and trade on it actively, given the magnitude and persistence of accruals anomaly. Second, informed investors, relative to other investors, are able to make refined assessments of earnings quality and better understand the value implications of accruals. However, previous studies generates quite mixed evidence. Bradshaw, Richardson, and Sloan (2001) document that *analysts* and *auditors* do not anticipate the consequences of high accruals. Richardson (2000) shows that *short sellers* do not systematically trade on accruals. However, both Beneish and Vargus (2002) and Collins, Gong, and Hribar (2003) demonstrate that insiders and institutional investors are able to profit from accruals mis-pricing.

Put aside the inconclusive evidence on whether the informed traders trade on accruals information or not. The real puzzle here is, if institutional investors or insiders indeed are trading on accruals, why does the accruals anomaly not disappear? Are accruals profits illusory, even for the informed traders? Lev and Nissim (2004) suggest that accruals strategy may not be attractive to institutional investors since extreme accruals firms have characteristics institutional investors tend to avoid (i.e., small size, low stock price and book-to-market ratio). Mashruwala, Rajgopal, and

[1]The literature has offered two primary explanations for the accruals anomaly: (1) the relation between firm's accrual generating process and future earnings is sufficiently complex and investors fail to identify the transitory nature the accruals (Sloan, 1996); (2) earnings have been managed opportunistically and investors fail to recognize the low persistence of accruals (Teoh, Welch, and Wong, 1998a, 1998b; Xie, 2001; and Ali, Hwang, and Tormbley, 2001).

Shevlin (2004) attribute the persistence of accruals anomaly to high arbitrage risk. They suggest that the accruals profits observed in security prices create an illusion of trading profit opportunities when, in fact, they can hardly be captured by investors.

We believe there are two principle difficulties associated with the interpretations of the various findings in prior literature. First, because informed traders are largely unobservable, prior literature tends to use analysts, auditors, short sellers, institutional investors, or insiders as proxies for informed traders without fully discounting their disparate incentives, differentiated information generating and processing capabilities, and different presence in firms' investor base. Second, although accruals strategy might be profitable but not implementable due to high trading costs, few previous studies have clearly quantified trading costs of implementing accruals strategies.[2]

We re-examine, in this paper, the size and persistence of accruals anomaly by investigating whether informed traders can profit from trading on accruals information after explicitly controlling for trading costs. Our research design choices provide empirical leverage for addressing the two difficulties mentioned above. First, we do not require informed traders to be identified ex ante, on an *ad hoc* basis. We leverage a recent development in the market microstructure literature and infer the extent of information-based trading for a given stock purely from the trading process. We compute probability of information based trading (PIN) for each firm quarter and use it as a measure of the extent of informed trading (see Easley, Kiefer, O'Hara, and Paperman 1996). The PIN measure is directly estimated from the trade data and the literature has firmly established it as a measure of the extent of informed trading (see, e.g., Easley, Hvidkjaer, and O'Hara, 2002, among others). In our context, firms with higher PIN are the ones whose stocks are actively traded by informed traders.

Second, a key contribution of this paper is that we directly estimate the trading cost of implementing accruals strategies. We use three different methods to estimate the trading cost of accruals strategies. We are able to document a sizeable abnormal returns accrued to the informed traders (ranging from 6.5% to 17.53%) even after we subtract the trading costs. This

[2] In their study of the book-to-market anomaly, Ali, Hwang, and Trombley (2003) show that high arbitrage risk deters arbitrage activity and is an important reason that the book-to-market effect exists. However, it is not clear whether the same explanation can be applied to the accruals anomaly. Mashruwala et al. (2004) offer similar evidence on the accruals anomaly. They compute the arbitrage risk as the residual variance from the regression based on asset pricing model, and show that high arbitrage risk discourages informed traders from exploiting the arbitrage opportunity. However, none of them directly estimate the trading costs of implementing these arbitrage strategies.

finding suggests that higher trading costs, although a crucial consideration for investors interested in extreme accruals stocks, is less likely to create a serious impediment to the likely arbitrageurs of these relative mispricings. That is, high trading cost is less likely to be the primary reason explaining the persistence of accruals anomaly.

Our analysis is based on a sample of 9,940 firm year observations, consisting of 2,170 firms with December fiscal year-ends and coverage on CRSP, Compustat, and TAQ over 1993-2002. We use both the Mishkin's (1983) test and the hedge portfolio test to examine whether the accruals mispricing is more pronounced for stocks that are actively traded by informed traders (the stocks with high PIN).

Our application of the Mishkin test compares the market's valuation coefficient on accruals with the forecasting coefficient of accruals for one-year ahead earnings. When we apply the Mishkin test to three equal sub groups sorted by PIN, we find that the market valuation coefficient on accruals for the sub group with the largest average PIN is 35% bigger than its forecasting coefficient. The market valuation coefficients on accruals for the medium and low PIN sub groups are respectively 24% and 16% bigger than their corresponding forecasting coefficients. The results show that the level of informed trading is positively correlated with the extent of accruals mis-pricing.

The hedge portfolio test investigates the magnitude of the potential mis-pricing by evaluating abnormal returns to hedge portfolios formed on the basis of accruals and PIN. A standard zero investment strategy in stocks in the top and bottom deciles of accruals, but confined to the one-third of stocks with the largest PIN, yields a mean one-year-ahead cumulative size and book-to-market adjusted abnormal return of 19.8%. We then use three different methods to estimate trading cost of implementing accruals strategy. We identify an trading cost ranging from 1.81% to 11.27%.

We note that the trading cost of executing the accruals strategies, based on the LDV measure suggested in Lesmond et al. (1999), amounts to 11.27%. Such large a trading cost easily leave the accruals strategy unprofitable to average investors, which may explain the persistence of accruals anomaly to a certain extent. But, the trading costs do not constrain the informed traders. After we subtract the trading cost from the accruals profits, we find that informed traders' arbitrage generates an abnormal return of 6.5%–17.53% after trading cost, which is real and far from illusory. Trading cost, or limited arbitrage due to higher arbitrage cost documented in Mashruwala et al.

(2004) and Mitchell, Pulvino, and Stafford (2002), is less likely to be the impediment that prevents the informed investors from profiting from accruals mis-pricing.

We also conduct several robustness checks to examine whether the significant abnormal return informed traders earn from accruals strategy might be driven by confounding factors such as size, glamor-value, or momentum effects. Our evidence rules out these effects as alternative explanations for informed traders' trading profits.

Informed traders' arbitrage activities, although generate sizeable abnormal returns, cannot eliminate accruals mis-pricing. This finding provides support for a recent literature arguing that information risk (information uncertainty) is nondiversifiable and is part of the systematic risk that explains cross sectional stock returns.[3] Since information is costly and information risk is non-diversifiable, only informed traders are able to see through the low persistence of accruals, make refined assessment of accruals quality, and profit from these arbitrage opportunities. As long as information risk exists, individual investors will trade against a group of informed traders and will require a premium to compensate the risk they are bearing. The abnormal return originating from accruals strategy reflects the value of information informed traders are endowed with. Our analysis, although cannot explain how informed investors emerge and prevail, does demonstrate that as long as there is non-diversifiable information risk and informed trading, we would expect to observe accruals mispricing.

Because informed trading is highly autocorrelated (e.g., PIN in year/quarter t-1 is highly correlated with PIN in year/quarter t), we can design a trading strategy to mimic the informed traders' behavior. Specifically, when we use PIN in year t-1, instead of contemporaneous PIN, to sort stocks and form accruals-based portfolios, we are able to generate an average abnormal return of 18.69%, suggesting a promising trading strategy for investors lacking proprietary information on earnings quality.

The rest of the paper proceeds as follows. Section 2 discuss the related literature and our

[3]Zhang (2004) shows that information uncertainty helps to explain price continuation anomalies. He defines information uncertainty as "ambiguity with respect to the implications of new information for a firm's value, which potentially stems from two sources: The volatility of a firm's underlying fundamentals and poor information". Francis, LaFond, and Schipper (2004) find that accruals quality is one primary source of information uncertainty and it has a large impact on a firm's costs of equity and debt. Easley, Hvidkjaer, and O'Hara (2002) argue and show that information risk is a non-diversifiable risk factor and is systematically priced by the market.

empirical framework. Section 3 describes the sample, variables, and descriptive statistics. Section 4 shows that accruals profits are much larger for informed traders. Section 5 demonstrate that accruals profits are also real for informed traders, after subtracting trading costs. We suggest a strategy for uninformed traders to mimick informed traders in Section 6. Section 7 concludes.

2 Related Literature and Empirical Framework

2.1 Accruals Anomaly

In a seminal work, Sloan (1996) finds that investors fail to correctly price the accrual component of earnings. In particular, the investors overweigh (underweigh) accruals (cash flows). Sloan shows that a hedge strategy of buying firms with low accruals and selling firms with high accruals earns a average size-adjusted abnormal return of 10.4% in the year following portfolio formation for 1962-1991. Later research confirms and expands Sloan's finding. Subramanyam (1996), Xie (2001), and Thomas and Zhang (2002), among others, find that specific accruals (i.e., abnormal accruals, inventories, etc.) are responsible for accruals anomaly. The relationship between accruals anomaly and other anomalies, such as post-earnings announcement drift (Collins and Hribar, 2003) and glamor-value anomaly (Desai, Rajgopal, and Venkatachalam, 2004), has also been investigated.

These efforts have greatly expanded our profession's understanding about the source and nature of accruals anomaly. However, one longstanding puzzle remains: Given the relatively simple exploitation strategy of the accruals anomaly, why would more sophisticated and well endowed investors not adopt accruals strategy and quickly dissipate the anomaly? The research so far has generated inconclusive evidence. Bradshaw et al. (2001) document that analysts and auditors do not anticipate the consequences of high accruals. Richardson (2000) shows that short sellers do not systematically trade on accruals. In a contrast, Beneish and Vargus (20002) and Collins et al. (2002) find that insiders and institutional investors are able to profit from accruals mis-pricing.

The persistence of accruals anomaly, combined with paucity of evidence in support of sophisticated investors actually profiting from accruals mispricing, make researchers wonder about the illusory nature of accruals profits. Lev and Nissim (2004) suggest that accruals strategy might not be attractive to institutional investors since extreme accruals firms have characteristics institutional investors tend to avoid (i.e., small size, low stock price and book-to-market ratio, and so on). Mashruwala, Rajgopal, and Shevlin (2004) find that extreme accrual deciles do not have close substitutes. They suggest that arbitrage risk impedes arbitrageurs from eliminating anomalies in equity markets (also see Shleifer and Vishny, 1997, and Mitchell, Pulvino, and Stafford, 2002).

In order to firmly establish that higher trading costs are preventing sophisticated investors from exploiting accruals mispricing, we need to provide evidence that informed traders cannot make noticeable abnormal returns in real time. Previous literature partially achieves the goal, but the interpretations of the evidence are subject to at least two caveats. First, prior literature tends to use analysts, auditors, short sellers, institutional investors, or insiders as proxies for informed traders without fully discounting their disparate incentives, differentiated information generating and processing capabilities, and different presence in firms' investor base. Second, prior research does not directly address whether informed traders can make profits after subtracting trading costs.

In this paper, we design our empirical framework to address the pitfalls in previous research. We use actual trading data to infer the extent of informed trading, without identifying informed traders ex ante and on an ad hoc basis. We also use three different methods to calculate the real cost of implementing accruals strategy. We find that informed traders are able to make significant abnormal returns after subtracting trading costs. In the rest of the section, we will discuss how we measure the extent of informed trading, and compute trade costs of implementing accruals strategy.

2.2 Measuring the Extent of Informed Trading

Easley, Kiefer, O'Hara and Paperman (1996) develop and use the PIN variable to measure probability of informed trading in the stock market. The measure is based on the market microstructure model introduced in Easley and O'Hara (1992), where trades can come from liquidity traders or from informed traders. The literature has established the PIN variable as a good measure of the extent of information based trading in various settings.[4]

Our description of the model and how we construct the PIN measure is as follows. There are three types of players in the game, liquidity traders, informed traders, and market makers. The arrival rate of liquidity traders who submit buy orders is ϵ and that of liquidity traders who submit

[4]See, e.g., Easley, Kiefer, O'Hara, and Paperman (1996); Easley, O'Hara, and Srinivas (1998); and Easley, Hvidkjaer, and O'Hara (2002), among many others.

sell orders is also given by ϵ. Every day, the probability that an information event will occur is α, in which case the probability of bad news is δ and the probability of good news is $(1-\delta)$. If an information event occurs, the arrival rate of informed traders is μ. Informed traders submit a sell order if they get bad news and a buy order if they get good news. Thus, on a day without information events which happens with probability $(1-\alpha)$, the arrival rate of a buy order and a sell order will both be ϵ. On a day with a bad information event (with probability $\alpha\delta$), the arrival rate of a buy order will be ϵ and the arrival rate of a sell order will be $\epsilon+\mu$. On a day with a good information event (with probability $\alpha(1-\delta)$), the arrival rate of a buy order will be $\epsilon+\mu$ and the arrival rate of a sell order will be ϵ. Let $\theta=(\epsilon,\alpha,\delta,\mu)$. The likelihood function for a single trading day is given by:

$$\begin{aligned} L(\theta|B,S) \quad &= \quad (1-\alpha)e^{-\epsilon}\frac{(\epsilon)^B}{B!}e^{-\epsilon}\frac{(\epsilon)^S}{S!}+\alpha\delta e^{-\epsilon}\frac{(\epsilon)^B}{B!}e^{-\epsilon+\mu}\frac{(\epsilon+\mu)^S}{S!} \\ &\quad +\alpha(1-\delta)e^{-\epsilon+\mu}\frac{(\epsilon+\mu)^B}{B!}e^{-\epsilon}\frac{(\epsilon)^S}{S!}, \end{aligned} \tag{1}$$

where B is the number of buy orders and S is the number of sell orders in a single trading day.[5]

Using the number of buy and sell orders in every trading day in a given quarter/year $M=(B_t,S_t)_{t=1}^{T}$ and assuming cross-trading day independence, we can estimate the parameters of the model $(\epsilon,\alpha,\delta,\mu)$ by maximizing the following likelihood function:

$$L(\theta|M)=\prod_{t=1}^{t=T}L(\theta|B_t,S_t). \tag{2}$$

Thus, we estimate the probability of informed trading PIN by dividing the estimated arrival rate of informed trades by the estimated arrival rate of all trades:

$$PIN=\frac{\alpha\mu}{\alpha\mu+2\epsilon}. \tag{3}$$

We maximize the likelihood function given in equation (1) for the parameter space θ and then calculate PIN for the period 1993-2002 on a quarterly basis. The standard error of PIN is calculated using the delta method. PIN is thus used as a measure of the extent of informed

[5]The trade direction is inferred from intraday data based on the algorithm proposed in Lee and Ready (1991).

trading in our empirical analysis.

2.3 Trading Cost Estimation

Assessing the profitability of accruals strategy to informed traders require us to explicitly estimate the trading costs. The empirical literature has generated a set of methods to estimate the trading costs (i.e., see Lesmond et al., 2004; Ke and Ramalingegowda, 2004). These methods have varying strengths and weaknesses. To offer a complete picture of how trading costs affect the profitability of accruals strategy, we use three different methods.[6]

2.3.1 Direct effective spread estimate

We first compute the direct effective spread by comparing the quoted spreads to the contemporaneous execution prices. It is calculated as:

$$DES_{i,t} = \frac{1}{12}\sum_{\tau=-18}^{-6} \left| \frac{P_{i,t+\tau} - \frac{1}{2}(Ask_{i,t+\tau} + Bid_{i,t+\tau})}{P_{i,t+\tau}} \right| \tag{4}$$

Similar to Lesmond et al. (2004), we determine the trading cost of a certain stock as the average of prior 12 monthly estimates starting six months before the actual portfolio formation date. We omit the few monthly firm estimates greater than 100% to control for the influence of outliers.

One problem with the DES measure is that it only captures bid-ask spread. Total trading costs however also include applicable commissions, price impact costs, taxes, short-sale costs, and other immediacy costs. Although other components of total trading costs may not be as large as bid-ask spread, failing to include them leads to underestimated total trading costs. DES defined in (4) thus underestimates the trading costs.

2.3.2 The LDV estimate

Directly controlling for all trading cost components is necessary but empirically challenging. Lesmond, Ogden, and Trzcinka (1999) propose a way to estimate the total trading costs (also see Lesmond, Schill, and Zhou, 2004). We follow Lesmond et al. (2004) and use the LDV estimate

[6]For each of the estimators we use a sample period that precedes the portfolio formulation period to estimate the trading costs. This is done to avoid contamination, either distributional or causal, between the portfolio formation and /or the performance returns.

as our second proxy for trading costs. The LDV estimate is a more comprehensive estimate of the cost of trading since it implicitly includes not only the spread component but also the implied commissions, immediacy costs, short sale costs, and some of the price impact costs.

We discuss in detail how we estimate the LDV measure in the Appendix. Since the LDV measure is a more comprehensive variable that captures various costs involved in trading, we use it as our main proxy for the trading costs. However, as discussed in Lesmond et al. (2004), LDV has several limitations as well. LDV is estimated based on the assumption that the underlying true return distribution is normally distributed, while observed or measured return distribution is non-normal, and that prices only respond to information when the value of the information is greater than the costs of trading.

2.3.3 Ex post trading costs based on Wermers' (2000) method

We use the Wermers' (2000) method to compute the ex post trading costs (both direct and indirect) incurred by informed traders in each calender quarter (also see Ke and Ramalingegowda, 2004). Specifically, we use the following two equations to estimate the cost of purchasing stock i during quarter t, $C_{i,t}^B$, and the cost of selling stock i during quarter t, $C_{i,t}^S$.[7]

$$\begin{aligned} C_{i,t}^B &= 1.098 + 0.092 Trsize_{i,t} - 0.084 Ln(mcap_{i,t}) + 13.807(\frac{1}{P_{i,t}}), \\ C_{i,t}^S &= 0.979 + 0.214 Trsize_{i,t} - 0.059 Ln(mcap_{i,t}) + 6.537(\frac{1}{P_{i,t}}). \end{aligned} \tag{5}$$

where $Trsize$ is the trade size (dollar value of trade divided by market capitalization of the stock over a calender quarter), $Ln(mcap)$ is the natural log of market capitalization of the stock (in thousands), P is the stock price.

We note that in (5), $Trsize$ controls for the effect of trade size on trading costs. $Ln(mcap)$ captures the liquidity effect. The inverse of stock price is included because proportional fixed trading cost is expected to decrease with stock price. We do not observe the size of informed traders' trades. We choose the 25th percentile of the size of all the trades incurred in a given

[7]Because there are no Nasdaq stocks in our sample and our sample period is 1993-2002, we can use a simplified model than the ones used in Wermers (2000), and Ke and Ramalingegowda (2004).

quarter and used it as a proxy for the trade size.[8] One weakness of this measure is that it is designed to gauge trading costs for mutual funds. It is not clear whether extreme accruals stocks would have some peculiar characteristics that make the Wermers' (2000) method less applicable in our context. Therefore, the magnitude of the this measure should be interpreted with caution.

3 Data and Descriptive Statistics

In our empirical analysis, we estimate probability of information-based trading (PIN) and use it as the proxy for the informed trading. Our initial sample thus comprises all firms with coverage on TAQ for the period 1993-2002. Following Easley et al. (1996), we confine our estimation of PIN to NYSE and AMEX stocks only. Using the trade data from TAQ and following the method laid out in Section (2.2), we estimate PIN for each firm quarter. The maximum likelihood algorithm does not converge in all firm quarter regressions, we are able to obtain 16,561 firm quarter observations with converged estimated parameters.

Panel A of Table 1 presents the descriptive statistics of the set of parameters characterizing informed trading, α, μ, δ, ϵ, and PIN. The summary statistics of these parameters are similar to those identified in previous studies (i.e., Easley, Hvidkjaer, and O'Hara, 2002). Take PIN as the example, the mean and median of PIN are 0.187 and 0.170 respectively. It has a maximum of 0.816 and a minimum of 0. The standard deviation of PIN is 0.087.

Throughout our analysis, we measure accruals using the balance sheet method (see Sloan 1996) as follows:

$$Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep, \tag{6}$$

where ΔCA = change in current assets (Compustat item 4), $\Delta Cash$ = change in cash/cash equivalents (Compustat item 1), ΔCL = change in current liabilities (Compustat item 5), ΔSTD = change in debt included in current liabilities (Compustat item 34), ΔTP = change in income taxes payable (Compustat item 71), and Dep = depreciation and amortization expense (Compustat item 14).

[8] Barclay and Warner (1993) show that informed traders tend to camouflage their private information and break down large trades into medium-sized ones. As a result, the medium-sized trades drive the majority of the stock price movements. In our analysis, we also use the median of all trade sizes in a given quarter as a proxy for trade size, and find quite similar result.

Following Sloan (1996), we scale accruals by average total assets (Compustat item 6) and label the resultant variable as $Accruals$. We then define $EARN$ as the income from continuing operations divided by average total assets. CFO is defined as the difference between $EARN$ and $Accruals$. We also calculate the abnormal accruals ($ABACC$) on the basis of the modified Jones' (1991) model.

For each firm-year observation, we choose the PIN measure estimated based on the second quarter's trade data (from April to June). It is the period during which the annual reports are released and informed traders start to form their portfolios.[9] For all the firms with coverage on Compustat and CRSP, we match them with the PIN measure. We delete the firm year observations, when the PIN measures are missing. The sample is further reduced by (1) eliminating financial services firms (SIC codes 6000-6700), (2) eliminating non-December fiscal year end firms, (3) firms with insufficient data to compute accruals, (4) firms with total assets less than on million dollars, and (5) firms with discontinued operations (Compustat item 66) exceeding 5% of total assets. We are left with 9,940 firm year observations in our final sample.

We then compute $Size$ as the market capitalization (in millions) of each firm at the end of year t-1. BM is the book value of equity divided by its market value at the end of year t-1. We form one-year-ahead portfolio return on April 30, which is four months after the fiscal year end. This arrangement ensures complete dissemination of accounting information in financial statements of the previous fiscal year (year t-1). $RAWRET$ is one year ahead raw buy-and-hold return which starts to accumulate on May 1. We define the size and book-market adjusted abnormal return, $ABRET$, which is computed by taking the raw buy-and-hold return and subtracting the buy-hold return on a size and book-to-market matched value-weighted portfolio of firms. The benchmark portfolios are reconstituted at the end of each June. We first sort stocks into deciles based on firm size at the end of year t-1, we then sort the stocks within each size decile further into quintile by book-to-market (BM). Monthly benchmark portfolio returns are then computed as the value-weighted holding period buy-and-hold return of each of the portfolios.

Panel B of Table 1 presents descriptive statistics for the above variables. The average income

[9] We also use the PIN measure estimated on the basis of the first quarter's trade data as an alternative. Using it to sort stocks yields the same qualitative results, although the abnormal return generated by accruals strategy is in general 80–100 basis points lower.

($EARN$), cash flow (CFO), $accruals$, and abnormal accruals ($ABACC$) in our sample are respectively 0.11, 0.154, -0.039, and -0.003. The average of $Size$ is US$7,091 million and the average book-to-market ratio (BM) is 0.588. Our sample firms on average earn a one-year-ahead buy-and-hold return of 11.09%. The average abnormal return ($ABRET$) for our sample firms is -0.18%.

Panel C of Table 1 presents the Pearson correlations among our variables. Interestingly, PIN is positively related with $Accruals$ (not significant though). Statistical evidence does not support the argument that informed traders mainly trade stocks with higher $Accruals$, implying that it is not the level of accruals, but the quality of accruals, that attracts informed traders. PIN is also negatively correlated with both $Size$ and BM (not significant), suggesting that informed trading tends to concentrate on small and glamor stocks.

4 Can Informed Traders Profit from Accruals Mispricing?

4.1 The Mishkin Test

We first employ the Mishin's (1983) approach to examine whether the market rationally prices accruals with respect to their one-year-ahead earnings implications better for firms with higher level of informed trading. We estimate the following regression system:

$$\begin{aligned} EARN_{t+1} &= \gamma + \gamma_1 CFO_t + \gamma_2 Accruals_t + v_{t+1} \\ ABRET_{t+1} &= \alpha + \beta(EARN_{t+1} - \gamma^* - \gamma_1^* CFO_t - \gamma_2^* accruals_t) + \epsilon_{t+1}. \end{aligned} \tag{7}$$

The first equation in (7) is a forecasting equation that estimates the forecast coefficients of CFO and $Accruals$ for predicting one-year-ahead earnings. The second equation is a valuation equation that estimates the valuation coefficients that the market assigns to accruals and cash flows respectively.

We estimate the two equations jointly using an iterative generalized nonlinear least-squares estimation procedure, proceeding in two stages. In the first stage, we jointly estimate the two equations without imposing any constraints on the parameters. To test whether the valuation coefficients (the ones with *) are significantly different from the forecasting coefficients, we estimate the equation system (7) jointly in the second stage after imposing the rational pricing constraints,

$\gamma_q = \gamma_q^*$. Mishkin shows that the following likelihood ratio statistic is asymptotically $\chi^2(q)$ distributed under the null hypothesis that the market rationally prices one or more earnings components with respect to their associations with one year-ahead earnings: $2NLn(SSR^c/SSR^u)$, where q equals to the number of constraints imposed, N is the number of sample observations, SSR^C is the sum of squared residuals from the constrained regressions in the second stage, and SSR^u is the sum of squared residuals from the unconstrained regressions in the second stage. We thus reject the rational pricing of one or more earnings components if the above likelihood ratio statistic is sufficiently large.

To test whether accruals mispricing is more conspicuous for firms with high PIN, we sort our sample into three equal-sized sub-samples by contemporaneous PIN (the PIN measures estimated based on the second quarter's trade data). The sub-sample with hte highest average PIN comprises stocks with the most intense informed trading. We apply the above procedure to the three sub-samples separately and reports the results in Table 2. Panel A of Table 2 reports the Mishkin test results for stocks with low PIN. The null hypothesis that $\gamma_2^* = \gamma_2$ is easily rejected. In fact, the market overprices accruals by as much as 16%. Panels B and C report the Mishkin test results for sub-samples with medium PIN and high PIN respectively. In both tests, the null hypothesis is rejected. We find that the market overprices accruals by 24% in the medium PIN group and 35% in the high PIN group. As the level of PIN increases, the accruals mispricing becomes more pronounced.

The results from Table 2 shows that accruals mispricing is more severe for stocks, when informed trading is the most intense. Another way to interpret is that confining the accruals strategy to the stocks when informed traders have most actively engaged in trading tends to generate a larger abnormal return. That is, the informed traders seem to be leveraging their proprietary information on firms' accruals quality to make profits.

4.2 The Portfolio Tests

The results from the Mishkin's test show that accruals mispricing is more pronounced in stocks with the highest average PIN. However, its economic magnitude is still not clear. In Table 3, we examine the economic magnitude by computing the one-year-ahead returns to various portfolios sorted by *accruals* and PIN. As in Sloan (1996), we form portfolio annually by assigning firms into deciles based on total accruals. Within each decile, we then sort the stocks further into three equal-sized groups based on PIN. Table 3 reports raw one-year-ahead buy and hold returns ($RAWRET$) and size and book-to-market adjusted abnormal returns ($ABRET$) to these portfolios.

The second row of Table 3 reports the abnormal return to each accruals decile for the whole sample. The return to the hedge portfolio formed by taking a long position in the lowest accrual decile and a short position in the highest accrual decile earns a hedge return of 13.3%, which is higher than Sloan's reported 10.4%, which can be accounted for by the differences in sample period, and the way of classifying samples.

Rows 3-5 reports the size and book-to-market adjusted abnormal returns to the thirty portfolios sorted by both accruals and PIN. The zero-investment strategy confined to the low PIN stocks (shown in Row 3) yields an abnormal return of 9.01% (t = 1.96). The zero investment hedge portfolio based on stocks with medium PIN generates an $ABRET$ of 15.10% (t=3.39). In a contrast, the zero investment strategy implemented by informed traders, that is, the strategy confined to stocks with high PIN, yields an abnormal return of 19.81% (t=4.01), which is far larger than those of the sample average and the other two PIN groups. Figure 1 plots the buildup of the size and book-to-market adjusted abnormal returns to the whole sample and the three accruals-PIN-based portfolios respectively. Clearly, the abnormal return to the accruals-based portfolio is mainly driven by the return behavior of the stocks with the highest average PIN.

The results from the hedge portfolio test corroborate the Mishkin test finding that accruals mispricing is more conspicuous among stocks with high level of informed trading. If informed traders choose to trade on their information about accruals, they are able to earn an abnormal return larger than that of an average investor in the market.

As an alternative check, we also calculate the Sharpe ratios for the various hedge portfolios. We find that the Sharpe ratio for the hedge portfolio with high PIN is as large as 1.01, which presents itself as a very lucrative investment opportunity difficult to forego.

4.3 Robustness Check

We examine in Table 4 whether our results are robust to various alternative specifications. We wonder whether our results are partially driven by the size effect given that the PIN measure in our analysis has a significant negative correlation with $Size$. Also, Desai et al. (2004) provide evidence that accruals anomaly is the glamor stock phenomenon in disguise. Therefore, we wonder whether the explanatory power of PIN can be partially attributable to the book-to-market ratio (BM). To take care of these concerns, we regress PIN against $Size$, BM, leverage ratio, year dummies, industry dummies, and stock exchange dummies.[10] The residuals of the PIN regression, which are orthogonal to firm size, book-to-market, and leverage ratio are retained and used as proxies for the level of informed trading.

We conduct a two-way classification of the stocks using the residual PIN and accruals. We first sort stocks into deciles by accruals. We then divide each decile into three equally-sized groups based on the residual PIN. We compute the one-year-ahead size and book-to-market adjusted abnormal returns on each portfolio. For brevity, we only report the returns on the two extreme accruals deciles (D1 and D10) in Panel A of Table 4. The zero investment strategy (with long position in the lowest accruals decile and short position in the highest accrual decile) generates an abnormal return of 6.9% for the group of stocks with low residual PIN, 11.5% for the medium residual PIN stocks, and 16.5% for the high residual PIN stocks. We observe a monotonic pattern in the abnormal stock return when the residual PIN increases, which indicates that the residual $PIN/accruals$ trading strategy contains information orthogonal to $Size$ and BM. That is, informed traders, when they actively trade on the information in accruals, can earn an abnormal return that cannot be accounted from by either size or value-glamor effect. Being informed pays off.

Xie (2001) finds that abnormal accruals are less persistent than normal accruals and the accruals anomaly might be driven by earnings management. As a robust check, we examine whether informed traders can profit from the trading strategy based on abnormal accruals in Panel B of Table 4. We first calculate the abnormal accruals according to the modified Jones' (1991) model. We then carry out the two-way classification of stocks by PIN and abnormal accruals. We first sort stocks in our sample into deciles by abnormal accruals. We then divide each decile into three

[10] We do not report the regression results for brevity. The results are available upon request.

equally-sized groups by PIN. For brevity, we only report the size and book-to-market adjusted abnormal returns on the extreme abnormal accruals deciles. As shown in Panel B of Table 4, the zero investment strategy with long position in the lowest abnormal accruals decile and short position in the highest abnormal accruals decile earns an abnormal return of 9.8% for the low PIN stocks, 10.8% for the medium PIN stocks, and 19.1% for the high PIN stocks. The abnormal returns generated by abnormal accruals strategy are largely accounted for by high PIN stocks. Put it another way, the informed traders' trading activity drives the abnormal accruals anomaly.

Our prior analysis has used the returns to the size and book-to-market matched portfolios as benchmarks to calculate abnormal returns. As a final robustness check, we also use the Fama-French four factor model to compute the abnormal returns of the accruals-PIN-based portfolios. This check is especially important because we do not control for the momentum effect in prior analysis.

We apply a two-way classification again by using *accruals* and PIN to sort the stocks into 30 portfolios. We calculate the equal-weighted monthly portfolio returns for each portfolio for the period from May 1 of year t to April 30 of year t+1. We then run a time-series regressions using the monthly portfolio returns against the Fama-French four factors as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i Momentum_t + \epsilon_{i,t}, \tag{8}$$

where i indicates the portfolio, $R_{i,t}$ is the monthly portfolio return in month t, $R_{f,t}$ is the monthly risk-free rate, $R_{m,t}$, SMB_t, HML_t, and $Momentum_t$ capture the market, size, book-to-market, and momentum effects in month t, respectively. The intercept from the regression, α_i, represents the abnormal monthly return generated by holding portfolio i. When we multiply α_i by 12, we obtain the annualized abnormal return to portfolio i.

We report in Panel C of Table 4 the results of using the Fama-French four factor model. Again, for expositional reason, we only report the abnormal returns on the extreme accruals deciles. We find that the zero-investment strategy confined to the high PIN stocks earns an abnormal return of 17.8%. The finding implies that after controlling for the market, size, book-to-market, and momentum effects, the informed traders can still earn an abnormal return of 17.8% by trading on accruals.

5 Are Accruals Profits Real?

Our analysis in Section 4 demonstrates that informed traders are able to earn an annualized abnormal return close to 20% by trading on accruals (or abnormal accruals). However, it is not clear whether such accruals profits are real for informed traders after we take into account the trading costs. Especially, it has been found that extreme accruals decile stocks tend to have higher arbitrage costs (Mashruwala et al. 2004), and unpopular characteristics that arbitrageurs tend to avoid (Lev and Nissim, 2004). One may wonder whether the persistence of accruals anomaly is due to higher trading costs of implementing the accruals strategy.

To calculate the real trading costs of implementing accruals stategy, we use the three methods discussed in Section 2.3 to estimate the trading costs. Because the returns to various portfolios are computed using an equal weighting, the trading costs are also equal-weighted. Our trading cost estimates represent the mean *round trip* cost for trading the stocks within the respective portfolios for which obtain estimates. We compute various trading costs under two different scenarios (1) the trading costs based on 100% turnover (that is, all the positions will be closed one holding period later); (2) the trading costs based on actual turnover. In the second scenario, we take into consideration that some stocks in the extreme accruals/PIN deciles remain in the same portfolios from one holding period to another. Thus, the ongoing informed traders do not need to close the entire positions. For example, if a stock is in high PIN - highest accruals portfolio last period and remain in the same portfolio for the subsequent period, the investors do not need to incur the costs of closing out the short and then re-sorting that stock. The trading costs in the second scenario are obviously lower, and likely reflect the actual trading costs incurred.

We report the mean proportion of stocks appeared in the high PIN/lowest accruals portfolio and high PIN/highest accruals portfolio that are retained for next holding period in Table 5. The proportions are 39.6% and 38.1%, respectively. In other words, when executing the accruals strategy, the informed traders can save 38.1% of the cost in the short position and 39.6% of the cost in the long position by holding the positions in those stocks into the next period.

We first compute the direct effective spread (DES) based on equation (4). The trading cost of a certain stock is computed as the average of prior 12 monthly estimates starting six months before the actual portfolio formation date. The mean DES for high PIN/lowest accruals portfolio, as shown in Table 5, is 3.49%. The mean DES for high PIN/highest accruals portfolio is 2.86%. Thus, the total round trip costs of implementing this zero-investment strategy are 6.35% (based on 100% turnover) and 3.88% (based on actual turnover). The profits after trading costs derived from the accruals strategy by the informed traders are thus 13.46% and 15.93% respectively.

The DES measure obviously underestimates the actual trading costs incurred, because it fails to capture price impact costs, applicable commissions, taxes, short-sale costs, and other immediacy costs. The LDV estimate discussed in Section 2.3.2 and the Appendix, although an indirect measure, is comprehensive in nature. We thus use LDV as a proxy for trading costs. For each stock in respective portfolios, we estimate $\alpha_1(i)$ and $\alpha_2(i)$ on the basis of return data during the prior 12 months starting six months before the portfolio formation start date. We then calculate the equal-weighted trading costs for respective portfolios.

As shown in Table 5, the mean LDV estimate for the high PIN/lowest accruals portfolio is 4.56% and the mean LDV estimate for the high PIN/highest accruals portfolio is 6.71%. Both are much higher than their corresponding DES measures, indicating that the trading costs tend to be higher after taking into account other cost components. Based on the indirect LDV estimates, we can estimate the profitability of the accruals strategy for informed traders after trading costs. With 100% turnover, the informed traders are able to earn an average size and book-to-market adjusted abnormal return of 8.54% after trading costs. Based on the actual turnover, the round trip cost of implementing the accrual strategy is 6.9%. The abnormal return after trading costs thus increases to 12.91%. The accrual profits after trading costs are still very lucrative to the informed traders.

Finally, we use the method proposed in Wermers (2000) (also see Ke and Ramalingegowda, 2004) to estimate the trading costs. We call it WTC. For each stock, we calculate the costs of buying and selling, $C^B_{i,t}$ and $C^S_{i,t}$ respectively, on the basis of the trading information and firm-specific information in the fourth quarter of year t-1. We assume the trade size to be the 25th percentile of the size of the trades occurred in that quarter.[11]

[11] Assuming the trade size to be the 50th percentile, 10th percentile, or 5 percentile of the size of the trades in that quarter, yields trading costs at different levels. But none of them could undermine our conclusion.

We report the results in Table 5. The mean cost estimate for the high PIN/lowest accruals portfolio is 1.73% and the mean cost estimate for the high PIN/highest accruals portfolio is 1.24%. Both are much lower than corresponding DES and LDV measures. Based on these cost measures, we compute that the average abnormal return for informed traders after the trading costs (100% turnover) is 16.84%. If we consider the case of actual turnover, then the actual round trip cost will be reduced to 2.28%, which leads to an average size and book-to-market adjusted abnormal return of 17.53% (after trading costs).

We also report the Fama-French four factor adjusted abnormal returns after trading costs in Table 5. Because the hedge returns based on the four-factor model are slightly smaller (17.77% compared to 19.81%), we observe slightly smaller hedge returns after trading costs. But they still range from 6.5% to 15.49%, which pose attractive opportunities to the informed traders. Accruals profits are real for the informed traders.

Our findings are consistent with several prior studies. Francis et al. (2004) show that it is not accruals level but the quality of accruals that is systematically priced by the market. The level of accruals becomes public information after the annual reports are released, but their quality remains uncertain. According to Francis et al. (2004), " Accruals quality tells investor about the mapping of accounting earnings into cash flows. Relatively poor accruals quality weakens this mapping, therefore increases information risk." Knowing a certain firm's accruals quality is costly. Such costs are non-diversifiable and may impede individual investors from trading on accruals. The persistence of accruals anomaly may be largely accounted for by the non-diversifiable information risk rather than the trading costs or higher arbitrage risk.

6 Mimicking Informed Traders

Our empirical findings show that informed traders are able to earn a sizeable abnormal return after trading costs by implementing accruals strategy. However, the strategy is not feasible for average investors because they do not have proprietary information on the accruals quality and cannot make refined judgement about the persistence of accruals. In our empirical analysis, we sort the stocks by $accruals$ (or abnormal accruals) and the contemporaneous PIN measure, and the latter is not known to average investors.

Our proxy for informed trading, PIN, however, is highly autocorrelated. We find that the PIN measure in year t-1 is significantly correlated with the PIN measure in year t at 0.56. Although it is still unclear what accounts for such a high autocorrelation in PIN,[12] the persistence of PIN makes it possible to design a trading strategy for average investors, on the basis of our empirical finding. Specifically, the individual investors can mimic informed traders' trading strategy. In stead of using contemporaneous PIN to sort stocks, an individual investor can estimate PIN based on the trades in year t-1 ($LPIN$). Although individual investors lack proprietary information about the accruals quality, they can still mimic informed traders' behavior by forming accruals based portfolios based on $LPIN$.

To test whether this strategy is implementable in real time, we replicate our prior analysis using $LPIN$. We carry out a two-way classification to sort the our sample stocks by $LPIN$ and *accruals* into thirty portfolios. We apply the hedge portfolio test and report the results in Table 7. As shown in Table 6, a zero-investment strategy with long positions in stocks with high $LPIN$/lowest *accruals* and short positions in stocks with high $LPIN$/highest *accruals* earns an average size and book-to-market adjusted abnormal returns of 18.7%. The hedge returns for medium and low $LPIN$ stocks are 14.78% and 12.04% respectively. We note that this ex ante trading strategy based on $LPIN$ and *accruals* generates an abnormal returns similar in magnitude to that of using contemporaneous PIN. Clearly, the individual investors can mimick the trading behavior of informed traders by computing $LPIN$ based on historical trade data.

7 Concluding Remarks

In this paper we show that the hedge returns to the accruals strategy, first documented by Sloan (1996), is much larger for stocks with higher levels of information based trading (higher PIN). We interpret this finding as the evidence of informed traders using their proprietary information about the quality of accruals to trade on accruals, and against individual investors. Therefore, the larger amount of abnormal returns accrued to the informed traders reflect the value of information, which is not accessible to everyone. We use three different methods to calculate the trading costs

[12]Maybe it is due to the fact that informed traders are more likely to be attracted to firms with certain characteristics and such characteristics do not change much across time.

incurred when the informed traders implement accruals strategies. We find that informed traders are able to obtain a sizable abnormal return after the trading costs by implementing the accruals strategy. Our findings show that the persistence of accruals anomaly is unlikely to be driven by higher trading costs, or arbitrage cost. The non-diversifiable information risk seems to explain the persistence of accruals anomaly. On the basis of the high autocorrelation in PIN, we also design a trading strategy for individual investors to mimick informed traders' strategy. We find such a mimicking strategy works pretty well and generates accruals profits equivalent to those collected by informed traders.

Appendix: The LDV Estimate

The intuition of the LDV estimate is that the trading costs for arbitrageurs are revealed in firm returns if arbitrageurs (informed traders) trade only when the returns associated with trading on mispricing exceed the costs of trading. The LDV approach is characterized by the following equation:

$$\begin{aligned} R(i,t) &= R(i,t)^* - \alpha_1(i) \quad if\ R(i,t)^* \leq \alpha_1(i) \\ R(i,t) &= 0 \quad if\ \alpha_1(i) \leq R(i,t)^* \leq \alpha_2(i) \\ R(i,t) &= R(i,t)^* - \alpha_2(i) \quad if\ R(i,t)^* \geq \alpha_2(i) \end{aligned} \tag{A. 1}$$

where $\alpha_1(i) \leq 0$ is the sell-side trading cost for stock i, $\alpha_2(i) \geq 0$ is the purchase side cost, $R(i,t)$ is the measured return from CRSP, $R(i,t)^*$ is the unobserved return in a frictionless market.

The informed traders' reservation price for trades, $R(i,t)^*$, is bounded by the applicable trading costs, $\alpha_1(i)$ and $\alpha_2(i)$. If trading costs are sizeable, Lesmond et al. (2004) argue that zero return days occur more frequently since new information must accumulated longer, on average, before arbitrage capital affects prices. As a result, securities with near zero trading costs experience few zero returns and securities with high costs experience more zero returns. Using the common 'market model' ($R(i,t)^* = b(i)R_M(t) + e(i,t)$), where $R_m(t)$ is the measured CRSP daily return on the market index and $e_{i,t}$ captures all other information, to generate stock returns, $\alpha_1(i)$ and $\alpha_2(i)$ for a given stock year can be obtained by maximizing the following log-likelihood function:

$$\begin{aligned} LnL &= \sum_{R1} ln\frac{1}{(2\pi\sigma_i^2)^{\frac{1}{2}}} - \sum_{1} \frac{1}{2\sigma_i^2}(R(i,t) + \alpha_1(i) - b(i)R_M(t))^2 \\ &\quad + \sum_{R2} ln\frac{1}{(2\pi\sigma_i^2)^{\frac{1}{2}}} - \sum_{2} \frac{1}{2\sigma_i^2}(R(i,t) + \alpha_2(i) - b(i)R_M(t))^2 \\ &\quad + \sum_{R0} ln(\Phi_2(i) - \Phi_1(i)), \end{aligned} \tag{A. 2}$$

where $R1$ and $R2$ denote the region where the measured return $R(i,t)$ in the non-zero negative and positive regions, respectively, and $R_M(t)$ is the return to market portfolio on day t. The other parameters $b(i)$ and σ_i^2 represent the respective market risk beta estimate and the variance of the nonzero observed returns. The first term corresponds to the negative market returns and second term corresponds to the positive market returns of equation (A. 1). The third term corresponds to the zero-return region that spans both positive and negative market returns and represents the nontrading region of the arbitrageur. The estimates of interest are $\alpha_1(i)$ and $\alpha_2(i)$, based on which we can calculate the round trip transaction costs for stock i, $\alpha_2 - \alpha_1$. We denote it as the LDV measure. Since the above difference is an estimate of investor's reserved returns, it is relatively comprehensive in nature (see Lesmond et al. (2004) for detail about how the LDV approach is applied).

References

[1] Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2001. Accruals and future stock returns: tests of the naive investor hypothesis, *Journal of Accounting Auditing and Finance*, Vol. 15, 2.

[2] Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003. Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics*, 69, 353-373.

[3] Barclay, M., Warner, J., 1993. Stealth trading and volatility. *Journal of Financial Economics* 34, 281-305.

[4] Beneish, D., and M. Vargus, 2002. Insider trading, earnings quality and accrual mispricing, *The Accounting Review*, 77(4): 755-792.

[5] Bradshow, Mark, Scott Richardson, and Richard G. Slaon, 2001. Do analyst and suditor use information in accruals? *Journal of Accounting Research*, 39(1), 45-74.

[6] Collins, D., G. Gong, and P. Hribar, 2003. Investor sophistication and the mispricing of accruals, *The Review of Accounting Studies*, 8(2-3): 251-276.

[7] Collins, D., and P. Hribar, 2000. Earnings-based and accrual-based market anomalies: one effect or two? *Journal of Accounting and Economics* 29(1): 101-123.

[8] Desai, Hemang, Shivaram Rajgopal, and Mohan Venkatachalam, 2004. Value-Glamour and accruals mispricing: one anomaly or two, *The Accounting Review*, Vol. 79 (2): 355-385.

[9] Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002. Is information risk a determinant of asset returns? *Journal of Finance*, 57, 2185-2221.

[10] Easley, David, Nicholas Kiefer, Maureen O'Hara, and Joseph Paperman, 1996. Liquidity, information, and less-frequently traded stocks, *Journal of Finance*, 51, 1405-1436.

[11] Easley, David, Maureen O'Hara, and P.S. Srinivas, 1998. Option volumn and stock prices: evidence on where informed traders trade, *Journal of Finance*, 53, 431-465.

[12] Fama, E., and J. McBeth, 1973. Risk, retrun and equilibirum: empirical tests, *Journal of Political Economy* 81, 607-636.

[13] Francis, Jennifer, Ryan LaFond, and Katherine Schipper, 2004. The market pricing of accruals quality, *Journal of Accounting and Economics*, forthcoming.

[14] Jones, J., 1991. Earnings management during import relief investigations, *Journal of Accounting Research*, 29 (Autumn): 193-228.

[15] Ke, Bin, and Santhosh Ramalingegowda, 2004. Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics*, forthcoming.

[16] Lee, Charles M. and Mark J. Read, 1991, Inferring trade direction from intraday data. *Journal of Finance*, 46, 733-746.

[17] Lesmond, D., Ogden, J.P., Trzcinka, C.A., 1999. A new estimate of transaction costs. *The Review of Financial Studies* 12, 1113-1141.

[18] Lesmond, David A., Michael Schill, and Chunsheng Zhou, 2004. The illusory nature of momenturm profits, *Journal of Financial Economics*, 71: 349-380.

[19] Lev, Baruch, and Doron Nissim, 2004. The persistence of the accruals anomaly, working paper.

[20] Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin, 2004. Why is the accrual anomaly not arbiraged away? working paper.

[21] Mishkin, F., 1983. A rational expectations approach to macroeconometrics: testing policy effectiveness and efficient markets models, Chicago, IL: University of Chicago Press for the National Bureau of Economic Research.

[22] Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2002. Limited arbitrage in equity markets, *Journal of Finance*, 67, 551-584.

[23] Richardson, S., 2003. Earnings quality and short-sellers, *Accounting Horizons*: 49-61.

[24] Shleifer, Andrei, and Robert Vishny, 1997. The limits of arbitrage, *Journal of Finance*, 52, 35-55.

[25] Sloan, Richard, 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, Vol. 71, 3:289-315.

[26] Subramanyam, K. R., 1996, The pricing of discretionary accruals, *Journal of Accounting and Economics*, 22: 249-281.

[27] Teoh, S. H., I. Welch, and T. J. Wong, 1998a. Earnings management and the underperformance of seasoned equity offerings, *Journal of Financial Economics*, 50: 63-99.

[28] Teoh, S. H., I. Welch, and T. J. Wong, 1998b. Earnings management and the long-run market performance of initial public offerings, *Journal of Finance* 53: 1935-1974.

[29] Thomas, J. and H. Zhang. Inventory changes and future returns. *Review of Acconting Studies* 7(2):163-187.

[30] Wermers, Russ, 2000. Mutual fund performance: an empirical decomposition into stock-picking talent, style, transction costs, and expenses, *Journal of Finance*, Vol. LV, No.4, 1655-1695.

[31] Xie, Hong, 2001. The mispricing of abnormal accruals, *The Accounting Review*, 76: 357-373.

[32] Zhang, X. Frank, 2004. Information uncertainty and stock returns, *Journal of Finance*, forthcoming.

Table 1 Descriptive Statistics, 1993-2003

Panel A of the table reports the summary statistics of information-based trading parameters on the basis of Easley et al. (1996). (see the text for detail). α is the probability of information event. μ is the arrival rate of information-driven trading for a particular trading day. δ is the probability of bad news. ε is the arrival rate of noisy trading. PIN is the probability that any trading occurring at time t is information-based. These parameters are estimated on a quarterly basis using TAQ database. Panel B reports the summary statistics of all other variables. Accruals (ACC) is defined as *(ΔCA - ΔCash) – (ΔCL- ΔSTD - ΔTP) – Dep*, where ΔCA = change in current assets (Compustat item 4), ΔCash = change in cash (Compustat item 1), ΔCL = change in current liabilities (Compustat item 5), ΔSTD = change in debt included in current liabilities (Compustat item 34), ΔTP = change in income taxes payable (Compustat item 71), and Dep = depreciation and amortization expense (Compustat item 14). EARN is the income from continuing operations divided by average total assets. CFO is defined as EARN minus Accruals. *ABACCs* are the abnormal accruals estimated using modified Jones' (1991) model. *Size* is the market capitalization (in millions of dollars) for each firm at the end of each fiscal year. Book-to-market (*BM*) is the book value of equity divided by its market valued at the end of the last fiscal. *RAWRETs* are one year ahead raw buy-hold returns which start to accumulate four months after the fiscal year end. *ABRETs* are calculated by taking the raw buy-hold return and subtracting the buy-hold return on a size and book-to-market matched value-weighted portfolio of firms. The benchmark portfolios are formed each June – we first sort stocks into deciles based on firm size, then split the size deciles into quintiles based on BM. Panel C shows the correlations among the variables in our sample. The P-values for the hypothesis of correlations are zero are in squared brackets. Note that Pearson correlations are shown above the diagonal. Our sample period is from January 1993 to December 2003.

Panel A: Descriptive statistics of information-based trading parameters

	N	mean	std. dev.	minimum	Q1	median	Q3	maximum
α	16561	0.381	0.197	0.00	0.247	0.363	0.482	1.00
μ	16561	46.242	68.096	0.00	8.559	20.570	52.767	707.144
δ	16561	0.404	0.278	0.00	0.178	0.364	0.600	1.00
ε	16561	58.596	129.73	0.188	4.910	14.463	49.319	654.62
PIN	**16561**	**0.187**	**0.087**	**0.000**	**0.127**	**0.170**	**0.227**	**0.816**

Panel B: Descriptive statistics of other variables

	N	mean	std	min	Q1	median	Q3	max
EARN	9940	0.110	0.247	-0.909	0.051	0.087	0.135	7.986
CFO	9940	0.154	0.189	-0.796	0.093	0.142	0.200	5.797
Accruals	9940	-0.039	0.078	-0.626	-0.074	-0.042	-0.008	1.688
ABACC	8920	-0.003	0.064	-0.624	-0.032	-0.002	0.027	0.441
Size	16561	7091	29607	3.71	456.52	1241	3924	845032
BM	16561	0.588	0.580	0.009	0.307	0.505	0.752	25.540
RAWRET	16561	11.09%	43.74%	-97.733%	-11.745%	8.050%	26.797%	895%
ABRET	16561	-0.18%	42.67%	-177.59%	-21.27%	-2.01%	15.61%	830%

Table 1 Continued

Panel C: Correlative Matrix (Pearson correlations are shown above the diagonal)

	PIN	*Accruals*	*ABACC*	*CFO*	*EARN*	*Size*	*BM*	*RAWRET*	*ABRET*
PIN	1	0.013	0.019	-0.039	-0.001	-0.190	-0.009	0.037	0.008
		[0.211]	[0.061]	[0.001]	[0.902]	[<0.001]	[0.279]	[0.001]	[0.298]
Accruals		1	0.812	-0.302	0.112	-0.020	-0.001	-0.051	-0.065
			[<0.001]	[0.001]	[0.001]	[0.058]	[0.9477]	[0.001]	[<0.001]
ABACC			1	-0.262	0.071	-0.028	-0.002	-0.063	-0.067
				[0.001]	[0.001]	[0.007]	[0.872]	[0.001]	[<0.001]
CFO				1	0.913	0.047	-0.010	0.035	0.055
					[0.001]	[0.001]	[0.335]	[0.001]	[0.001]
EARN					1	-0.010	-0.002	0.008	0.026
						[0.241]	[0.777]	[0.379]	[0.003]
SIZE						1	-0.002	-0.022	0.010
							[0.853]	[0.014]	[0.266]
BM							1	-0.001	-0.005
								[0.910]	[0.550]
RAWRET								1	0.878
									[0.001]
ABRET									1

Table 2 Nonlinear Generalized Least Squares Estimations (The Mishkin Test) of the Market Pricing of CFO and Accruals with Respect to Their Implications for One-Year-Ahead Earnings for Sub-samples Sorted by PIN

This table reports the results of the following regressions for three sub-samples sorted by PIN:

$$EARN_{t+1} = \gamma + \gamma 1\ CFO_t + \gamma 2\ Accruals_t + v_{t+1}$$

$$ABRET_{t+1} = \alpha + \beta(EARN_{t+1} - \gamma^{*} - \gamma 1^{*} CFO_t - \gamma 2^{*} Accruals_t) + \varepsilon_{t+1}$$

In above regressions, Accruals (ACC) is defined as $(\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep$, where ΔCA = change in current assets (Compustat item 4), ΔCash = change in cash (Compustat item 1), ΔCL = change in current liabilities (Compustat item 5), ΔSTD = change in debt included in current liabilities (Compustat item 34), ΔTP = change in income taxes payable (Compustat item 71), and Dep = depreciation and amortization expense (Compustat item 14). EARN is the income from continuing operations divided by average total assets. CFO is defined as EARN minus Accruals. PIN is the estimated probability of information-based trading, which is a proxy for the intensity of informed trading in this paper. It is estimated on the basis of Easley et al. (1996) (see the text for detail). ABRETs are calculated by taking the raw buy-hold return, inclusive of dividends and any liquidating distributions and subtracting the buy-hold return on a size and book-to-market matched value-weighted portfolio of firms. The benchmark portfolios are formed each June. The return accumulation period begins four months after the fiscal year-end of the year in which the level of accruals is measured. LR Statistic = $2NLn(SSR^c/SSR^u)$.

Panel A: Low PIN sample (N=3,233)

Parameter	*Estimate*	*Asymptotic Std. Error*	*Parameter*	*Estimate*	*Asymptotic Std. Error*
γ1 (CFO)	0.948	0.035	$\gamma1^*$ (CFO)	0.848	0.35
γ2 (Accruals)	0.876	0.019	$\gamma2^*$ (Accruals)	1.019	0.101

$\gamma2^*/\gamma2$ = 1.16	*Null Hypotheses:*	*LR Statistic*	*Significant level*
	$\gamma1^* = \gamma1$	4.565	0.05
	$\gamma2^* = \gamma2$	9.160	<0.01

Panel B: Medium PIN sample (N=3,313)

Parameter	*Estimate*	*Asymptotic Std. Error*	*Parameter*	*Estimate*	*Asymptotic Std. Error*
γ1 (CFO)	0.964	0.011	$\gamma1^*$ (CFO)	0.965	0.081
γ2 (Accruals)	1.264	0.025	$\gamma2^*$ (Accruals)	1.571	0.218

$\gamma2^*/\gamma2$ = 1.24	*Null Hypotheses:*	*LR Statistic*	*Significant level*
	$\gamma1^* = \gamma1$	0.082	0.80
	$\gamma2^* = \gamma2$	9.838	<0.01

Panel C: High PIN sample (N=3,265)

Parameter	*Estimate*	*Asymptotic Std. Error*	*Parameter*	*Estimate*	*Asymptotic Std. Error*
γ1 (CFO)	*0.884*	*0.007*	$\gamma1^*$ (CFO)	*0.867*	*0.032*
γ2 (Accruals)	*0.836*	*0.018*	$\gamma2^*$ (Accruals)	*1.123*	*0.09*

$\gamma2^*/\gamma2$ = 1.35	*Null Hypotheses:*	*LR Statistic*	*Significant level*
	$\gamma1^* = \gamma1$	2.92	0.10
	$\gamma2^* = \gamma2$	45.039	<0.001

Table 3 One-Year Ahead Returns to Various Portfolios

The sample (9,940 observations) comprises all US common stocks (except financial firms) on NYSE/AMEX with December 31 year-ends and coverage on CRSP, Compustat, and TAQ from 1993 to 2003. Accruals (ACC) is defined as *(ΔCA - ΔCash) – (ΔCL- ΔSTD - ΔTP) – Dep*, where Δ*CA* = change in current assets (Compustat item 4), ΔCash = change in cash (Compustat item 1), Δ*CL* = change in current liabilities (Compustat item 5), Δ*STD* = change in debt included in current liabilities (Compustat item 34), Δ*TP* = change in income taxes payable (Compustat item 71), and *Dep* = depreciation and amortization expense (Compustat item 14). PIN is the estimated probability of information-based trading, which is a proxy for the intensity of informed trading in this paper. It is estimated on the basis of Easley et al. (1996) (see the text for detail). Portfolios are formed annually by assigning firms into deciles based on *ACC* in year t. Within deciles, we also sort the stocks into three equal groups by *PIN*. For each portfolio, we compute the one-year ahead raw stock returns (*RAWRETs*), and benchmark-adjusted abnormal returns (*ABRETs*). *ABRETs* are calculated by taking the raw buy-hold return, inclusive of dividends and any liquidating distributions and subtracting the buy-hold return on a size and book-to-market matched value-weighted portfolio of firms. The benchmark portfolios are formed each June. The return accumulation period begins four months after the fiscal year-end of the year in which the level of accruals is measured. The returns are measured in percent. t-statistics are in parentheses.

	1	2	3	4	5	6	7	8	9	10	Hedge Portfolio 1-10
RAWRET	19.182	13.563	13.787	12.877	10.307	10.171	8.869	9.046	9.475	5.410	13.772
	(3.871)	(3.327)	(2.976)	(3.271)	(2.238)	(2.354)	(2.237)	(1.916)	(2.466)	(1.397)	(6.50)
ABRET	7.388	-0.088	2.454	0.911	-1.911	-0.452	-3.712	-4.003	-0.297	-5.909	13.297
(whole sample)	(3.924)	(-0.058)	(0.913)	(0.501)	(-0.716)	(-0.237)	(-1.847)	(-1.218)	(-0.952)	(-2.590)	(7.40)
ABRET	2.596	-1.549	1.838	3.460	1.390	-3.519	-0.015	-3.989	-5.288	-6.414	9.011
(low PIN)	(0.99)	(-0.79)	(0.821)	(1.619)	(0.521)	(-1.514)	(-0.004)	(-1.148)	(-2.180)	(-2.037)	(1.96)
ABRET	8.405	-0.820	-0.241	-0.413	-3.870	-0.527	-5.668	-2.760	0.723	-6.699	15.104
(Medium PIN)	(2.715)	(-0.308)	(-0.066)	(-0.135)	(-1.299)	(-0.185)	(-3.505)	(-1.059)	(0.230)	(-2.406)	(3.39)
ABRET	11.915	2.915	4.368	3.316	-2.825	-1.009	-4.387	-3.181	-1.245	-7.894	**19.807**
(High PIN)	(4.090)	(0.725)	(1.036)	(1.385)	(-0.698)	(-0.614)	(-1.558)	(-0.506)	(-0.790)	(-2.360)	**(4.01)**

Table 4 Returns to Portfolios Sorted by Alternative Variables

Panel A of the table reports the one-year ahead benchmark adjusted buy and hold abnormal returns (*ABRETS*) for portfolios sorted by the residual *PIN*, which is the residual of the OLS regression of PIN against firm size, book-to-market, leverage ratio, year dummies and industry dummies. We first sort the stocks into deciles by *Accruals* and then sort each decile into three equally groups according to the residual *PIN*. Panel B of the table reports *ABRETs* for portfolio sorted by *ABACC* (*abnormal accruals*) and *PIN*. Panel C reports *ABRETS* for portfolios sorted by *PIN* and *Accruals*. In Panel C, we calculate the abnormal stock returns using the Fama-French four-factor model. We model the abnormal return as the intercepts of the four-factor regression model for monthly excess return. The model is:

$$R_{it}\text{-}R_{ft}=\alpha+b_i(R_{mt}\text{-}R_{ft})+s_i\, SMB_t+h_i\, HML_t+m_i\, Momentum_t+\varepsilon_{it}$$

where R_{mt}-R_{ft}, SMB, and HML are as defined in Fama and French (1996) and momentum is the momentum factor. For each of the 30 *Accruals/PIN* portfolios, we run the time-series regression using the four-factor model. The intercepts multiplied by 12 are reported. Refer to Tables 1-3 for variable definitions. Returns are in percentage term. t-statistics are in parentheses.

Panel A: *Accruals* and residual PIN (*RPIN*) classifications

		Accruals Deciles		
		D1	D10	**D1-D10**
	Low	4.573	-2.326	**6.899**
		(0.253)	(-0.954)	**(2.432)**
Residual PIN	Medium	8.351	-3.103	**11.454**
		(2.273)	(-1.240)	**(3.322)**
	High	9.260	-7.274	**16.534**
		(2.590)	(-1.502)	**(3.557)**

Panel B: *Abnormal accruals* (ABACC) and *PIN* classifications

		Abnormal Accruals Deciles		
		D1	D10	**D1-D10**
	Low	2.347	-7.466	9.814
		(0.894)	(-2.605)	(2.20)
PIN	Medium	4.699	-6.147	10.846
		(1.901)	(-2.482)	(3.387)
	High	7.297	-11.774	**19.072**
		(2.701)	(-2.372)	**(5.095)**

Panel C: Accruals and PIN classifications (using four-factor model)

		Accruals Deciles		
		D1	D10	**D1-D10**
	Low	3.852	-3.521	7.373
		(0.00)	(-0.959)	(1.01)
PIN	Medium	2.408	-7.699	10.107
		(0.593)	(-2.601)	(1.91)
	High	9.199	-8.567	**17.766**
		(1.979)	(-2.021)	**(2.15)**

Table 5 Estimates of Trading Costs and Profits from Accruals Trading Strategy

The table reports the one-year ahead benchmark-adjusted abnormal returns and various trading cost estimates associated with portfolios sorted by *Accruals* and *PIN*. We first report the position retained proportion, which is the mean ratio of stocks that remain in the respective portfolio in the following holding period. We then use three different methods to estimate transaction costs. The first one is the direct effective spread, DES (see the text for definition). For each stock, we obtain the average ask and bid quotes for the last trading hour for a randomly selected day during the third and fourth week of each calendar month for a total of 12 estimates per year. We determine transaction costs for each of the portfolio as the average prior 12 estimations staring six months before the actual portfolio formation date. The second measure is an indirect measure suggest in Lesmond et al. (2004), LDV. LDV is more comprehensive in nature and is estimated on a stock-year basis. (see the text for detail). The third method is based on Wermers (2000) and Ke and Ramalingegowda (2004) where the costs of buying and selling stocks are separately estimated. Since we do not know the trade size of the informed traders, for each stock, we select the 25th percentile of the trade size of all trades incurred in the fourth quarter of year t-1. We call it *WTC*. For each method, we report trading costs in two different scenarios: one is based on 100% turnover and the other is based on the actual turnover. The portfolio transaction costs are the equal-weighted average of individual stocks' transaction costs. Returns are in percentage term.

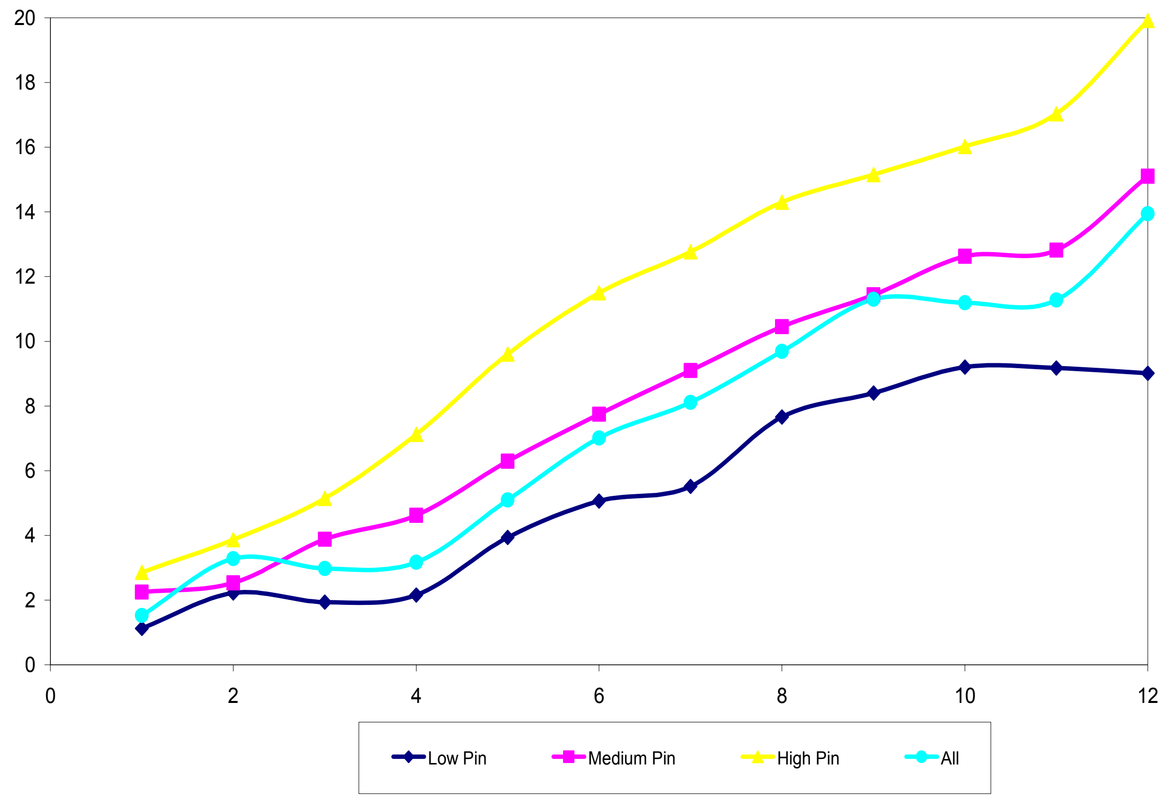
	Accruals Deciles (high PIN only)		Hedge Returns (size and BM)		Hedge Returns (the four-factor model)	
	D1	D10	before trading costs	net of trading costs	before trading costs	net of trading costs
Portfolio positions retained (% of D1 or D10)	39.6%	38.1%				
!00% turnover						
DES	3.49	2.86	19.81	**13.46**	17.77	**11.42**
LDV	4.56	6.71	19.81	**8.54**	17.77	**6.5**
WTC	1.73	1.24	19.81	**16.84**	17.77	**14.8**
Actual turnover						
DES	2.11	1.77	19.81	**15.93**	17.77	**13.89**
LDV	2.75	4.15	19.81	**12.91**	17.77	**10.87**
WTC	1.04	0.77	19.81	**17.53**	17.77	**15.49**

Table 6 Mimicking Informed Traders' Accruals Strategies

The sample (9,940 observations) comprises all US common stocks (except financial firms) on NYSE/AMEX with December 31 year-ends and coverage on CRSP, Compustat, and TAQ from 1994 to 2003. *Accruals*, *RAWRET, ABRET* are defined in Table 1. We estimate PIN on the basis of Easley et al. (1996). We sort the stocks into 30 portfolios based on *Accruals* and ***lagged PIN.*** That is, we estimate a stock's probability of information-based trading in year t-1 and use it as a sorting criterion. Since *lagged PIN* can be obtained *ex ante*, the hedge portfolio sorted by lagged PIN can be formed *ex ante*. The returns are measured in percentage term. t-statistics are in parentheses.

	1	2	3	4	5	6	7	8	9	10	Hedge Portfolio 1-10
RAWRET	19.182	13.563	13.787	12.877	10.307	10.171	8.869	9.046	9.475	5.410	13.772
	(3.871)	(3.327)	(2.976)	(3.271)	(2.238)	(2.354)	(2.237)	(1.916)	(2.466)	(1.397)	(6.50)
ABRET (whole sample)	7.388	-0.088	2.454	0.911	-1.911	-0.452	-3.712	-4.003	-0.297	-5.909	13.297
	(3.924)	(-0.058)	(0.913)	(0.501)	(-0.716)	(-0.237)	(-1.847)	(-1.218)	(-0.952)	(-2.590)	(7.40)
ABRET (low laggedPIN)	7.687	1.964	-0.126	2.676	1.200	0.121	-0.096	-5.491	-4.569	-4.352	12.039
	(2.007)	(0.761)	(-0.076)	(0.724)	(0.346)	(0.044)	(-0.026)	(-2.194)	(-1.159)	(-1.266)	(1.61)
ABRET (Medium lagged PIN)	9.979	0.875	6.630	-2.628	-6.342	3.502	-2.414	-6.245	1.198	-4.797	14.776
	(2.074)	(0.303)	(1.877)	(-0.951)	(-1.549)	(0.897)	(-0.880)	(-1.765)	(0.511)	(-0.813)	(2.02)
ABRET (High lagged PIN)	12.155	1.208	2.741	5.324	-1.179	-1.668	-1.461	-4.022	-2.443	-6.536	18.691
	(1.815)	(0.273)	(0.504)	(1.672)	(-0.290)	(-0.363)	(-0.581)	(-0.838)	(-0.750)	(-1.668)	(3.21)

Figure 1 The Size and book-to-market adjusted abnormal returns from trading on accruals information to the low PIN, medium PIN, and high PIN portfolios, and to the whole sample



This figure plots the build-up of the average size and book-to-market adjusted abnormal returns from trading on accruals information to four portfolios - the low PIN, medium PIN, and high PIN portfolios, and the whole sample – from the portfolio formation month (month 1) to one year after the portfolio formation (month 12). Returns are measured from May 1 through April 30 of the following year, and are computed in percent (along the vertical axis). The horizontal axis captures the number of months since the formation of the portfolios.